Currency Crises and their Early Warning Systems

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Jeroen van den Berg
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Chapter 1

Introduction to Early Warning Systems

Since the collapse of the Bretton-Woods system of fixed exchange rates, the occurrence of currency crises has strongly increased (Bordo, Eichengreen, Klingebiel, and Martinez-Peria, 2001), fuelling academic literature on this topic. Until the mid-1990s, research was mainly focussed on finding explanations for currency crises. The first empirical models were based on Krugman (1979) and Flood and Garber (1984), stressing that if macroeconomic policies are inconsistent with the pegged exchange rate, a forced abandonment of the peg will occur. Specifically, the behaviour of macroeconomic variables around periods of crisis or currency peg abandonments is examined (Eichengreen, Rose, and Wyplosz, 1995, 1998; Frankel and Rose, 1996; Sachs, Tornell, Velasco, Calvo, and Cooper, 1996). Especially right after severe crises the call for early warning signals by governing bodies tends to increase. This happened for example after the recent credit crunch crisis (Neuger and Deen, 2008), but also after the Mexican (1994-1995) and Asian (1997) crises. This has resulted in the emergence of two main types of Early Warning Systems (EWSs). The first EWS was a signalling model proposed by Kaminsky, Lizondo, and Reinhart (1998) (KLR), Kaminsky and Reinhart (1999). The other main type of EWS is the limited dependent variable model, where the probit branch was initiated by Berg and Pattillo (1999) (BP) and the logit branch by Kumar, Moorthy, and Perraudin (2003) (KMP).

Outside the academic world, most of the institutions are using (some improved version of) these two main types of Early Warning System. At the International Monetary Fund (IMF), three models are used. 1) A signalling approach model very similar to the original model by KLR that monitors many macroeconomic variables for 'unusual' behaviour. The probability of a crisis is then calculated based on the number of signals of unusual behaviour; 2) the Developing Country Studies Division (DCSD) model, which is a multivariate panel probit with the macroeconomic factors that have had the best track record in the past as explanatory variables; and 3) the Policy Development and Review (PDR) model, which is the DCSD model extended with balance sheet and institutional variables. In the private sector we have the GS-WATCH model of Goldman-Sachs, the Credit Suisse First Boston Emerging Markets Risk Indicator (CSFB-EMRI) and the Deutsche Bank Alarm Clock (DBAC). All of these are logit based early warning systems. A short description of the models used in practice is given in Table 1.1. Although the seminal EWSs have their fair share of extensions and improvements, many alternatives have been proposed. These models will be discussed in turn.

Of course, in order to build a model to predict currency crises one first needs to define what a currency crisis actually is. Strictly speaking, a currency crisis can only occur under a fixed exchange rate regime. A crisis is then defined as a forced abandonment of the current currency peg resulting either in a realignment of the currency or even in a complete abandonment of the fixed exchange regime. Does this then mean that currency crises can not occur under a floating exchange rate regime? No. Even floating currencies can suffer from a strong depreciation as a results of a speculative attack. Surely such a depreciation has a more disruptive effect on an economy than a controlled (minor) realignment of the fixed exchange rate. Especially when the realignment is such that it brings the real exchange rate more in line with the fundamentals, thereby decreasing the possibility of future speculative attacks. In most situations, it is sensible to define currency crises as events occurring on the exchange market that have a disruptive effects on a country's economy. In many empirical studies a currency crisis is therefore defined as a large depreciation (or devaluation). At this point two issues arise. First, how large is a large depreciation? There is no clear rule on the definition of a large depreciation. However, a depreciation is only likely to be disrupting if it is substantially larger than most other depreciations. Therefore depreciation is typically considered large when it exceeds its mean by more than two or three standard deviations. The second issue is whether the definition of a crisis should include unsuccessful speculative attacks. In response to a speculative attack on the currency, authorities can decide to intervene on the foreign exchange market in two ways. The intervention can be either directly by selling foreign currency or indirectly by raising the interest rate. As these countering actions can have a adverse effect on economic growth, one might decide to include these unsuccessful attacks in the crisis definition.

Many empirical studies indeed use the above mentioned rationale to construct a crisis indicator. The most commonly used approach for dating crises consists in taking the changes in exchange rates, international reserves and interest rates. Assign weights[1] to each and combine them into an index of speculative exchange rate pressure. A threshold level is then defined and a period of crisis is identified when the index exceeds this threshold. This idea of an Exchange Market Pressure Index (EMPI) was developed by Eichengreen et al. (1995, 1998) to capture pressure on a currency under both flexible and fixed exchange rate regimes. Under a

[1]Generally the inverse of their respective variances.

Table 1.1: EWS Models used in Public and Private Sector

Institution	EWS	Description
Currency Crises		
International Monetary Fund	KLR Crisis Signals	Indicator approach based on Kaminsky et al. (1998). Crisis probability is a composite index from a large set of monthly indicators that signal a crisis when they cross a certain threshold.
	DCSD	Developing Country Studies Division model. Multivariate probit model based on five macroeconomic predictor variables to predict currency crises.
	PDR	Policy Development and Review model. DCSD model with added balance sheet and institutional variables.
Goldman-Sachs	GS-WATCH	Predicts likelihood of a crisis, identified through EMPI, in 3 months through a logit model with mostly binary transformed macro-economic explanatory variables. Contagion is one of two continuous explanatory variables, and is measured as a weighted average of the exchange rate and reserve changes of all other countries.
Credit Suisse	CSFB-EMRI	Credit Suisse First Boston Emerging Markets Risk Indicator. Predicts the one month ahead probability of a depreciation, larger than 5 percent and at least double of preceding month, from a logit model based on macro-economic variables that are standardised with respect to their country-specific mean and variance. Generates 1-month ahead predictions.
Deutsche Bank	DBAC	Deutsche Bank Alarm Clock. Jointly estimates probabilities of large depreciation and large interest rate increase through a logit two-equation model. Generates 1-month ahead predictions.
Banking Crises		
Federal Reserve	CAMELS	Indicates the health of financial institutions based on 6 groups of indicators: Capital, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk)
	SEER	System to Estimate Examination Ratings. Based on SEER risk rank and SEER rating. SEER rating is a prediction of the next CAMELS rating through call report examination data. SEER risk rank is the probability that a bank will become undercapitalised within 2 years. A warning is issued when SEER risk rank is greater that 2 percent and SEER rating is 3 or worse.
Office of Comptroller Currency	CANARY	Bank monitoring system consisting of 4 components: Benchmarks, Credit Scope, Market Barometers, and Predictive Models.
Federal Deposit Insurance Company	SCOR	Statistical CAMELS Off-Site Ratings. Stepwise ordered logit model based on Call Reports to predict the probability for a bank of being assigned each of the 5 ratings as well as the probability of a downgrading.
French Banking Commission	SAABA	Système d'aide À l'Analyse BAncaire. Classifies banks into 5 categories based on anticipated solvency ratio, making use of internal and external rating data. Used to predict bank solvency 3 years ahead.
Asian Development Bank	Economic Monitor	The monitoring system consists of: a set of macroeconomic indicators, a non-parametric and a parametric EWS model, and a set of leading indicators of business cycles.

pure floating regime, the EMPI will increase through a depreciating exchange rate, while under a fixed exchange rate system the index will go up through a decrease of international reserves and/or an increase of the interest rate as a response to a speculative attack. Among the studies that use this approach, the exact definition of a crisis still varies considerably[2]. In particular, there are differences with respect to the inclusion of the interest rate changes, the weighting of the index components, the choice for real or nominal numbers and the threshold level.

Using the pressure index defined above, both successful and unsuccessful speculative attacks are identified. Others choose to restrict their analysis to successful attacks, identifying periods of crisis as periods in which the currency depreciates by more than a certain threshold percentage[3]. Often an additional requirement is that the depreciation needs to have accelerated with respect to the previous period in order to exclude periods immediately after a crisis and periods of controlled depreciation.

Yet other researchers use the pressure index in a slightly different manner. Ghosh and Ghosh (2003) consider only periods that are identified via the EMPI, but also have led to a decrease in GDP growth rate of minimum 3 percentage points. As such, only currency crises that have had a real impact are studied. Burkart and Coudert (2002) combine the dates found by KLR via the EMPI, with the dates found by Milesi-Ferretti and Razin (1998) that are based on depreciations larger than some threshold, and further revise the dates using 'expert judgement'. Zhang (2001) and Tudela (2004) avoid the decision about the weighting in the EMPI altogether by using the components of the pressure index separately. A crisis is then identified as a period when at least one of the components exceeds its own threshold.

Regardless of how the binary series is constructed, Harding and Pagan (2011) showed nevertheless that such constructed binary variables are not independently distributed over time. A typical time series of the binary crisis indicator consists of alternating sequences of zeros and ones, usually by default as a direct result of the construction procedure. Failing to take into account this Markov process type time dependence in an estimation of a regression on this data, may therefore lead to potentially invalid inference.

Finally, some studies reject the use of a binary crisis indicator. Their main argument is to avoid the loss of information relating to the severity of the speculative attack, that occurs when transforming a continuous index into the binary crisis variable. When transforming to a binary variable, an episode of specula-

[2]These studies include Berg, Borensztein, and Pattillo (2004), Berg and Coke (2004), Berg and Pattillo (1999), Bussiere and Fratzscher (2006), Caramazza, Ricci, and Salgado (2004), Edison (2003), Kamin, Schindler, and Samuel (2007), Kaminsky et al. (1998), Kaminsky and Reinhart (1999), Krkoska (2001), Kwack (2000), Peltonen (2002) and Weller (2001)

[3]These include Edison (2003), Brueggemann and Linne (2002), Kumar et al. (2003), Esquivel and Larrain (1998) and Osband and Van Rijckeghem (2000)

tive pressure that remains just below the threshold is considered a tranquil period similarly to times without speculative pressure. Alternatively, an extreme speculative attack is treated equal to a moderate one that only marginally exceeds the threshold. This alternative consists in using a continuous crisis variable such as the EMPI[4]. Like with the binary crisis variable, some authors prefer to look only at speculative attacks that have resulted in actual depreciations or reduced market returns (Abiad, 2003; Grier and Grier, 2001). Finally, Martinez-Peria (2002) combines the three components of the pressure index into a 3-dimensional VAR in order to capture possible dynamic interlinkages between the exchange rate, international reserves and interest rate differential. Unlike in the limited dependent variable models, using a continuous dependent variable it is not immediately obvious to calculate the probability of crisis as the output of most continuous variable models is not confined to the $[0, 1]$ interval. An often arbitrary transformation is then required to find a probability measure.

An overview of the type of models and crisis definitions used among the studies is given in Table 1.2. In the following sections we will discuss the advantages and limitations of the modelling techniques in the seminal Early Warning Systems and their spin-offs, followed by proposed alternative models. Finally, an overview is given of the topics that are addressed in this thesis.

1.1 Seminal Early Warning Systems

In this section the basic concepts and ideas behind the seminal Early Warning Systems (EWS) are explained. We start with the origin of the Early Warning System after which the discussion will focus on the technical aspects of the proposed models as well as their spin-offs. The section ends with a more empirical view.

1.1.1 Signalling Approach

In the 'first generation' models of Krugman (1979) and Flood and Garber (1984) it is shown that under fixed exchange rates and excess money demand, a domestic credit expansion leads to a gradual loss of international reserves. When the amount of reserves has sufficiently decreased, a speculative attack occurs, depleting the stock of international reserves instantaneously and forcing the governing body to abandon the parity. Both papers noticed that most speculative attacks were preceded by a real appreciation and the worsening of the trade balance, possibly due to an expansionary fiscal policy. In contrast, the 'second generation' models (e.g. Obstfeld, 1986) view currency crises as shifts between multiple equilibria instigated by self-fulfilling speculative attacks. Due to the multiple equilibria, the timing of the attack can no longer be determined. As a result, speculative at-

[4] For example Arias and Erlandsson (2004), Cerra and Saxena (2002), Krkoska (2001) and Vlaar (2000)

Table 1.2: Methods & Specifications

Research	Approach	Crisis Definition
Kaminsky, Lizondo and Reinhart (1998)	signalling	EMPI(1)[a] $>$ mean + 3 standard deviations (high inflation periods separate)
Kaminsky and Reinhart (1999)	signalling	EMPI(1)[a] $>$ mean + 3 standard deviations (high inflation periods separate)
Edison (2003)	signalling	FR[b]; EMPI(1)[a] $>$ mean + 2.5 standard deviations (high inflation periods separate)
Brueggemann and Linne (2002)	signalling	20% depreciation of nominal exchange rate w.r.t. US dollar in 10 trading days.
Berg and Patillo (1999)	probit	EMPI(1)[a] $>$ mean + 3 standard deviations (high inflation periods separate)
Berg, Borensztein and Patillo (2004)	probit	EMPI(1)[a] $>$ mean + 3 standard deviations (high inflation periods separate)
Berg and Coke (2004)	panel probit	EMPI(1)[a] $>$ mean + 3 standard deviations (high inflation periods separate)
Kamin, Schindler and Samuel (2007)	probit	EMPI(2)[c] $>$ mean + 1.75 standard deviations
Esquivel and Larrain (1998)	panel probit (random effects)	real exchange rate change $>$ 15%, or $>$ 2.54 standard deviations while also larger than 4%.
Caramazza, Ricci and Salgado (2004)	panel probit	EMPI(1)[a] $>$ mean + 1.645 standard deviations (high inflation periods separate)
Kumar, Moorthy and Perraudin (2003)	panel logit	unanticipated currency crash[d]; total depreciation crash[e]
Bussiere and Fratzscher (2006)	multinomial panel logit	EMPI(4)[f] $> \mu + 2\sigma$
Weller (2001)	panel logit	EMPI(1)[a] $>$ mean + 3 standard deviations (high inflation periods separate)
Tudela (2004)	duration (proportional hazards)	change in nominal exchange rate, nominal interest rate or international reserves exceeds individual threshold. Threshold is 1.5 st.dev. above mean (1.5 st.dev. below mean for reserves).
Zhang (2001)	duration (autoregressive conditional hazards)	change in nominal exchange rate or international reserves exceeds individual threshold. Threshold is 3 st.dev. above mean for the former and 3 st.dev. below mean for the latter.
Burkart and Coudert (2002)	Fisher discriminant analysis	combination of the identified crises by KLR, Milesi-Ferretti and Razin (1998) threshold and expert judgement
Cerra and Saxena (2002)	Markov Switching	determined endogenously by Markov switching model, based on continuous EMPI(1)[a]
Martinez (2002)	Markov Switching	determined endogenously by Markov switching model, based on 3-dimensional VAR with the dimensions being changes in exchange rate, international reserves and interest rate differential
Abiad (2003)	Markov Switching	determined endogenously by Markov switching model, based on nominal exchange rate changes
Arias and Erlandsson (2004)	Markov Switching	determined endogenously by Markov switching model, based on continuous EMPI(2)[c]
Ghosh and Ghosh (2003)	Binary Recursive Tree	EMPI(1)[a] $>$ mean + 2 standard deviations, and GDP growth declines by 3 percentage points
Grier and Grier (2001)	OLS Regression	exchange rate depreciation as dependent variable
Vlaar (2000)	mixture of normal distributions	EMPI(1)[a] as continuous dependent variable
Krkoska (2001)	Restricted VAR	EMPI(3)[g] is one of the endogenous variables in the VAR
Peltonen (2006)	Artificial Neural Network	EMPI(1)[a] $>$ mean + 2 standard deviations (high inflation periods separate)
OsbandVanRijckeghem (2000)	Identify 'safe'-zones based on indicator values	Depreciation of exchange rate $>$ 10%, and $>$ mean + 2 standard deviations (12-month mean, 24-month standard deviation)

[a] EMPI(1) is defined as in Kaminsky and Reinhart (1999): weighted average of nominal exchange rate and international reserves percentage changes

[b] Frankel and Rose (1996): currency crisis if 1) nominal exchange rate depreciates more than 25% and 2) depreciation increased more than 10% compared to the previous period

[c] EMPI(2) is defined as weighted average of real exchange rate and international reserves two-month percentage changes.

[d] 5% or 10% depreciation of the nominal exchange rate w.r.t. the US dollar corrected for the interest rate differential

[e] 5% or 10% depreciation of the nominal exchange rate w.r.t. the US dollar and the depreciation doubled compared to the previous period

[f] EMPI(4) is weighted average of real effective exchange rate, international reserves and real interest rate percentage changes

[g] EMPI(3) is defined as in Eichengreen et al. (1998): weighted average of nominal exchange rate, international reserves and nominal interest rate percentage changes

tacks can also occur even when the macroeconomic policy is consistent with the currency peg. In the 'second generation' models therefore, the direct relationship between 'bad' fundamentals and the crisis is loosened, whereas speculators' beliefs about other speculators' actions are the corner factor, thereby opening up the possibility for a contagion effect. Morris and Shin (1998) proved that a unique equilibrium may nevertheless exist when information discrepancies exist between speculators with respect to observing the fundamentals. In such a case, uncertainty about other people's expectations can still cause a speculative attack, even when all speculators know that the fundamentals are consistent with the currency peg. Not every economy appears to be equally susceptible to the contagion effect of a crisis. In 'third generation' crisis models it is explored how problems in the banking and financial sector interact with currency crises. Krugman (1999) explains the linkage between a financial crisis and a currency crisis through firms' balance sheets. A weakening currency increases the domestic value of the foreign debt of the firms, reducing their ability to invest and sparking a decrease in output. A similar argument explains the linkage between banking crises and currency crises through the foreign debt of banks. E.g. Burnside, Eichenbaum, and Rebelo (2001, 2004) show that a high amount of foreign debt makes the banking system as well as the currency vulnerable to speculative attacks. Bruinshoofd, Candelon, and Raabe (2008) use the same rationale to show that the transmission of the contagion effect to a country depends on the strength of its banking sector.

From the first generation models, one could state that the appropriate macroeconomic variables are expected to exhibit extreme behaviour just before a crisis. These macroeconomic variables can therefore be used as a leading indicator for an upcoming crisis. This has led to the Early Warning System based on the signalling approach. The signalling approach has been developed by Kaminsky et al. (1998) (KLR); Kaminsky and Reinhart (1999). The main idea is to use macro-economic variables that are related to the causes of financial crises as identified by Krugman (1979) and Flood and Garber (1984), as early indicator for upcoming crises. Although it is empirically not possible to capture speculators' expectations directly, variables that are expected to influence these expectations are included among the 105 candidate indicators. In particular, the indicators can be classified into seven categories: (1) External Sector, (2) Financial Sector, (3) Real Sector, (4) Public Finances, (5) Institutional and Structural indicators, (6) Political Variables, and (7) a binary variable indicating a crisis elsewhere as a measure of contagion. When an indicator shows extreme behaviour, i.e. it moves beyond a certain threshold level, it signals the future occurrence of a crisis.

The desired signalling horizon is set to 24 months. This means that the indicators are expected to lead a crisis by at most two years. If this is indeed the case, it is a 'correct signal', otherwise it is a 'false alarm' or 'noise'. In each month one can classify the performance of an indicator into one of the categories in Table 1.3, where an ideal indicator maximises categories A and D and minimises B and C. This will help to endogenously determine the threshold levels of the indicators.

	Crisis (within 24 months)	No Crisis (within 24 months)
Signal was issued	A	B
No signal was issued	C	D

Table 1.3: Signal Classifications

As mentioned before, a warning signal is issued when an indicator moves beyond a certain threshold value. For each variable a joint threshold value is determined for all countries in the sample. It is set at the percentile that minimises the noise-to-signal ratio[5] such that the number of correct signals is as high as possible while keeping the number of false alarms as low as possible[6]. An indicator is considered to be useful in predicting a crisis when the probability conditional on a signal of that indicator is larger than the unconditional probability. The conditional probability of crisis for an indicator is defined as the proportion of signals that is followed by at least one period of crisis in the next 24 months, whereas the unconditional probability is simply the number of crisis periods as a fraction of the total number of observations[7].

In an empirical exercise using a 1970-1995 monthly dataset with 15 emerging and 5 developed economies KLR examine which of the indicators performs best in terms of correct and false signals, in terms of average lead time and in terms of persistence of the signals. Measured jointly over all countries, out of the 105 candidates, 15 indicators are found by KLR to be useful in terms of conditional versus unconditional probability. Amongst them are the 12-month change of international reserves, real exchange rate, domestic credit, credit to the public sector and inflation.

The signalling approach has several shortcomings. First, every indicator is considered on an individual basis. This makes it hardly possible to take into account the interactions between the different macroeconomic characteristics. Second, the threshold level of a signal for each variable is determined such that it optimises the noise-to-signal ratio. Naturally, this ratio depends on the dataset. When

[5]The noise-to-signal ratio is defined as: $\frac{B/(B+D)}{A/(A+C)}$.

[6]This method has been criticised by Candelon, Dumitrescu, and Hurlin (2009) who claim that mimimising the noise-to-signal ratio leads to numerous false alarms. They opt for another method that maximises simultaneously the sensitivity (hit rate) and specificity (1 - false alarm rate).

[7]The conditional and unconditional probabilities are given by:

$$P(\text{Crisis} \mid \text{Signal}) = \frac{\text{A}}{\text{A+B}}$$

$$P(\text{Crisis}) = \frac{\text{A+C}}{\text{A+B+C+D}}$$

the sample is modified, most likely also the threshold value will change, making it a very ad-hoc procedure. Third, because of the translation of the continuous variables into binary signals, there is a loss of information in the sense that the model does not distinguish between a minor and major deviations. Fourth, it is very difficult in this model setup to find an accurate estimate of the probability of a crisis. As the probability estimate depends directly on the performance of an indicator in the sample, it is very likely that the estimate is subject to a sample bias. Kaminsky (1999) controls for this problem calculating a different probability for every indicator by forming one single composite crisis indicator. This composite index is calculated as a weighted sum of the individual indicators with the inverse noise-to-signal ratio as weights. As the weights do not add up to one, the index can also not be used as probability measure leading to the impossibility of calculating a conditional probability. Besides, this method does not remove the sample dependency of the probability of crisis. Finally, the choice of weights in the composite signal index remains somewhat arbitrary.

1.1.2 Limited Dependent Variable Model

To overcome some of the previous shortcomings, a limited dependent variable framework was proposed as alternative. Within this framework the probability of crisis is readily defined and the loss of information through the transformation of the macroeconomic indicators into binary signals disappears.

Berg and Pattillo (1999) were the first to propose a probit model as an Early Warning System. The model is a standard multivariate probit model with a binomial dependent variable that takes the value one when there is a crisis in any of the h subsequent periods. The variables that were used as indicator in the KLR model are now used as explanatory factors. This single country model can be represented as follows:

$$C_t^h = \beta' X_t + \varepsilon_t, \qquad t = \{1, \dots, T\} \tag{1.1}$$

where C_t^h is defined as the leading indicator of a crisis at time t with $h = 24$, and X_t is a matrix containing the explanatory variables. The probability of a crisis occurring within 24 months can easily be inferred from the estimated counterpart of the dependent variable. The performance of the probit model is compared to the original KLR model for the Asian Crisis. Both models are estimated on monthly data from 1970-1995 on the same 20 countries as in KLR. Out-of-sample predictions are then made for the period 1995:5-1997:12. To enhance the comparison between the non-parametric signalling approach and the parametric probit model, the probit is said to issue a warning signal for a crisis when the estimated probability rises over a given cut-off level. For the signalling approach the same is done with the probability corresponding to the composite crisis indicator. For both models the binary warning signal is then evaluated as the percentage of correct signals in the months leading up to a crisis, where in terms of the matrix in Table 1.3 the ideal model has only non-zero values in cells A and D. For both (ad hoc) cut-off levels for the crisis probability of 50% and 25%, the probit model outperforms the signalling model both in- and out-of-sample.

It may be clear that the results of a model heavily depend on the seemingly arbitrary decision made by the researcher about the cut-off threshold that determines at which probability of a crisis a warning signal is issued. When this threshold is low, few crisis will be missed but this comes at the expense of more false alarms. When the threshold is high, it is exactly the opposite. A researcher must therefore make a trade-off between failing to identify crises (type II errors) and having many false alarms (type I errors). Berg, Borensztein, and Pattillo (2004) quantify this trade-off via a loss function. It is defined as the sum of the percentage of missed crises and the percentage of false alarms. With this loss function, the optimal threshold level can be determined endogenously from the model.[8] Nevertheless, the loss function might serve a different purpose for different users of the Early Warning System. One can imagine for example that a policy maker might be more concerned about failing to signal a crisis than an impartial researcher as the loss associated with a missed crisis has more severe economic consequences than having a few extra false alarms. To capture these different levels of risk-aversion, Bussiere and Fratzscher (2006); Fuertes and Kalotychou (2007) allowed the weight (θ) of the two components of the loss function to be determined by the user of the EWS to determine which cutoff point TH gives the best trade-off between the false alarms and the missed crises:

$$\text{Loss}(TH) = \theta \cdot P(\text{No Signal} \mid \text{Crisis}) + (1-\theta) \cdot P(\text{Signal} \mid \text{No Crisis}). \quad (1.2)$$

Notice that θ close to 1 indicates a high aversion toward failing to signal a crisis, while θ close to 0 puts indicates a stronger focus on not giving too many false crisis signals.

The number of crises per country in a typical dataset can be as low as one or even none, resulting in a very low variability in the dependent variable of the probit models thus hampering a consistent estimation. To increase the number of observations, the panel dimension is often exploited. Even though this imposes a homogeneity assumption on the causes of currency crises not only over time, but also across countries. Most studies choose to pool, either with or without country-specific effects (e.g. Esquivel and Larrain, 1998; Van Rijckeghem and Weder, 2001, 2003; Caramazza, Ricci, and Salgado, 2004; Kamin, Schindler, and Samuel, 2007). The homogeneity assumption is not the only issue when using panel data techniques in this setting however. The validity of the estimation is guaranteed by assuming independence across the cross-section dimension. Most likely when different countries make up the cross-section dimension, the independence assumption is violated. In a way, the added considerations with respect to the independence and homogeneity are the price to pay in order to get sufficient

[8] Candelon, Dumitrescu, and Hurlin (2009) propose an alternative perspective by maximising the sensitivity (A/(A+C)) and specificity (D/(B+D)) of the model, which is in essence the inverse of the loss function by Berg et al. (2004).

observations to consistently estimate the probit model in this setting.

The dependent variable in the probit model in (1.1) is by construction strongly serially correlated. Whenever this variable takes the value one, it will be one for the next $h-1$ periods as well. This artificially induces serial correlation in the errors of the model. The probit estimates are still consistent but their standard errors are underestimated. Berg and Coke (2004) propose two solutions to this problem. The first solution is to estimate Heteroscedasticity- and Autocorrelation-Corrected (HAC) standard errors. The second alternative is to use bootstrap estimates of the standard errors. When applying the corrected estimators to the original data of Berg and Pattillo (1999), it turns out that only three of five variables remain significant at the 5 percent level because of the higher standard errors. Additionally, it is noteworthy that the HAC and bootstrap estimates correspond fairly closely.

Crises are by definition extreme events. As such, they lie in the tail of the distribution of realisations. As an Early Warning System's main concern is to model these extreme observations, it seems appropriate to make use of a distribution that has more weight on the tails. As the logit model is based on the extreme value distribution as opposed to the normal distribution of the probit, it makes for a good alternative (Kumar, Moorthy, and Perraudin, 2003). In the logit setup, the estimated regression is the same as in the probit case. The dependent variable is a binary variable that takes the value 1 when a crisis will occur in the near future and several macroeconomic characteristics act as explanatory variables. The probability of a crisis occurring in the near future can be found from the regression results as follows:

$$P[C_{i,t}^{h}=1]=\frac{\exp(\hat{\beta}'X_{i,t})}{\exp(1+\hat{\beta}'X_{i,t})}, \tag{1.3}$$

$$P[C_{i,t}^{h}=0]=\frac{1}{\exp(1+\hat{\beta}'X_{i,t})} \qquad i=\{1,\ldots,N\}, t=\{1,\ldots,T\}, \tag{1.4}$$

where $C_{i,t}^{h}$ is the dependent variable of the model as in the probit, $\hat{\beta}$ is the logit estimate of the parameters, and $X_{i,t}$ the matrix of explanatory variables.

Kumar et al. (2003) opt for a different method by taking the point of view of an investor. Episodes of crisis are therefore defined slightly different as well. On the one hand there is the unanticipated depreciation crash, a situation in which the return for an investor who goes short in the domestic currency and invests that money in US bonds is higher than a certain percentage. On the other hand are the total depreciation crashes, which are periods in which the depreciation vis-à-vis the US Dollar exceeds a certain percentage and this depreciation is more than double of the previous period. Even though this definition is similar to Frankel and Rose (1996) who use it to exclude periods of smooth but high depreciation, the rationale for the acceleration requirement follows from the assumption that markets' expectations of the exchange rate are based on last month's movements.

The fat-tailed extreme value distribution underlying the logit model is expected to pick up currency crashes (tail-end observations) better than the normal distribution of the probit. Indeed, in terms of explanatory power, the logit model outperforms the probit both in- and out-of-sample (Kumar et al., 2003). Nevertheless, the logit suffers from the same concerns as the probit, such as the low variability and the strong autocorrelation in the dependent variable described above[9].

1.1.3 Extensions and Empirical Issues

One of the empirical issues mentioned above is how to deal with the period following a crisis. The fundamentals of an economy still need to go through an adjustment process before they reach their long run steady state. A comparison of the mean values of fundamentals in the pre-crisis year, the post-crisis year, and the 'tranquil' periods, confirms this claim (Bussiere and Fratzscher, 2006). Whereas in the tranquil and pre-crisis periods there is on average overvaluation of the currency, it is found that in the 12 months following a crisis the exchange rate is typically undervalued. Similarly, the growth of real GDP is negative in the first year following crises, in contrast to the tranquil periods and even the pre-crisis months. Further, the short-term debt to reserves ratio and domestic credit growth are slightly higher than in tranquil months. Even though in these periods the probability of a new crisis is not larger or smaller than in tranquil months, the characteristics on the basis of which the predictions are made, still exhibit contrasting patterns. If the EWS fails to recognise this difference, there is a potential danger of a post-crisis bias. To cope with it, Bussiere and Fratzscher (2006) transform the binomial dependent variable into a multinomial one. Based on crisis dates determined via the Exchange Market Pressure Index, the dependent variable distinguishes three states of the world. The 12 months leading up to a crisis are State 1; the 12 months following a crisis are State 2; and the remaining periods are the tranquil months (State 0). When compared to traditional (binary) Early Warning Systems, the predictive performance for 32 emerging markets in 1993-2001 of the multinomial logit EWS is better both in- and out-of-sample.

As recognised by Berg and Coke (2004), the binary crisis indicator that acts as the dependent variable in logit EWSs exhibits strong autocorrelation by construction. It seems therefore logical that the lagged dependent variable is a good predictor for a crisis in the current period. Candelon, Dumitrescu, and Hurlin (2010) therefore choose to estimate a dynamic panel logit model to predict currency crises in fifteen developing economies. Using the unified testing framework of Candelon et al. (2009), it is shown that the dynamic panel logit model outperforms a set of benchmark models, including a static version of the panel logit. A critical remark must be made however. Because the binary dependent variable is close to having a unit root, the estimation of this dynamic panel logit suffers from

[9] Hartmann, Straetmans, and De Vries (2010) show that cross-sectional dependence could also be an issue when the variables in the model have a distribution with heavy tails.

two problems. First, the estimator converges very slowly. This issue is tackled by the authors through the use of a Constrained Maximum Likelihood Estimator, resulting in convergence for almost all estimated subsamples. The second problem however, still holds. As a result of the manner in which it is constructed, the lagged crisis indicator dominates the estimations. In almost all subsamples it is highly significant, whereas a limited number of independent explanatory variables retain their significance when the dynamics are introduced. This is a problem because the explanatory power of the model then comes from the artificially constructed time dependence in the dependent variable. All things considered, one needs to be very careful when introducing dynamics into a limited dependent variable EWS.

Naturally, the set of crisis indicators is also a subject of discussion as well as their robustness across different countries. As KLR based their set of indicators on crisis episodes in industrial countries, it could very well be that a different set of variables is required for developing or transition economies. One might consider indicators of capital flight risk or banking sector fragility. For this purpose Edison (2003) develops a benchmark model for the signalling approach of KLR and performs several robustness checks using a 28 country dataset of developing and industrialised economies for the period 1970-1999. The original indicators intended for industrial countries also work well for the developing countries thereby showing their robustness across country samples. Brueggemann and Linne (2002) apply the model to 8 emerging economies. Aside from the KLR indicators, good predictive power is also found for the ratio lending rate over deposit rate and the size of deposits relative to GDP. The good performance of these banking sector indicators is most likely caused by underdeveloped banking regulations in a fast growing financial market. It also indicates an interlinkage between currency and banking crises, thus highlighting the issue of a ‘twin crisis’ problem. This finding is confirmed by Weller (2001) who finds financial liberalisation as one of the culprits of the increased number of banking and currency crises in emerging economies. Specifically, following liberalisation, more liquidity enters an emerging economy, leading to an increase in speculative financing which in turn increases the likelihood of borrower default. As such, the chance of an outflow of international capital rises. Separate logit regressions on the pre- and post-liberalisation subsamples of 27 emerging economies show that the sensitivity to changes in indicators of vulnerability such as high short-term loans and a real exchange rate overvaluation increases after financial liberalisation. However, the observation that the general likelihood of a currency crisis occurrence decreases over time after liberalisation, confirms the view that the vulnerability to crisis should decrease in stable financial markets, where suitable institutions have been established. The increased vulnerability following financial liberalisation is then mainly caused through the lack of appropriate financial regulations and institutions. Emerging economies are therefore more vulnerable to the ‘twin crisis’ problem.

The last application of the seminal crisis models we will discuss here is the study of Kamin et al. (2007). They use probit models to identify the effect of domestic versus external factors on the probability of crisis in emerging markets. To this end, a dataset of 26 countries from 1981-1999 is used. An interesting finding of the study is that, compared to the domestic variables, the external variables have on average a limited effect on the probability of crisis over time, but that they contribute more to the spikes in the probability during the actual times of crisis. It results that domestic variables are the main factors determining the vulnerability of a country's economy, but that swings in the external variables might just be the factor that pushes an economy 'over the edge' into a crisis. This shows that a government can have an impact on a countries' proneness for crisis by managing their fiscal and monetary policy, accumulating less debt and providing an environment for strong GDP growth. Even though the vulnerability of crisis under poor (domestic) fundamentals is higher, this study links the occurrence of a crisis to the swings of external variables.

A joint problem for all (static) limited dependent variable models is that it is assumed that observations of the binary crisis indicator are independent over time. As mentioned above, Harding and Pagan (2011) show that this assumption is clearly violated. While the time dependence can theoretically be approximated by estimating a dynamic version of the probit/logit, the exact formulation of such a model is not straightforward. In most applications of limited dependent variable models to predicting currency crises, a static model is estimated. It must therefore be kept in mind that these models are possibly misspecified.

1.2 Other Methods

As discussed above, the seminal Early Warning Systems have not been flawless in performance, both technically and in terms of empirical results. Because they are based on the first-generation models of Krugman (1979) and Flood and Garber (1984), these EWSs have performed poorly for crises that are not evidently caused by misaligned macroeconomic fundamentals only (e.g. the Asian Crisis). However, it has been shown that a currency crisis does not necessarily need to be preceded by ongoing fiscal deficits, rising debt or falling reserves. Bad news alone about future deficits can trigger a currency crisis through the expectations of agents (Corsetti, Pesenti, and Roubini, 1999; Burnside, Eichenbaum, and Rebelo, 2001; Lahiri and Vegh, 2003). In this situation there will be no sign of poor fiscal policy in the periods preceding a crisis. In these models it is argued that the government will bail out troubled banks and that this is financed (partly) by printing money. When market agents find out that some banks are failing, they anticipate the printing of money at some point in the future. The speculative attack then takes place before the actual printing. Therefore, a currency crisis can take place without being preceded by misalignments of the macroeconomic fundamentals such as money growth, fiscal deficits, debt or reserves.

The theory that agents' expectations can trigger a speculative attack originally comes from the multiple equilibria model by Obstfeld (1994, 1996). Within this second-generation model the decisions of the central bank depend on the inflation and the deviation of output from its natural rate, where the level of output is determined through an expectations-augmented Phillips curve. This leads to the possibility of self-fulfilling expectations. Suppose for some fixed exchange rate that market agents expect a devaluation. The decision about maintaining or abandoning the peg depends on the costs associated with either outcome. If the government chooses not to devalue, inflation will be lower than expected. It follows that output will be below its natural rate. So the cost of maintaining the currency peg is the lost output. The costs of a devaluation are high inflation and possible loss of credibility of any future peg. If these are sufficiently low, the government can follow the expectations of agents and abandon the currency peg. Equivalently, when expectations are that the exchange rate will remain fixed, the optimal strategy for the government is to indeed maintain the fixed rate if the (short-term) gains from an unexpected devaluation are not too large. For a more detailed discussion of second-generation models and the exact requirements for more than one equilibrium and thereby self-fulfilling expectations, see Jeanne (2000).

The poor performance of the standard Early Warning Systems in explaining currency crises that have no clear basis in bad macroeconomic fundamentals, has led to a variety of alternative EWSs. These alternative models use different methodologies, in part to deal with the technical issues the seminal models suffer from and in part to include additional features that might capture the effects associated with the second-generation and third-generation models. The remainder of this section discusses the types of models that have been proposed along with their strengths and weaknesses.

1.2.1 Duration Approach

As discussed above, within the theory of second-generation models it is possible that expectations of agents lie at the basis of a currency crisis. In their analysis of fixed exchange rate regimes in Latin America, Klein and Marion (1997) discovered that after filtering out exogenous effects, the likelihood of a breakdown of the currency peg depends on the duration of the current regime. In the first few months after the fixed exchange regime has been installed, the probability of a devaluation increases and towards the end of the first year, it starts to decrease. An explanation of this duration dependence could be that a newly formed fixed exchange rate lacks credibility in the first months and only gains the confidence of market agents later. Klein and Marion (1997) recognise the duration dependence but explicitly reject a duration analysis as in the standard duration models the explanatory variables are assumed fixed throughout an entire period in a certain state. This is no problem when the aim of the study is to explain the duration of unemployment and the explanatory variables are workers' characteristics[10], or

[10] For example in Kiefer (1988); Pudney and Thomas (1995); Grogan and Van den Berg (2001)

when trying to determine the effect of a new drug on life expectancy and the explanatory variables are the patient's data[11]. However, when the aim is to explain the duration until the next breakdown of the fixed exchange rate regime or the next crisis, the determining factors (mostly macroeconomic variables) are most likely to change regularly. To be able to apply a duration analysis to currency crises and capture agent's expectations through duration dependence, an alternative duration model has been proposed that accommodates the duration model to time-varying explanatory factors.

Tudela (2004) strives to explain the origin of currency crises for the 20 OECD countries during the period 1970-97. A semiparametric Cox-Proportional Hazards (PH) duration model is used to relate the occurrence of crises to on the one hand, macroeconomic explanatory variables, and on the other hand, the duration pattern of the non-crisis or tranquil periods. Following the critic of Klein and Marion (1997) on standard duration models, Tudela proposes a modified duration model allowing for time-varying explanatory variables. Using this approach, one can study a country's probability to exit the state of tranquility into a currency crisis state, while accounting for duration dependence as a determinant of the likelihood of currency crises and also including macroeconomic explanatory variable as used by other researchers. Regarding the macroeconomic variables, the results are similar to findings throughout the literature. Variables influencing the probability of exit into a currency crisis state are swings in import and export growth, openness, bank deposits, claims on government and foreign portfolio investment, and the real effective exchange rate. Regarding the duration dependence, it is found that the probability of currency crisis decreases with the duration of the current period, which supports the observation of Klein and Marion (1997) and the notion that a currency gains credibility with agents when it is free of crisis for a longer period.

The semiparametric duration model as described above has two main weaknesses. The first weakness is the fact that the time dependent part of the Cox-PH model is non-parametric. In such a model, only the impact of the macroeconomic explanatory variables on the probability of crisis is estimated whereas the effect of the time spent in the current period of tranquility is measured as the residual of the estimation. Even though this method offers the greatest amount of flexibility in the relationship between the time since last the crisis and the probability of transition into crisis, it also means that the duration of the current spell plays no role in determining the hazard rate, the probability of transition. The time dependence that is found from the Cox-PH model has then a purely illustrative effect to gain insights into the distribution of the times between two crisis periods. The second weakness of the model is the lack of dynamics. This makes any conclusions about expected future durations difficult to draw.

A possibility to include dynamics in a duration model is the Autoregressive Conditional Duration (ACD) framework of Engle and Russell (1997, 1998). In the

[11] See for example Douglas and Hariharan (1994); Hamilton and Hamilton (1997).

ACD the expected duration of the next period conditional on the past durations is modelled as a function of lagged observed durations and of lagged conditional expected durations. The ACD model however, does not allow for new information about explanatory variables to enter the model during a spell between two events. When applied to the type of data it was originally developed for, the duration between two observations in high frequency tick-by-tick data, the emergence of new information between two events is not very likely. In contrast, the datasets in the crisis literature are typically at a much lower frequency. The periods of tranquility between two devaluations and/or currency crises span several months. As each month new observations of the explanatory variables become available, the model needs to be able to take into account this new information even if the period of tranquility does not end. The Autoregressive Conditional Hazards (ACH) model by Hamilton and Jordá (2002) allows to model such a feature.

The ACH model is based on the same equation for the expected duration of the next period as the ACD. This equation is transformed to calender time and together with the time-varying explanatory variables included in the equation of the hazard rate. Because Hamilton and Jordá (2002) assume an Exponential distribution of the durations, the hazard rate is defined as the inverse of the sum of the expected duration and the explanatory variables. Zhang (2001) uses the model to explain the Asian crisis and it is found that a shorter duration of the previous period increases the hazard rate (=instantaneous probability) of a new crisis, which indicates that recent turmoil decreases the confidence of agents in the currency's stability. The ACH model as defined and used by Hamilton and Jordá (2002) and Zhang (2001) has two major shortcomings. The first is the assumption of an Exponential distribution of the durations. This effectively means that the time spent in the current period, no longer has an effect on the probability of crisis. The second shortcoming is that through the inclusion of the explanatory variables additively, the hazard rate is not automatically guaranteed to be between 0 and 1. Even though this issue is circumvented by a smoothed cut-off rule, it seems inappropriate that a probability value can take values outside the $[0, 1]$ interval. A solution to these issues is provided in Chapter 4.

1.2.2 Markov Switching Approach

As shown in Jeanne and Masson (2000), the multiple equilibria model of Obstfeld (1994, 1996) can be modelled directly using a Markov-Switching model with as many states as equilibria. In most applications that model the occurrence of financial crises, the number of equilibria is assumed to be two. In the world and the accompanying Markov-Switching model two states are defined: A tranquil state and a high-volatility or speculative attack state.[12] As a result, the Markov-Switching model also has two states. The advantage of the Markov-Switching framework over for example the limited dependent variable models is that many

[12] See for example Cerra and Saxena (2002), Martinez-Peria (2002), Abiad (2003), Arias and Erlandsson (2004)

of the ad hoc decisions can be avoided. For example, the dependent variable of the logit and probit models is typically a binary variable that is derived from a market pressure index or exchange rate changes. A crisis is then defined when the respective series crosses a certain threshold. Determining such a threshold is not necessary in a Markov-Switching setup. Besides eliminating the arbitrary decision about the threshold, using the continuous pressure index also prevents any loss of information about the severity of the pressure on the currency. The Markov-Switching model has another advantage over most other model types, as it delivers a probability of crisis as well as the state of the world as output. This last feature is particularly convenient as it avoids the ad hoc decision that is required with most other models to determine the periods of crisis. In other models, the periods of crisis are determined as those periods in which the probability of crisis exceeds some cut-off value. Because the state of the world is part of the output, there is no need to define such a cut-off value under the Markov-Switching approach.[13]

While the empirical studies that employ the Markov-Switching approach vary in different respects, the results also show common features. Martinez-Peria (2002) examines speculative attacks in the European Monetary System using a 3-dimensional VAR for the three components of the pressure index by Eichengreen et al. (1998); changes in exchange rate, international reserves, and interest rate differential. Findings indicate that both variables related to the fundamental stability of a country and variables related to agents' expectations have a significant impact on the probability of transition between the two states of tranquility and speculative pressure. One would expect that this finding can be extended to the Asian Crisis. Applied to Indonesia, Cerra and Saxena (2002) find using the pressure index of ERW as dependent variable, that indeed domestic factors (financial and nonfinancial), political factors as well as contagion[14] play an important role in the occurrence of speculative attacks. Others (e.g. Abiad, 2003; Arias and Erlandsson, 2004) have also examined other Asian countries. It is confirmed that not only poor domestic fundamentals have caused the crisis, but that also external shocks (political and non-political) and contagion played their part. However, an important note must be made at this point. For the different countries, different factors were found to be most influential. This finding supports our claim in Chapter 2 that the homogeneity that is implicitly assumed when pooling data across countries is most likely not going to hold.

A last remark must be made with respect to the Markov-Switching approach when applied to currency crises. In empirical papers it is assumed that the world can be in only two states, a tranquil state and a high-volatility or turmoil state. As shown theoretically by Jeanne and Masson (2000) this assumption is not by definition valid, nor is it necessary as the Markov-Switching model also works

[13] Harding and Pagan (2002) show that in the Markov-Switching model an unobserved threshold is used to determine the state of the world.

[14] The pressure indices of Korea and Thailand are included as explanatory variables to capture market sentiment not otherwise captured.

with more than two states. The idea of more than two equilibria is empirically supported by Bussiere and Fratzscher (2006), who find success when defining a third state of the world, namely the transition period in the months following a crisis. Therefore caution is required when making assumptions about the states of the world.

1.2.3 Less Commonly Used Alternatives

As no existing model is able to predict every currency crisis perfectly, or even explain all crises with the same model ex-post, many alternative models are still being developed. In this section we discuss other types of models that have been used to explain and/or predict currency crises. For different reasons these alternatives have (not yet) had many follow-ups. Therefore there are often only one or two studies mentioned per method.

The first alternative discussed here is the Fisher Discriminant Analysis (FDA), employed by Burkart and Coudert (2002) to explain currency crises in 15 emerging market economies. There are two states of the world, the 'crisis' state and the 'tranquil' state. Periods of crisis are determined via one of the dating methods explained in the introduction. The FDA tries to find a linear combination of the included fundamentals that results in the highest difference in group means between the two states relative to its variance. The performance is measured according to this difference in means. There are a few issues associated with this method. First, an issue linked to the score of an observation. As it is the value of the linear combination of explanatory variables compared to the mean of the scores in the tranquil state, the results heavily depend on the stationarity properties of the explanatory variables. A second weakness is the fact that the probability of crisis is not a continuous output, but a step function depending on the risk category in which the score is classified. Third, the method does not allow for any econometric testing of the significance of the included explanatory variables. The decision to include a variable is based on a cut-off value completely at will of the researcher.

Ghosh and Ghosh (2003) aim to include structural variables into EWSs such as rule of law, corporate sector governance and corporate financing structure. Given that these structural variables only change occasionally, their ability to predict crises in a time-series setting is by construction limited. However, by analysing their interactions with macroeconomic fundamentals the vulnerable economies can be identified. To incorporate these interactions, the Binary Recursive Tree (BRT) technique is used. In this methodology, for each indicator a threshold is determined. The sample is then split into two branches based on the threshold of the best indicator. For each of these branches, the process is repeated with the best indicator for that branch until some stopping rule. The strength of the BRT technique is clearly the possibility to model more accurately the complex interactions between the governance, corporate and macroeconomic characteristics of a country. This comes at the cost however, of reducing all explanatory variables to binary series and thereby losing a lot of information. A further weakness of the model is the complexity of the estimations procedure because at each node the threshold value must be determined for each variable. This makes the procedure cumbersome, hence not attractive as Early Warning System.

The signalling and limited dependent variable EWSs are based on a binary crisis variable. Not only is in the construction of this variable an *ad hoc* decision required to determine the threshold level. A lot of information about the severity of the crisis is lost as well. To avoid information loss, some authors refrain from this transformation altogether and use a continuous dependent variable. Grier and Grier (2001) use the exchange rate depreciation as dependent variable in an OLS regression, while Krkoska (2001) develops a 5-dimensional VAR with the continuous pressure index, real exchange rate, industrial production, FDI and current account as the endogenous variables. Even without any additional exogenous parameters this gives 25 parameters to be estimated. For each additional variable, five more parameters enter the model. Given the limited size of a typical dataset, a large number of (ad hoc) restrictions need to be imposed on the VAR to keep the model tractable. These restrictions need to be imposed a priori, thereby leaving the method exposed to the discretion of the researcher. A general disadvantage of using a continuous variable as a measure of currency crisis is that it becomes very difficult to defer a sensible measure for the probability of crisis as it remains unclear at which level of depreciation or other measure one speaks of a crisis. Vlaar (2000) however proposes an alternative method with the continuous Exchange Market Pressure Index as dependent variable, but avoids these problems by modelling the pressure index as a draw from a mixture of two normal distributions. The distributions correspond to two regimes, one for tranquil times and one for times of turmoil. Both the probability of entering the crisis regime and the severity of the crisis depend on the economic situation. In practice, the model has a tendency to generate relatively many false alarms. Due to the randomness of the draw from the mixed distribution, it can happen that a crisis is signalled for no apparent reason. For example, Vlaar (2000) falsely detects one third of the tranquil periods as a crisis period.

Artificial Neural Networks (ANN) are successfully employed to model other binary models such as bank failures. Peltonen (2006) proposes such a setup as Early Warning System. This model works in three layers, an input layer (the economic characteristics), a hidden layer, and an output layer (the crisis signal). The inputs affect the hidden variables in the middle layer and these in turn determine whether or on there is a crisis signalled. This 'black box' mechanism has a few drawbacks. Firstly, the strength of the ANN model, its extreme flexibility to fit well to the data can lead to overfitting. Secondly, a closed form solution is not guaranteed. This makes interpreting the coefficients more difficult than with linear models. When compared with a probit model on a dataset of 24 emerging countries, the ANN model performs only marginally better than the probit. Due to its low transparency and difficult to interpret output combined with only marginally improved results, the ANN approach does not make an attractive practical Early Warning System.

Whereas most studies aim to identify the situations in which a currency crisis is most likely to occur, Osband and Van Rijckeghem (2000) take the opposite route by identifying 'safety zones'. Based on these safety zones, the values of macroeconomic fundamentals are identified for which currency crises never occur. These fundamentals can then be used as guidelines for policymakers to keep the currency free of speculative attacks. This coincides with the theory about the possibility of multiple equilibria and the self-fulfilling expectations (Obstfeld, 1994). The existence of multiple equilibria however, depends on the fundamentals. Specifically, under sufficiently strong fundamentals, a speculative attack may even never occur (Krugman, 1979; Jeanne, 1997; Flood and Marion, 1999). The identification of safety zones might be troubled by a possible drawbacks. Suppose that somewhere in the past a crisis has occurred in a situation in which the fundamentals were pretty solid. This could then lead to very high thresholds of guaranteed safety. As a result very few observations are considered 'safe', thereby removing almost all practical use of the model. A second issue is that the model is in essence not an EWS. Nevertheless, it can be used in combination with other early warning systems. By filtering out 'safe' currencies first, the fit of the existing EWS can improve as the danger of pooling non-homogenous data reduces.

1.3 Concluding Remarks

The literature on Early Warning Systems has soared along with the increased occurrence of financial turmoil. In this chapter many types of Early Warning Systems for currency crises have been discussed, each with their own strengths and weaknesses. Notwithstanding the vast amount of literature, several issues have not (yet) been resolved. Nor has an Early Warning Systems been developed that perfectly predicts all crises. One thesis is not enough to tackle all these issues at once, therefore the choice is made to tackle some in our view very problematic ones on the way to hopefully a better Early Warning System. Therefore, the models in this thesis will also have some shortcomings. This section gives an overview of the specific issues that will be addressed in the remaining chapters of this work.

A considerable amount of papers (inter alii Berg and Coke, 2004; Esquivel and Larrain, 1998; Caramazza et al., 2004; Kumar et al., 2003; Bussiere and Fratzscher, 2006; Weller, 2001), adopt a panel data framework where data for several countries are pooled. This pooling is mainly motivated by an efficiency argument because pooling countries increases the number of useful observations. As such, it should lead to a gain in accuracy when estimating the underlying models. In this setup, it is important however to verify the cross-sectional homogeneity of the individual country models. Through pooling one makes the assumption that not only the same factors are supposed to explain adequately financial crises, but also that the parameters may be assumed constant and homogenous across the cross section dimension. Under these restrictive assumptions, heterogeneity can then be captured by a fixed effect dummy and all other features of the models are assumed to be common to all the countries in the panel. This assumption contradicts however two well-known features of financial crises: First, not all crises have the same underlying causes. While some are the consequences of macroeconomic fundamentals, others might be driven by psychological factors such as the self-fulfilling prophecy or by a weak bank balance sheet. Second, the literature on the Asian Crisis of 1997-98 has shown that spill-over effects are important determinants in the transmission of a financial crisis. This means that turmoil can be transmitted from one country to another, possibly leading to dynamic cross-sectional dependence. The aggregation and pooling of these countries might not only lead to a loss of information, but when the cross-sectional dependence is not accounted for, it could also severely affect the estimation and inference. Chapter 2 focusses on this poolability issue. Applying a panel-logit model of emerging market economies, it is shown that researchers should not naively pool all the data available for a maximum number of countries, because the quality of the prediction would seriously decrease. A preliminary analysis of optimal country clusters before setting up the panel-logit model is proposed.

From Chapter 3 on, the analyses are based on the duration approach. This approach facilitates that the probability of crisis can depend on the duration since the last crisis, which acts as an approximation for the sentiments of market agents. This duration dependence was recognised by Klein and Marion (1997) and developed into an EWS by Tudela (2004). In Chapter 3 a fully parametric alternative is proposed to the semiparametric duration model of Tudela. The model is also used to examine the probability to exit the crisis state. This information is useful for policymakers to adjust their strategy for dealing with an ongoing crisis.

The duration EWS as developed in Chapter 3 does not allow for any time dynamics. It may be expected however that the expectation of the duration of the current period until crisis depends on the most recent durations. Therefore, in Chapter 4 a modified version of the Autoregressive Conditional Hazard (ACH) model by Hamilton and Jordá (2002) is used to introduce these dynamics. In the original ACH, the probability of transition could drop below 0. The proposed modification ensures that this probability stays between 0 and 1. The ACH model combines the dynamics of the Autoregressive Conditional Duration (ACD) approach of Engle and Russell (1997) with time-varying economic fundamentals into a model for the probability of transition from one state to another. The analysis in Chapter 4 focusses on explaining all tension on the exchange market as opposed to focussing only on tension that resulted in a currency crisis. This approach has two advantages: Firstly, there is no need to define an ad hoc threshold value to determine the extreme values of the index that proxies the crisis. Secondly, the problem of too few useful data points (i.e. the number of crises) reduces, as periods of increasing tension are defined irrespective of the severity of the tension.

Chapter 5 concludes this thesis. The chapter summarises the results and limitations of the preceding chapters. One of the shortcomings in the literature that is not addressed in the preceding chapters, is the issue of capturing and modelling market sentiments. Because market agents' expectations are at the core of the self-fulling prophecy and financial contagion, an empirical exercise is performed with survey data as explanatory variables. This is applied to the EWS of Chapters 3 and 4. The thesis ends with some additional insights based on the performed exercise with the survey data, along with possible extensions to the literature.

Chapter 2

A Cautious Note on Using Panel Models to Predict Financial Crises

Fortunately, most countries don't get hit by a financial crisis too often. Consequently, modelling crises for a single country becomes very difficult as there are often so few observations that a model cannot be properly specified. To counter this issue, a panel data framework across countries is often used to build Early Warning Systems for financial crises. In this chapter we investigate the implicit homogeneity assumption that is made when pooling data in a panel setup. In case of the Early Warning Systems the implicit assumption is that crises are homogenously caused by identical factors. It turns out that this assumption is not always valid. In this chapter we therefore suggest a preliminary step aiming at forming optimal country clusters based on Hausman test results for poolability.[1]

2.1 Introduction

The financial turmoils in the last decades have stimulated researchers in explaining and predicting crises. As a consequence, academic literature on financial crises has soared. As the branch of literature is extensively discussed in Chapter 1, we here only provide a short recap of the papers that are of most interest for this chapter. One of the first to address the causes of a financial crisis were Eichengreen, Rose, and Wyplosz (1995, 1998). Afterwards, the literature focussed more on developing countries (Frankel and Rose, 1996; Sachs, Tornell, Velasco, Calvo, and Cooper, 1996). Simultaneously, models to predict the occurrence of a financial crisis have been developed. The first idea, proposed by Kaminsky, Lizondo,

[1]This chapter is based on the paper Van den Berg, Candelon, and Urbain (2008) published in *Economics Letters 101(1)*, 80-83.

and Reinhart (1998), involves building an Early Warning System (EWS) using a signalling approach. They consider a large set of indicators relating to the external position, the financial sector, the real sector, the institutional structure and the fiscal policy of a particular country. When these indicators cross a certain threshold, the model signals the probability of a future financial crisis. Berg and Pattillo (1999) show that a simple probit-based model strongly outperforms the signal approach using within sample and out-of-sample forecasts and recommend the use of discrete choice techniques. The endogenous variable ($C^h_{i,t}$) represents the occurrence of a crisis at most h-months ahead. If a crisis occurs within the next h periods $C^h_{i,t}$ takes a 1, otherwise a 0.[2] Several major criticisms have been addressed to these models.

First, the results highly depend on the definition of the crisis. The literature provides several methods to date financial crises. For example, the definition of the financial crisis can be more strict or less strict and can encompass only successful attacks or also unsuccessful ones. Bussiere and Fratzscher (2006) for example propose to consider a post-crisis regime, such that the crisis variable takes a zero in tranquil periods, a one before and during the crisis and a two for post-crisis periods. This modification is expected to tackle the problem of the post-crisis bias. Lestano, Jacobs, and Kuper (2003) distinguish between currency crises, banking crises and debt crises. They use 4 different crisis determinants for currency crises and determine the banking and debt crises with the help of IMF reports and central banks.

Second, as pointed out by Berg and Coke (2004), the approach advocated by Berg and Pattillo (1999) results in artificial serially correlated errors due to (i) the fact that often forecast horizons are longer than the frequency at which the forecast is being updated, (ii) the way the the crises variable is constructed as a binary variable that takes the value one for the periods $[t-h, t-1]$ when a crises occurs at time t. Consequently, the standard errors will be biased. Berg and Coke (2004) propose to use a robust HAC covariance matrix or bootstrap method to calculate the standard errors. Recently however, it has been shown by Harding and Pagan (2011) that the serial dependence of the constructed dependent variable even threatens the consistency of the estimation. The alternating sequences of zeros and ones in the dependent variable gives the variable a Markov process type time dependence. Failing to take into account this specific dependence, could therefore lead to potentially invalid inference.

Third, several studies (in particular Kumar, Moorthy, and Perraudin, 2003) have noticed that crisis events are less frequent than non-crisis ones. Indeed, the probit model is not adequate to model events that are in the tail of a distribution, and a logit model is preferred.

Fourth, seminal EWSs such as Berg and Pattillo (1999) exclusively focus on

[2]Berg and Pattillo (1999) found that the model performed at best when $h = 24$ months.

individual countries. Several papers however (Shortland, 2004; Fuertes and Kalotychou, 2007; Kumar et al., 2003, inter alii), have considered the possibility of adopting a panel data framework where data for several countries are pooled. Such an extension is mainly motivated by an efficiency argument since pooling countries increases the number of useful observations and is supposed to lead to a gain in accuracy when estimating the underlying discrete choice models. A crucial untested assumption however is the homogeneity of the parameters, e.g. the assumption that not only the same factors are supposed to explain adequately financial crises, but also that the parameters may be assumed constant and homogenous across the cross-section dimension. Under these restrictive assumptions, heterogeneity can be captured by a fixed effects dummy and all other features of the models are assumed to be common to all the countries in the panel and the data can be pooled for estimation and inference. This contradicts nevertheless two well-known features of financial crises: First, not all crisis are the consequences of macroeconomic fundamentals, but they might also be driven by psychological factors as the self-fulfilling prophecy or by a weak bank balance sheet. Second, the recent literature has shown that spill-over effects are important determinants in the transmission of a financial crisis, meaning that "ground-zero" countries are first hit and then transmit the turmoil, leading to strong , possibly dynamic cross-sectional dependence. Aggregating and pooling these countries might not only lead to a loss of information but could also severely affect the estimation and inferences.

This chapter proposes a deeper analysis of the panel-logit model as EWS. Based on the arguments of Harding and Pagan (2011), it can be questioned whether a static probit or logit should be used at all to model the constructed binary crisis indicator. In this chapter however, the focus is exclusively on the poolability issue. We show that emerging market forecasters should not naively pool all the data available for a maximum number of countries, because the quality of the prediction would seriously decrease. We advise them to perform a preliminary analysis of optimal country clusters before setting up the panel-logit model. The chapter is organised as follows: In Section 2.2, the competing models (full, regional, cluster and individual) are presented. In Section 2.3, the ability of these models to predict financial crises is investigated. Section 2.4 concludes.

2.2 The Empirical Models

Four different models are investigated. The first one, called "Naive Model" (NM) integrates all the countries and all the data available in a pooled panel-logit framework. The second model, called "Regional Model" (RM), only integrates countries in the same geographical region. In this model, it is assumed that financial crisis will affect all the countries lying in the same region similarly and simultaneously. The third model, called "Cluster Model" (CM) only includes countries which can be statistically pooled. In order to determine these clusters of countries, we follow the iterative approach of Kapetanios (2003).

The procedure of Kapetanios (2003) allows the researcher to not only test if a panel is 'poolable' (i.e. the homogeneity assumption is not violated), but it also determines which of the members of the cross-section is causing the rejection of poolability. Through a sequence of tests, the method distinguishes the poolable from the non-poolable series. The poolable series then form an optimal cluster. Consider our panel logit:

$$C_{i,t}^{h} = \alpha_i + \beta_i' X_{i,t-1} + \varepsilon_{i,t}, \qquad i = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{2.1}$$

with $\varepsilon_{i,t}$ Normally distributed and $Cov(\varepsilon_{i,t}, \varepsilon_{j,t}) = 0$ for $i \neq j$.[3] Furthermore, $C_{i,t}^{h}$ is the binary constructed crisis variable signalling a crisis h months ahead and $X_{i,t-1}$ is the $k-$dimensional matrix of explanatory variables. For the purpose of the test, the nature of the cross-sectional individual effect α_i does not need to be specified as the test holds for both random and fixed effects. The null hypothesis of the test for poolability is of course given by:

$$H_0 : \beta_i = \beta \quad \forall i = 1, \ldots, N. \tag{2.2}$$

Under the assumption that there exists a $\sqrt{NT}$-consistent, asymptotically normal estimator ($\tilde{\beta}$) for β, and a $\sqrt{T}$-consistent, asymptotically normal estimator ($\hat{\beta}_i$) for β_i, a simple Hausman type statistic can be employed. For a given i, a test that $\hat{\beta}_i = \tilde{\beta}$ can be based on the test statistic:

$$HM_i = (\hat{\beta}_i - \tilde{\beta})' Var(\hat{\beta}_i - \tilde{\beta})^{-1} (\hat{\beta}_i - \tilde{\beta}), \tag{2.3}$$

which is distributed $\chi^2(k)$. A sequential procedure is employed to determine an optimal cluster m (CL_m) of countries.[4] Starting at the full sample (Naive Model), this test is performed for each country separately, resulting in N test statistics. If the supremum of these statistics rejects the null hypothesis, the series with the maximum difference between the individual estimate of the vector β and its estimate obtained using the pooled dataset, is considered as non-poolable and is removed from the dataset. The poolability test is then applied to the remaining series and the procedure is then repeated until the poolability test does not reject the null hypothesis for some subset (CL_m) of the original set of series or until we are left with a set of one series. After a poolable cluster has been found, the procedure is re-applied to the remaining series that were previously considered non-poolable in order to detect a potential second cluster. This process ends when no more clusters are found. The remaining countries do not belong to any cluster and are modelled individually.

The fourth model, called "Country model" (CoM) is the logit model estimated for each individual country and constitutes a benchmark. With the exception of

[3] Cross-sectional dependence is not considered here and is left for further research.

[4] A set of countries is called an optimal cluster if $\beta_i = \beta_m$, for all countries in the set, where β_m is the vector of coefficients corresponding to the complete cluster.

the Country Model, we are dealing with panel-logit models. Therefore particular attention was devoted to the correct specification of country-specific terms, which can be fixed or random. Hausman tests conclusively determine the fixed effects model superior in all cases.[5]

2.2.1 Data, Crisis Indicator and Performance Indicators

The dataset covers 12 countries from the regions Latin-America and Asia: Argentina, Brazil, Mexico, Peru, Uruguay, Venezuela, Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand. Data are at monthly frequency, adjusted for seasonality and run from January 1985 to January 2005.[6] The data is obtained via Datastream[7].

As explanatory variables for the hazard rate we selected several macroeconomic variables relating to different aspects of the economy. Corresponding to those used in Kumar, Moorthy, and Perraudin (2003), we use variables from the external sector, the financial sector and the real sector. Notice that all explanatory variables enter the regression one month lagged. This way, at time t, the probability of a crisis is affected only by variables which are observable at time t. Following Kumar et al. (2003), the impact of extreme values is reduced by dampening every variable via the transformation $y_t^{\mathrm{New}} = (\mathrm{sign\,of\,} y_t) * \ln(1 + |\, y_t |\,)$.

The external sector can be separated into the current account and the capital account. Because we use monthly data, we cannot use the quarterly data for the current account and capital account directly. We therefore approximate these factors by other variables that are available on a monthly basis. The first variable relating to the current account is the annual growth rate of exports. Because a decrease in exports indicates a loss in international competitiveness, it can lead to a recession and business failures (Dornbusch, Goldfajn, and Valdes, 1995). Hence we expect a decrease in exports to increase the probability of a crisis. The other variable related to the current account is the imports annual growth rate. For imports the theory is not so clear. On the one hand an decrease in imports could be an indication of weakening of economic activity, while on the other hand an increase in imports can be caused by a strong overvaluation of the real exchange rate (Kaminsky and Reinhart, 1999). To proxy the capital account, the real interest rate differential with respect to the United States as well as the growth in international reserves are used. For the latter we expect that a decrease in reserves lowers the leverage of the central bank to deal with speculative attacks and therefore increases the probability of crisis. A high real interest rate differential is typically associated with a high amount of pressure on the currency as the increased domestic interest rate could be a response to excess supply of the currency

[5] Models are estimated by Newton Raphson's Maximum Likelihood using Stata 10.1 software.

[6] Due to the limited data availability is was unfortunately not possible to construct a consistent dataset dating further back than 1985.

[7] Sources are the IMF-IFS database and the national banks of the respective countries.

(see Eichengreen et al., 1995).

The second aspect of the economy we consider is the financial sector. It has been shown by McKinnon and Pill (1996) that currency crises, most notably those accompanied by a banking crisis (labelled as "twin crises"), have often been preceded by periods of financial liberalisation. Facilitated by the more relaxed reserve requirements for banks, the financial liberalisation tends to make people and banks overconfident in the stability of the currency, leading to excessive (foreign) borrowing. The banking sector now becomes vulnerable to speculative attacks (Krugman, 1979). Overborrowing results in an increase in the M2 multiplier as well as growth of domestic credit relative to GDP (McKinnon and Pill, 1998). For both these variables it holds that a higher ratio indicates higher vulnerability and therefore a higher probability of crisis. To capture the credit risk rating and the willingness of banks to lend, the ratio lending rate over deposit rate is included. An increase in this ratio indicates that banks require a high risker premium on their loans. The higher risk premium is a direct consequence of a lower economic stability. We also include the ratio M2 over reserves. An increase of the ratio is caused both by an increase in M2 money and decrease in reserves. The higher this ratio, the more vulnerable is the economic system to speculative attacks (Calvo and Mendoza, 1996). The ratio M2 over reserves is included both as levels and as growth rate, because not only an increase in the ratio increases the vulnerability, but also a ratio that is simply high. The final financial variable is the growth of bank deposits. A decrease in this variable shows capital flight and bank runs, a clear indicator of an imminent crisis (Goldfajn and Valdes, 1997).

The last aspect of the economy captured by the variables, is the real sector of the economy. As a proxy for output growth we use the industrial production growth rate. A decrease in industrial production growth is the sign of a weakening domestic economy and therefore an increase in the probability of crisis.

The reason for the transformation of most of the explanatory variables to their annual growth rates is not only the benefit that we can have data at a monthly frequency. As a crisis is by definition a sudden change with respect to a previous time period, we believe that we must also use the changes in our explanatory variables instead of the levels. The transformation also makes data for different countries more comparable: Even though the level of, for example, international reserves can differ substantially at any point in time, the percentage changes in reserves will be a lot closer together and are also likely to react in a similar way across countries in case of a crisis. Furthermore, missing values in the middle of the sample are interpolated using cubic splines. Missing values at the beginning or end of the sample are dropped.

The periods of crisis are determined via the Exchange Market Pressure Index (EMPI) (see Eichengreen et al., 1995). This EMPI is the weighted average between the 6-month change in the exchange rate with respect to the US dollar and (the negative of) the 6-month change in the international reserves where the weights are chosen such that the variance of the two factors are equal. The sample is split into high inflation periods and low inflation periods, because volatility is typically higher in periods of high inflation. The cutoff point is when the 6-month inflation is more than 50%. For both subsamples, a crisis is signalled when the EMPI exceeds the threshold of the mean plus two times the standard deviation.[8]

The respective quality of the four models in consideration is measured in terms of the performance as crisis predictor. For this purpose, three traditional in-sample goodness-of-fit indicators (see Diebold, 2004) are defined as:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - C_{24,t})^2, \tag{2.4}$$

$$LPS = \frac{1}{T}\sum_{t=1}^{T} \left[(1 - C_{24,t})\ln(1 - P_t) + C_{24,t}\ln(P_t)\right], \tag{2.5}$$

$$KS = \frac{A}{A+C} - \frac{B}{B+D}, \tag{2.6}$$

where T is the sample size, P_t is the fitted crisis probability, A is the number of correctly predicted crises, B counts the number of false alarms, C are the missed crises and D stands for the correctly predicted tranquil periods. It is straightforward to notice that the quality of a model increases as QPS and LPS move close to 0, and KS approaches 1.[9]

2.3 The Results

As mentioned in the previous section, the procedure to find poolable country clusters by Kapetanios (2003) is an iterative process. The intermediate and final results of this process are presented in this section as well as a reverse method to validate the findings.

Table 2.1 shows the intermediate results of the Kapetanios approach. The top two panels in the table show the process towards the formation of two clusters in Latin America. We start with the full regional sample. It turns out that Uruguay has the highest Hausman statistic and in the next stage it is removed from the sample. In the second stage Brazil is deleted followed by Argentina in the third stage, finally leading to a 'poolable' cluster of three countries: Mexico, Peru and Venezuela. After the cluster has been identified, it is checked if the remaining

[8] As pointed out in Chapter 1, this method of defining periods of crisis has its shortcomings. In the absence of a universal consensus about which dating method is best, we choose the method that comes closest to capturing the fluctuations on the exchange rate market.

[9] Alternative criteria based on the Receiving Operating Characteristic curve to evaluate the forecasting ability of models for binary variables are also available (see Candelon et al., 2009)

Country	Stage of cluster-finding process				
	1st Stage	2nd Stage	3st Stage	4th Stage	5th Stage
Argentina	26.34	30.99	**54.86**	-	-
Brazil	61.72	**79.46**	-	-	-
Mexico	49.85	58.72	44.58	42.75	-
Peru	30.25	24.11	41.79	14.48	-
Uruguay	**78.12**	-	-	-	-
Venezuela	39.15	38.61	37.62	41.55	-
Argentina	36.74	36.01	-	-	-
Brazil	59.18	49.10	-	-	-
Uruguay	**77.70**	-	-	-	-
Indonesia	29.16	29.09	27.81	30.04	26.33
Korea	29.77	29.57	29.13	46.66	1.94
Malaysia	43.70	52.09	**63.60**	-	-
Philippines	63.31	61.74	56.17	**53.91**	-
Taiwan[a]	**69.94**	-	-	-	-
Thailand[a]	**69.94**	**65.04**	-	-	-
Malaysia	27.61	9.04	-	-	-
Philippines	**75.22**	-	-	-	-
Taiwan[a]	53.68	28.66	-	-	-
Thailand[a]	53.68	28.66	-	-	-

Starting at the regional sample, the country with the highest Hausman statistic (current sample vs single country) is deleted in each stage (in bold). The countries in the cluster are then removed from the sample and for the remaining countries the process is repeated.

[a] The single-country models of both Taiwan and Thailand result in a perfect fit due to collinearity between the dependent variable and the explanatory variables. For Taiwan and Thailand the Hausman test is therefore performed with respect to their joint 2-country model.

Table 2.1: Intermediate top-down results for finding optimal clusters

Base Country	Paired Country Argentina	Brazil	Mexico	Peru	Uruguay	Venezuela
Argentina	-	**36.01**	76.47	52.01	62.51	84.32
Brazil	**49.10**	-	60.37	55.61	90.15	85.50
Mexico	48.80	48.50	-	**43.81**	55.94	**39.99**
Peru	46.91	51.03	**11.90**	-	94.59	**28.58**
Uruguay	51.07	60.28	98.02	73.59	-	41.99
Venezuela	48.69	59.34	**73.96**	**35.14**	59.80	-

Base Country	Paired Country Indonesia	Korea	Malaysia	Philippines	Taiwan	Thailand
Indonesia	-	**26.33**	45.19	60.21	32.52	46.30
Korea	**1.94**	-	64.34	73.70	29.20	85.68
Malaysia	49.35	36.52	-	42.93	**32.09**	**13.03**
Philippines	60.66	26.14	48.40	-	28.01	77.70
Taiwan[a]	75.78	39.70	**26.54**	65.18	-	-
Thailand[a]	61.66	53.83	**27.94**	62.11	-	-

In each row the Hausman test statistics of the 2-country models vs the single-country model of the base country are presented. The statistics for the countries in the same cluster are given in bold.

[a]For Taiwan and Thailand, the Hausman tests are performed with respect to their joint 2-country model. Their bilateral poolability test is therefore degenerate.

Table 2.2: Bilateral poolability test results

country set still includes another poolable (sub)set. A second cluster is identified, namely Argentina and Brazil, leaving Uruguay as part of no clusters. For the Asian region a similar process leads to the identification of two clusters: Indonesia and Korea, and Malaysia, Taiwan and Thailand. The Philippines do not belong to any cluster.[10] Due to the sequential form of the cluster-finding process, it might be the case that for some countries a non-optimal clustering occurs. We therefore examine the bilateral poolability of the countries. Hausman tests are performed to compare the parameter estimates of the model based on the single country with the two-country models. The results are summarised in Table 2.2. For each country, with only one exception, it can be seen that the lowest values for the Hausman statistic (per row) correspond to the respective cluster partners. This result confirms that the identified clusters are indeed the groups of most poolable countries.

As it turns out, the optimal clusters are smaller than the regional samples. It means that pooling the data, even by region, is rejected by Hausman's test. Economically, it signifies that the factors explaining the recent crises are generally not identical across the countries. The four clusters that are found turn out to

[10]Notice here that in the first stage of the first Asian cluster Thailand could have been removed instead. This case was explored and it leads to the same end-result as Taiwan would be removed from the sample in the very next stage.

Country	Cluster	vs Total Sample		vs Region		vs Cluster	
		Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Argentina	Brazil	61.13	0.0000	53.08	0.0000	36.01	0.0001
Brazil	Argentina	67.59	0.0000	61.72	0.0000	49.10	0.0000
Mexico	Peru, Venezuela	59.54	0.0000	49.85	0.0000	42.75	0.0000
Peru	Mexico, Venezuela	34.03	0.0007	30.25	0.0026	14.48	0.2709
Uruguay	-	80.28	0.0000	78.12	0.0000	-	-
Venezuela	Mexico, Peru	42.76	0.0000	39.15	0.0001	41.55	0.0000
Indonesia	Korea	46.99	0.0000	29.16	0.0037	26.33	0.0096
Korea	Indonesia	30.40	0.0024	29.77	0.0030	1.94	0.9995
Malaysia	Taiwan, Thailand	12.47	0.4084	43.70	0.0000	9.04	0.6996
Philippines	-	63.74	0.0000	63.31	0.0000	-	-
Taiwan/ Thailand[a]	Malaysia	57.84	0.0000	69.94	0.0000	28.66	0.0073

For each country three Hausman-based test are performed: The model estimated using only the individual country versus respectively the total sample, the regional sample and the cluster.

[a]Due to their degenerate single-country models, For this reason the comparisons are performed with respect to their joint 2-country model.

Table 2.3: Results of the Kapetanios test for poolability

be very reasonable from an economic point of view. Argentina and Brazil were in the late 80's characterised by hyper inflation (Kiguel and Liviatan, 1995). Financial crises match these periods of extreme inflation rates and end with the stabilisation plans established in the early 90's. Inflation is here the fundamental underlying variable that affects the EWS in this cluster. The cluster Mexico, Peru and Venezuela seems to have less economic basis, although it must be noted that all three countries are characterised by a powerful minority with political power, thereby making economic reforms towards a free market and globalisation very difficult Philip (1999). On the contrary, the occurrence of the Asian crisis (for most of the Asian countries the only crisis episode detected in our sample) in both Indonesia and Korea is similar and has been driven by excessive borrowing and risk taking (see Evrensel and Kutan, 2006) leading to the moral hazard problem (Haggard and MacIntyre, 2001). With respect to the cluster Malaysia, Taiwan and Thailand, the structural similarity around the Asian crisis is straightforward. As they were characterised by poor institutional local financial markets, the decrease in the returns on investments has forced these countries to an increase in short-term foreign exchange borrowing (Claessens, Djankov, and Lang, 1999; Kuo, 2001) making the economies vulnerable to speculation.

2.3.1 Comparing the Four Models

For each country we have defined four models, the Naive Model (NM), the Regional Model (RM), the Cluster Model (CM) and the Country Model (CoM).[11] In this section we examine the poolability of the three panel models and evaluate the

[11]The full estimation results are tabulated in Appendix A at the end of this chapter.

	Optimal Cluster	Goodness of fit	NM	RM	CM	CoM
Argentina	Brazil	QPS	0.2461	0.2409	0.2135	0.1895
		LPS	-0.3833	-0.3738	-0.3362	-0.2844
		KS	0.4245	0.4437	0.5025	0.5862
Brazil	Argentina	QPS	0.3366	0.3868	0.3009	0.2349
		LPS	-0.5296	-0.5778	-0.4619	-0.3859
		KS	0.4095	0.2942	0.4923	0.5675
Mexico	Peru, Venezuela	QPS	0.2662	0.2653	0.2256	0.0639
		LPS	-0.4733	-0.4319	-0.3390	-0.1082
		KS	0.5285	0.5194	0.5625	0.9220
Peru	Mexico, Venezuela	QPS	0.1833	0.1818	0.0867	0.0961
		LPS	-0.3235	-0.3150	-0.2556	-0.1827
		KS	0.7116	0.8055	0.9333	0.8994
Uruguay	(none)	QPS	0.3855	0.3672	0.0996	0.0996
		LPS	-0.6032	-0.5739	-0.1583	-0.1583
		KS	0.3065	0.3329	0.8393	0.8393
Venezuela	Mexico, Peru	QPS	0.3866	0.3431	0.2731	0.1678
		LPS	-0.5616	-0.5130	-0.4297	-0.2587
		KS	0.3656	0.4748	0.5553	0.7613
Indonesia	Korea	QPS	0.2898	0.2145	0.1321	0.1109
		LPS	-0.4521	-0.3313	-0.2071	-0.1738
		KS	0.1822	0.6687	0.7351	0.7583
Korea	Indonesia	QPS	0.1885	0.1623	0.1241	0.0452
		LPS	-0.3183	-0.2607	-0.1903	-0.0749
		KS	0.1537	0.5990	0.5990	0.9245
Malaysia	Taiwan, Thailand	QPS	0.1786	0.0929	0.0443	0.0269
		LPS	-0.2848	-0.1663	-0.0748	-0.0420
		KS	0.4580	0.8164	0.9032	0.9466
Philippines	(none)	QPS	0.3688	0.2915	0.1187	0.1187
		LPS	-0.5502	-0.4444	-0.1909	-0.1909
		KS	-0.0200	0.4358	0.7716	0.7716
Taiwan[a]	Malaysia, Thailand	QPS	0.1481	0.0558	0.0668	-
		LPS	-0.2397	-0.0871	-0.1101	-
		KS	0.6813	0.8863	0.8663	-
Thailand[a]	Malaysia, Taiwan	QPS	0.1917	0.2328	0.1325	-
		LPS	-0.3109	-0.3686	-0.2012	-
		KS	0.3366	0.2367	0.6580	-

[a]The single-country models of both Taiwan and Thailand result in a perfect fit due to collinearity between the dependent variable and the explanatory variables. For this reason they are removed from the table.

Table 2.4: In-sample performance of the empirical models

performance of all four models in terms of within sample goodness-of-fit. To evaluate the forecasting capabilities of the models, one might argue that out-of-sample estimations are needed. Inoue and Kilian (2006) show however, that the comparison of within-sample and out-of-sample performance give very similar results. We therefore deem it sufficient to evaluate only the within-sample performance.

Table 2.3 shows the results of the Hausman test on the comparison between the panel models and the single-country models. For most countries the regional model is closer to the single-country model than the naive model, indicating that regional pooling at least should give slightly better results than a naively pooled model. However, the cluster model is by far, and consistently for all countries, better poolable than the other two models. This confirms once more that the implicit homogeneity assumption made when pooling data, must first be checked.

The outcome that the optimal clusters are smaller than the regional samples is supported by the goodness-of-fit indicators. Table 2.4 shows that the CM always outperforms NM and RM. Even if the CoM still performs slightly better than the CM in terms of in-sample prediction, the gain due to the higher precision of the estimator might be justified in this case. To illustrate the predicting power of each of the models, the probability of a financial crisis is plotted in Figure 2.1. The results outlined by the goodness-of-fit indicators are confirmed. Nevertheless the figure points out that the loss due to the use of naive or regional panel-logit models is particularly large for Uruguay, Venezuela, Indonesia, Malaysia and the Philippines.

2.4 Concluding Remarks

In conclusion, this chapter suggests that crisis forecasters should not naively pool all the data available for a maximum number of countries, because the quality of the prediction would seriously decrease. We advise them to perform a preliminary analysis of optimal country clusters before setting up the panel-logit model.

In this chapter we propose to examine the poolability of a panel using Hausman tests. Based on the results of these tests, optimal clusters can be formed. Unsurprisingly it turns out that the optimal clusters are smaller than the whole set of countries and also smaller than the set of countries located in the same region. This means that pooling data, even by region, might not be valid. Economically, this leads to the conclusion that the factors explaining currency crises are generally not identical across countries. Four optimal clusters are found: a) Argentina and Brazil, b) Mexico, Peru and Venezuela, c) Indonesia and Korea and d) Malaysia, Taiwan and Thailand. As the optimal clusters are formed such that the homogeneity assumption is not violated within them, one would expect that the Cluster Model performs better in terms of predicting and explaining crisis periods. This hypothesis is indeed supported by our goodness-of-fit measures.

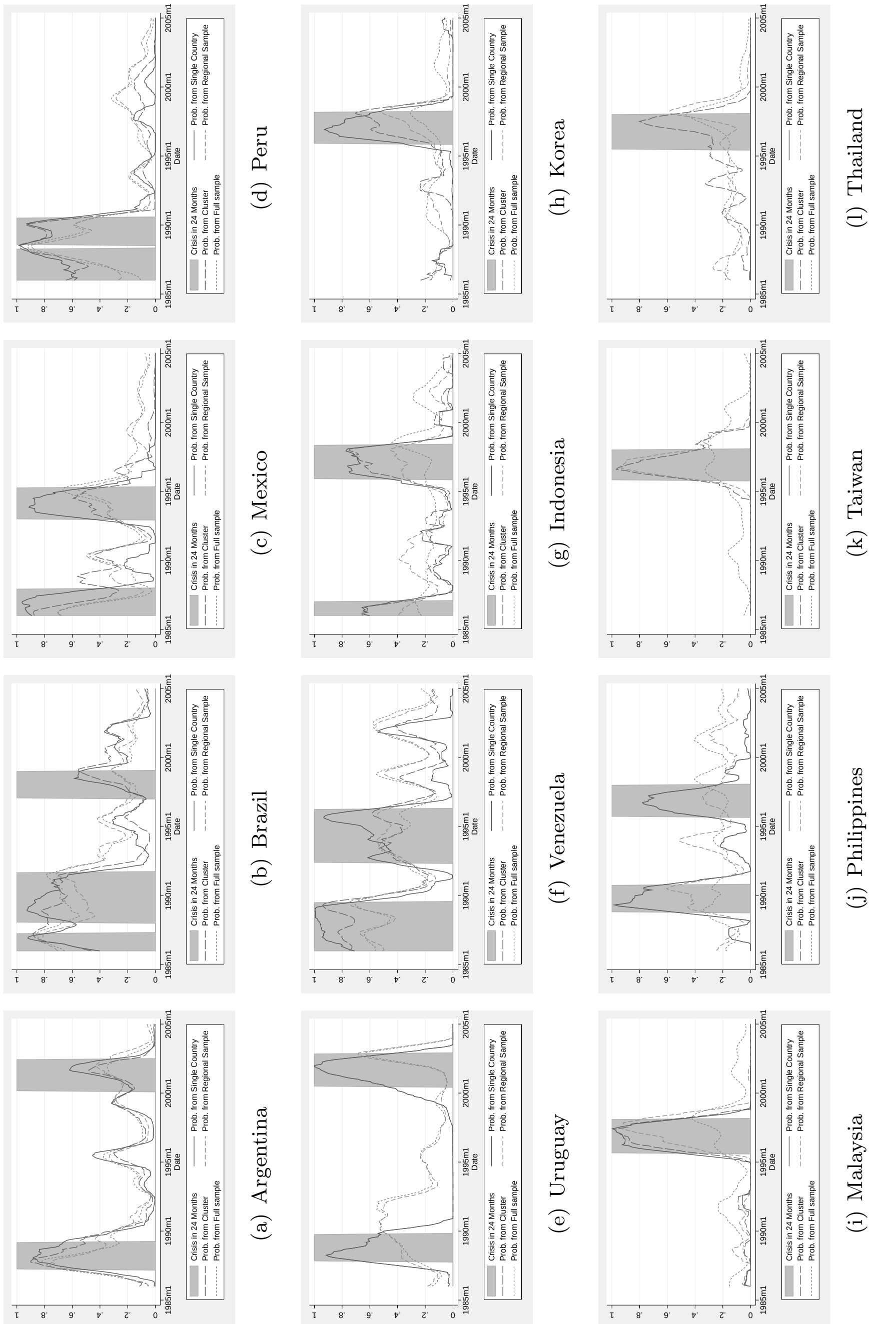


Figure 2.1: Predicted Probability of a Crisis

2.A Appendix: Full Estimation Results

This appendix contains the estimation results for the naive, regional, cluster and country models tabulated separately per country.

Table 2.5: Estimation Results for Argentina

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-0.050	-1.296	1.956	-
	(0.319)	(0.380)	(0.806)	(1.449)	
Imports Growth	-0.619**	-1.100***	-1.925**	-3.363*	+/-
	(0.311)	(0.375)	(0.800)	(1.774)	
Reserves Growth	-1.972***	-1.866***	-0.442	-2.025	-
	(0.333)	(0.382)	(0.651)	(1.322)	
Real Int. Rate Differential	-0.155	-0.145	-0.295	**-0.950****	+
	(0.201)	(0.193)	(0.245)	(0.415)	
M2 Multiplier Growth	1.992	1.121**	0.716	2.280	+
	(0.428)	(0.451)	(0.746)	(1.639)	
Domestic Credit/GDP Growth	0.146	**-0.783****	0.611	**-2.169****	+
	(0.290)	(0.361)	(0.538)	(1.045)	
Lending/Deposit Rate	**-2.511*****	**-2.125*****	0.135	2.089	+
	(0.294)	(0.323)	(0.502)	(2.571)	
M2/Reserves	2.070***	0.809**	5.408***	3.589**	+
	(0.304)	(0.330)	(0.765)	(1.532)	
M2/Reserves Growth	-0.335	0.555	0.099	0.415	+
	(0.331)	(0.384)	(0.769)	(1.861)	
Bank Deposits Growth	-0.685***	-1.653***	0.154	-0.401	-
	(0.246)	(0.300)	(0.573)	(0.971)	
Industrial Production Growth	-1.284**	-0.924	-4.118*	-13.987***	-
	(0.237)	(0.922)	(2.234)	(5.260)	
Log-likelihood	-1153.3	-637.83	-182.76	-65.117	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.6: Estimation Results for Brazil

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-0.050	-1.296	-5.411***	-
	(0.319)	(0.380)	(0.806)	(1.356)	
Imports Growth	-0.619**	-1.100***	-1.925**	1.350	+/-
	(0.311)	(0.375)	(0.800)	(1.182)	
Reserves Growth	-1.972***	-1.866***	-0.442	**3.306****	-
	(0.333)	(0.382)	(0.651)	(1.365)	
Real Int. Rate Differential	-0.155	-0.145	-0.295	-0.620	+
	(0.201)	(0.193)	(0.245)	(0.413)	
M2 Multiplier Growth	1.992	1.121**	0.716	2.543*	+
	(0.428)	(0.451)	(0.746)	(1.316)	
Domestic Credit/GDP Growth	0.146	**-0.783****	0.611	2.761**	+
	(0.290)	(0.361)	(0.538)	(1.117)	
Lending/Deposit Rate	**-2.511*****	**-2.125*****	0.135	1.340*	+
	(0.294)	(0.323)	(0.502)	(0.705)	
M2/Reserves	2.070***	0.809**	5.408***	8.804***	+
	(0.304)	(0.330)	(0.765)	(1.407)	
M2/Reserves Growth	-0.335	0.555	0.099	0.337	+
	(0.331)	(0.384)	(0.769)	(1.119)	
Bank Deposits Growth	-0.685***	-1.653***	0.154	**5.612*****	-
	(0.246)	(0.300)	(0.573)	(1.999)	
Industrial Production Growth	-1.284**	-0.924	-4.118*	-1.623	-
	(0.237)	(0.922)	(2.234)	(3.446)	
Log-likelihood	-1153.3	-637.83	-182.76	-88.365	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.7: Estimation Results for Mexico

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-0.050	0.375	**9.415****	-
	(0.319)	(0.380)	(0.605)	(4.463)	
Imports Growth	-0.619**	-1.100***	-0.750	-19.225***	+/-
	(0.311)	(0.375)	(0.594)	(7.380)	
Reserves Growth	-1.972***	-1.866***	-0.433	**12.942*****	-
	(0.333)	(0.382)	(0.683)	(3.573)	
Real Int. Rate Differential	-0.155	-0.145	-1.031	17.416**	+
	(0.201)	(0.193)	(1.074)	(7.231)	
M2 Multiplier Growth	1.992	1.121**	**-3.034*****	**-22.045*****	+
	(0.428)	(0.451)	(0.984)	(5.526)	
Domestic Credit/GDP Growth	0.146	**-0.783****	-0.429	22.267***	+
	(0.290)	(0.361)	(0.740)	(6.921)	
Lending/Deposit Rate	**-2.511*****	**-2.125*****	**-10.791*****	**-53.675*****	+
	(0.294)	(0.323)	(1.320)	(12.581)	
M2/Reserves	2.070***	0.809**	1.950***	2.697	+
	(0.304)	(0.330)	(0.667)	(2.912)	
M2/Reserves Growth	-0.335	0.555	2.284**	13.311***	+
	(0.331)	(0.384)	(0.659)	(4.168)	
Bank Deposits Growth	-0.685***	-1.653***	-3.641***	-8.364***	-
	(0.246)	(0.300)	(0.589)	(2.182)	
Industrial Production Growth	-1.284**	-0.924	**3.091****	-8.389	-
	(0.237)	(0.922)	(1.367)	(14.030)	
Log-likelihood	-1153.3	-637.83	-234.56	-24.771	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.8: Estimation Results for Peru

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-0.050	0.375	-3.677	-
	(0.319)	(0.380)	(0.605)	(2.336)	
Imports Growth	-0.619**	-1.100***	-0.750	1.357	+/-
	(0.311)	(0.375)	(0.594)	(1.530)	
Reserves Growth	-1.972***	-1.866***	-0.433	-2.512	-
	(0.333)	(0.382)	(0.683)	(1.730)	
Real Int. Rate Differential	-0.155	-0.145	-1.031	-2.705	+
	(0.201)	(0.193)	(1.074)	(2.623)	
M2 Multiplier Growth	1.992	1.121**	**-3.034*****	-3.649	+
	(0.428)	(0.451)	(0.984)	(2.989)	
Domestic Credit/GDP Growth	0.146	**-0.783****	-0.429	1.085	+
	(0.290)	(0.361)	(0.740)	(1.722)	
Lending/Deposit Rate	**-2.511*****	**-2.125*****	**-10.791*****	**-9.293*****	+
	(0.294)	(0.323)	(1.320)	(2.813)	
M2/Reserves	2.070***	0.809**	1.950***	1.212	+
	(0.304)	(0.330)	(0.667)	(1.689)	
M2/Reserves Growth	-0.335	0.555	2.284**	-1.636	+
	(0.331)	(0.384)	(0.659)	(1.666)	
Bank Deposits Growth	-0.685***	-1.653***	-3.641***	-11.096***	-
	(0.246)	(0.300)	(0.589)	(3.207)	
Industrial Production Growth	-1.284**	-0.924	**3.091****	**14.824*****	-
	(0.237)	(0.922)	(1.367)	(5.227)	
Log-likelihood	-1153.3	-637.83	-234.56	-41.848	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.9: Estimation Results for Uruguay

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-0.050	-	2.242	-
	(0.319)	(0.380)		(2.242)	
Imports Growth	-0.619**	-1.100***	-	-4.362*	+/-
	(0.311)	(0.375)		(2.313)	
Reserves Growth	-1.972***	-1.866***	-	0.552	-
	(0.333)	(0.382)		(6.236)	
Real Int. Rate Differential	-0.155	-0.145	-	44.461***	+
	(0.201)	(0.193)		(16.740)	
M2 Multiplier Growth	1.992	1.121**	-	1.549	+
	(0.428)	(0.451)		(5.419)	
Domestic Credit/GDP Growth	0.146	**-0.783****	-	**-5.873****	+
	(0.290)	(0.361)		(2.994)	
Lending/Deposit Rate	**-2.511*****	**-2.125*****	-	**-5.240****	+
	(0.294)	(0.323)		(2.601)	
M2/Reserves	2.070***	0.809**	-	**-13.872*****	+
	(0.304)	(0.330)		(4.302)	
M2/Reserves Growth	-0.335	0.555	-	5.369	+
	(0.331)	(0.384)		(5.647)	
Bank Deposits Growth	-0.685***	-1.653***	-	2.314	-
	(0.246)	(0.300)		(5.856)	
Industrial Production Growth	-1.284**	-0.924	-	-6.242	-
	(0.237)	(0.922)		(5.864)	
Log-likelihood	-1153.3	-637.83	-	-36.245	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.10: Estimation Results for Venezuela

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-0.050	0.375	0.785	-
	(0.319)	(0.380)	(0.605)	(1.096)	
Imports Growth	-0.619**	-1.100***	-0.750	-0.608	+/-
	(0.311)	(0.375)	(0.594)	(1.120)	
Reserves Growth	-1.972***	-1.866***	-0.433	-8.529***	-
	(0.333)	(0.382)	(0.683)	(2.838)	
Real Int. Rate Differential	-0.155	-0.145	-1.031	-1.328	+
	(0.201)	(0.193)	(1.074)	(2.987)	
M2 Multiplier Growth	1.992	1.121**	**-3.034*****	**-11.402*****	+
	(0.428)	(0.451)	(0.984)	(3.383)	
Domestic Credit/GDP Growth	0.146	**-0.783****	-0.429	**-10.561*****	+
	(0.290)	(0.361)	(0.740)	(2.803)	
Lending/Deposit Rate	**-2.511*****	**-2.125*****	**-10.791*****	**-5.009***	+
	(0.294)	(0.323)	(1.320)	(3.019)	
M2/Reserves	2.070***	0.809**	1.950***	77.691	+
	(0.304)	(0.330)	(0.667)	(70.768)	
M2/Reserves Growth	-0.335	0.555	2.284**	4.463*	+
	(0.331)	(0.384)	(0.659)	(2.579)	
Bank Deposits Growth	-0.685***	-1.653***	-3.641***	-0.666	-
	(0.246)	(0.300)	(0.589)	(1.864)	
Industrial Production Growth	-1.284**	-0.924	**3.091****	**7.242*****	-
	(0.237)	(0.922)	(1.367)	(2.689)	
Log-likelihood	-1153.3	-637.83	-234.56	-59.247	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.11: Estimation Results for Indonesia

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-3.137***	-13.011***	-14.643***	-
	(0.319)	(0.811)	(2.348)	(3.500)	
Imports Growth	-0.619**	1.489**	2.941**	-0.092	+/-
	(0.311)	(0.730)	(1.357)	(1.961)	
Reserves Growth	-1.972***	-1.932***	-10.624	-20.865***	-
	(0.333)	(0.713)	(2.213)	(5.700)	
Real Int. Rate Differential	-0.155	9.740***	33.140***	72.624***	+
	(0.201)	(2.659)	(7.150)	(18.961)	
M2 Multiplier Growth	1.992	4.565***	7.163***	0.476	+
	(0.428)	(1.171)	(2.377)	(6.199)	
Domestic Credit/GDP Growth	0.146	2.612***	-2.502	-1.036	+
	(0.290)	(0.649)	(2.283)	(3.099)	
Lending/Deposit Rate	**-2.511*****	**-3.766*****	6.176**	4.631	+
	(0.294)	(0.991)	(2.681)	(6.519)	
M2/Reserves	2.070***	5.289***	39.741***	121.547***	+
	(0.304)	(0.713)	(8.370)	(33.358)	
M2/Reserves Growth	-0.335	**-1.388***	**-12.409*****	**-20.486*****	+
	(0.331)	(0.778)	(0.659)	(5.191)	
Bank Deposits Growth	-0.685***	**2.290*****	**16.764*****	**15.374*****	-
	(0.246)	(0.634)	(0.589)	(3.562)	
Industrial Production Growth	-1.284**	-4.715	-6.004**	-12.485***	-
	(0.237)	(1.173)	(2.879)	(4.057)	
Log-likelihood	-1153.3	-379.80	-90.993	-39.796	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.12: Estimation Results for Korea

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-3.137***	-13.011***	-41.490***	-
	(0.319)	(0.811)	(2.348)	(12.129)	
Imports Growth	-0.619**	1.489**	2.941**	12.634	+/-
	(0.311)	(0.730)	(1.357)	(9.380)	
Reserves Growth	-1.972***	-1.932***	-10.624	-37.908***	-
	(0.333)	(0.713)	(2.213)	(12.908)	
Real Int. Rate Differential	-0.155	9.740***	33.140***	14.525	+
	(0.201)	(2.659)	(7.150)	(49.440)	
M2 Multiplier Growth	1.992	4.565***	7.163***	19.411**	+
	(0.428)	(1.171)	(2.377)	(8.537)	
Domestic Credit/GDP Growth	0.146	2.612***	-2.502	63.632***	+
	(0.290)	(0.649)	(2.283)	(23.120)	
Lending/Deposit Rate	**-2.511***	**-3.766***	6.176**	55.267***	+
	(0.294)	(0.991)	(2.681)	(18.779)	
M2/Reserves	2.070***	5.289***	39.741***	112.948***	+
	(0.304)	(0.713)	(8.370)	(33.517)	
M2/Reserves Growth	-0.335	**-1.388***	**-12.409***	**-43.710***	+
	(0.331)	(0.778)	(0.659)	(16.852)	
Bank Deposits Growth	-0.685***	**2.290***	**16.764***	**67.869***	-
	(0.246)	(0.634)	(0.589)	(19.248)	
Industrial Production Growth	-1.284**	-4.715	-6.004**	**73.616***	-
	(0.237)	(1.173)	(2.879)	(27.530)	
Log-likelihood	-1153.3	-379.80	-90.993	-17.152	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.13: Estimation Results for Malaysia

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-3.137***	-9.258***	-0.252	-
	(0.319)	(0.811)	(3.172)	(9.682)	
Imports Growth	-0.619**	1.489**	1.550	-21.470	+/-
	(0.311)	(0.730)	(2.630)	(15.383)	
Reserves Growth	-1.972***	-1.932***	3.127	31.522	-
	(0.333)	(0.713)	(2.221)	(23.643)	
Real Int. Rate Differential	-0.155	9.740***	**-29.084***	232.246	+
	(0.201)	(2.659)	(16.619)	(198.54)	
M2 Multiplier Growth	1.992	4.565***	-5.104	34.741	+
	(0.428)	(1.171)	(3.346)	(33.385)	
Domestic Credit/GDP Growth	0.146	2.612***	21.467***	116.411*	+
	(0.290)	(0.649)	(4.587)	(60.496)	
Lending/Deposit Rate	**-2.511***	**-3.766***	**-9.380***	-105.479	+
	(0.294)	(0.991)	(2.790)	(86.208)	
M2/Reserves	2.070***	5.289***	5.333***	3.661	+
	(0.304)	(0.713)	(0.864)	(2.475)	
M2/Reserves Growth	-0.335	**-1.388***	7.330***	5.275	+
	(0.331)	(0.778)	(2.530)	(3.980)	
Bank Deposits Growth	-0.685***	**2.290***	-3.007***	8.702	-
	(0.246)	(0.634)	(1.159)	(10.886)	
Industrial Production Growth	-1.284**	-4.715	3.483	-29.492	-
	(0.237)	(1.173)	(3.238)	(38.923)	
Log-likelihood	-1153.3	-379.80	-88.434	-9.6082	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.14: Estimation Results for the Philippines

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-3.137***	-	1.328	-
	(0.319)	(0.811)		(2.584)	
Imports Growth	-0.619**	1.489**	-	8.518***	+/-
	(0.311)	(0.730)		(2.913)	
Reserves Growth	-1.972***	-1.932***	-	-17.155***	-
	(0.333)	(0.713)		(3.862)	
Real Int. Rate Differential	-0.155	9.740***	-	**-25.201****	+
	(0.201)	(2.659)		(11.749)	
M2 Multiplier Growth	1.992	4.565***	-	35.820***	+
	(0.428)	(1.171)		(7.650)	
Domestic Credit/GDP Growth	0.146	2.612***	-	1.736	+
	(0.290)	(0.649)		(1.298)	
Lending/Deposit Rate	**-2.511*****	**-3.766*****	-	0.670	+
	(0.294)	(0.991)		(3.344)	
M2/Reserves	2.070***	5.289***	-	85.564***	+
	(0.304)	(0.713)		(15.379)	
M2/Reserves Growth	-0.335	**-1.388***	-	**-2.578*****	+
	(0.331)	(0.778)		(0.512)	
Bank Deposits Growth	-0.685***	**2.290*****	-	**13.133*****	-
	(0.246)	(0.634)		(2.967)	
Industrial Production Growth	-1.284**	-4.715	-	-6.937	-
	(0.237)	(1.173)		(4.140)	
Log-likelihood	-1153.3	-379.80	-88.434	-43.709	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Table 2.15: Estimation Results for Taiwan / Thailand

Variable	Naive Model	Regional Model	Cluster Model	Country Model	Exp. Sign
Exports Growth	-0.612*	-3.137***	-9.258***	-	-
	(0.319)	(0.811)	(3.172)		
Imports Growth	-0.619**	1.489**	1.550	-	+/-
	(0.311)	(0.730)	(2.630)		
Reserves Growth	-1.972***	-1.932***	3.127	-	-
	(0.333)	(0.713)	(2.221)		
Real Int. Rate Differential	-0.155	9.740***	**-29.084***	-	+
	(0.201)	(2.659)	(16.619)		
M2 Multiplier Growth	1.992	4.565***	-5.104	-	+
	(0.428)	(1.171)	(3.346)		
Domestic Credit/GDP Growth	0.146	2.612***	21.467***	-	+
	(0.290)	(0.649)	(4.587)		
Lending/Deposit Rate	**-2.511*****	**-3.766*****	**-9.380*****	-	+
	(0.294)	(0.991)	(2.790)		
M2/Reserves	2.070***	5.289***	5.333***	-	+
	(0.304)	(0.713)	(0.864)		
M2/Reserves Growth	-0.335	**-1.388***	7.330***	-	+
	(0.331)	(0.778)	(2.530)		
Bank Deposits Growth	-0.685***	**2.290*****	-3.007***	-	-
	(0.246)	(0.634)	(1.159)		
Industrial Production Growth	-1.284**	-4.715	3.483	-	-
	(0.237)	(1.173)	(3.238)		
Log-likelihood	-1153.3	-379.80	-88.434	-	

Note: Fixed effects dummies are not included in the table for brevity.
Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%

Chapter 3

Using Proportional Hazards Models to Predict Currency Crises

This chapter aims at explaining the occurrence of currency crises using the duration of the time spent in the tranquil (or non-crisis) period as well as macroeconomic variables. A duration model is estimated for 17 countries from Latin America and Asia over the period 1985-2005. We use fully parametric methods to estimate a proportional hazards model and examine if the time already spent in the tranquil state is a determinant of the probability to exit into a crisis state. The results indicate that the baseline hazard increases exponentially with time for the crises in Asia, whereas the crises in Latin America exhibit a constant baseline hazard. Performance measures indicate that the model works exceptionally well for the Asian countries. The baseline hazard of recovery increases with time for all types of crises.

3.1 Introduction

A few decades ago, Krugman (1979) and Flood and Garber (1984) made an initial effort to explain the collapse of fixed exchange rate regimes as a result of balance-of-payments problems. Later, Frankel and Rose (1996); Eichengreen, Rose, and Wyplosz (1995) examined the behaviour of macroeconomic variables around episodes of financial turmoil. The information that the behaviour of these variables can contain information about an imminent crisis soon led to the first Early Warning Systems (EWS). Early Warning Systems have appeared in several forms. Kaminsky, Lizondo, and Reinhart (1998) developed a signalling model in which a large set of macroeconomic variables is monitored for signals to indicate an upcoming crisis. Alternatively, probit- and logit-models have been proposed including macroeconomic fundamentals as explanatory variables (Berg and Pattillo, 1999; Kumar, Moorthy, and Perraudin, 2003). For crisis periods caused by 'bad' fundamentals, the first generation crisis models (e.g. Flood and Garber, 1984), the above EWS models perform very well (e.g. the Tequila crisis).[1] However, not all periods of crisis are caused by bad fundamentals; such as for example the 1997-98 Asian crisis. As the macro economic characteristics of these countries are not 'poor' in the months prior to the crises, the above Early Warning Systems do not perform so well in terms of picking up these type of crisis. Evidently other factors play a role in determining currency stability and hence the probability of a crisis occurring. We turn to the duration framework to examine if the time that has passed since the last crisis is a good way to measure currency stability.

Duration models are most frequently used in failure-time frameworks such as unemployment models (e.g. Kiefer, 1988; Pudney and Thomas, 1995; Grogan and Van den Berg, 2001), bank-failure models (e.g. Whalen, 1991; Sales and Tannuri-Pianto, 2005; Dabós and Escudero, 2004) or the medical literature (e.g. Douglas and Hariharan, 1994; Hamilton and Hamilton, 1997). In the unemployment literature for example, the probability of finding a job is modelled as depending on the duration of unemployment moderated with the characteristics of the subjects. Typically, a person's characteristics such as education, working experience etc., do not change in a spell of unemployment. If one wishes to apply a duration model to explain the probability of going into crisis, it cannot be assumed that the characteristics of a country (the macro economic variables) are constant throughout the time between two crises. For this reason the duration approach is not widely used to model currency crises. As far as we know, only Tudela (2004) uses a modified duration model allowing for time-varying explanatory variables that can be applied to modelling currency crises. Specifically the semi-parametric Cox-Proportional Hazards (PH) model (Cox, 1972) is adapted. In the Cox-PH model, the time dependent part is effectively not estimated. The effect of the elapsed time since the last crisis on the probability of crisis is only measured as a residual of the estimation.

This chapter's contribution is threefold. First, we propose a fully parametric alternative to the semiparametric Cox Proportional Hazards model as described in Tudela (2004) to be able to use the time dimension more strongly. This is desirable as the time dimension of the hazard function (the baseline hazard) is used to capture those determinants of the probability of crisis that are not captured by the macroeconomic explanatory variables. We allow for different parameterisations of the baseline hazard in order to find the optimal form. Second, next to the probability to enter a crisis, the exit out of the crisis situation is also modelled as it might be interesting to see which factors contribute to a fast recovery from a crisis. This information can be used by policymakers to determine their strategy of dealing with a crisis. Third, for both the entry and exit of the crisis

[1] As in the previous chapter, only the for this chapter relevant papers are mentioned here. For an extensive discussion of the crisis literature, please refer to Chapter 1.

we examine the influence of regional effects via subsamples and evaluate the predictive power of the model. As noticed by Glick and Rose (1999), contagion often spreads regionally, independent of macroeconomic characteristics of the countries. The baseline hazard in the subsample estimation can capture this regional effect. An Early Warning System based on duration analyses should therefore be more suitable for second or third generation crisis models.

The remainder of the chapter is organised as follows: In Section 3.2 we present the model as well as other methodological issues. Section 3.3 provides a short description of the data and the definition of a crisis. In Section 3.4 we determine the optimal form of the hazard function, evaluate our regression results and examine the predictive performance of our models. Section 3.5 concludes.

3.2 Parametric Proportional Hazards Model

A duration analysis is used to model the probability that a country moves from a tranquil state to a state of crisis or vice versa. Just like traditional early warning systems, the duration model makes use of macroeconomic explanatory variables to determine the probability of entering (or exiting) a crisis state. In addition, the duration model also takes into account the time already spent in the current state, as a proxy for beliefs of market agents about currency (in)stability.[2] This setup allows for the fact that these beliefs can change as the period in the current state lengthens. A baseline hazard decreasing with time would mean that investors believe that a longer duration of the period in the current state signals stability and expect this to continue. If the hazard increases as the duration of the current period lengthens, the opposite is true; the longer the period of tranquility, the sooner investors expect it to end.

In this paper we only employ duration models from within the proportional hazards (PH) framework. The PH framework has the convenient property that the hazard function[3] can be decomposed into two different parts. One part depending on the explanatory variables and one part depending on the time already spent in the current state. Under PH, we can therefore write the hazard function for country i at time t as:

$$\lambda_{i,t}(\mathbf{X}_{it}, \boldsymbol{\beta}, \lambda_0(t)) = \lambda_0(t) g(\mathbf{X}_{it}, \boldsymbol{\beta}), \tag{3.1}$$

where we can take the most commonly used form for $g(\cdot)$:

$$g(\mathbf{X}_{it}, \boldsymbol{\beta}) = \exp(\boldsymbol{\beta}' \mathbf{X}_{it}), \tag{3.2}$$

[2] See Lancaster (1990) and Kalbfleish and Prentice (2002) for an extensive discussion of duration models.

[3] In continuous time, the hazard function is defined as the instantaneous probability of transition from State 1 to State 2 at time t, given that we are currently in State 1. In discrete time, the hazard function represents the probability of transition to State 2 at time t given that we are in a State 1 at time $t-1$.

with $\mathbf{X}_{it}$ denoting the set of time-varying explanatory variables and $\lambda_0(t)$ being the time dependent part also known as the baseline hazard function. The baseline hazard function is exactly that part of the hazard function that remains when the effect of the explanatory variables is filtered out by setting it to zero. In practice this means that $g(\cdot) = \exp(\beta_0)$ if $\boldsymbol{\beta}'\mathbf{X}_{it}$ includes a constant or that $g(\cdot) = 1$ if there is no constant. Under the semi-parametric Cox-PH model, the function $\lambda_0(t)$ is left unspecified. The time dependent part is then implied by the part that depends on the explanatory variables, but it has no impact on the estimation of the coefficients. In our model, the baseline hazard takes a specific parametric form such that the effect of the time already spent in the current state can be explicitly estimated.

Within the proportional hazards framework, the baseline hazard can be based on one of the following three distributions: i) Exponential, ii) Weibull, or iii) Gompertz (Kalbfleish and Prentice, 2002). The associated functional forms of the baseline hazard are listed in Table 3.1. When the duration of the time spent in a certain state does not hold any information, the baseline hazard function is constant and the exponential distribution is obtained. Under the Exponential form the beliefs of investors therefore do not influence the probability of crisis. In this situation the occurrence of crises can be best predicted by macroeconomic variables only. Both the Weibull and the Gompertz hazard function are generalised forms of the Exponential case that allow for the hazard rate to depend on the time already spent the current state. Under the Weibull distribution the hazard can increase or decrease with duration depending on the value of p. Notice that when $p = 1$, the baseline hazard becomes constant and the Weibull reduces to the Exponential form. Under the Gompertz distribution the hazard rate can increase or decrease exponentially with time spent in the current state. When $\gamma = 0$, the hazard rate becomes constant as in the Exponential case. In the estimation of the parametric PH duration models, an intermediate model in which the coefficients of the explanatory variables (except for the constant) are kept at zero is estimated first. This intermediate model is the parametric baseline hazard function and its likelihood serves as the null likelihood for estimation of the full model. In this full model the ancillary parameter and the coefficients of the explanatory variables are estimated jointly by maximum likelihood.

Model	Baseline Hazard (λ_0)	Ancillary Parameter
Exponential	$\exp(\beta_0)$	-
Weibull	$p\,t^{p-1}\exp(\beta_0)$	p
Gompertz	$\exp(\gamma t)\exp(\beta_0)$	γ

Table 3.1: Parametric Forms for the Proportional Hazards Model

We prefer to use one of the fully parametric models over the partially non-parametric Cox-PH model, because the Cox-PH model does not exploit the extra information from the durations like the fully parametric models do. A disadvantage is that we now have to determine which specification of the baseline hazard should be used. A formal comparison of the possible forms is performed using information criteria[4]. The optimal form of the hazard function is determined separately for each of the different models.

In duration models, the survival function S_t is the probability that the time of transition to another state is later than time t. In terms of the survival function, the hazard rate is defined as the (negative) percentage change in the survival function: $\lambda_{i,t} = -S'_t/S_t$. Transferring this to a discrete time crisis model, the hazard rate represents the probability of moving to a crisis at time t given that we are in a tranquil state at time $t-1$. Noticing that the survival function can be represented as $S_t = \exp(-\int_0^t \lambda(v)\mathrm{d}v)$, the hazard function for an individual i at time t in a proportional hazards setting can be formulated as:

$$\lambda_{i,t} = \frac{S_{t-1} - S_t}{S_{t-1}} = 1 - \frac{S_t}{S_{t-1}} = 1 - \exp[-\exp(\boldsymbol{\beta}'\mathbf{X}_{it} + \Gamma_t)], \tag{3.3}$$

where

$$\Gamma_t = \ln\left[\int_{t-1}^{t} \lambda_0(v)\mathrm{d}v\right]. \tag{3.4}$$

As can be seen from equation (3.4), Γ_t is defined as (the logarithm of) the total amount of baseline hazard (λ_0) the country is exposed to in the period between time $t-1$ and time t. The Γ_t does not depend on the explanatory variables and represents the time dependent part of the hazard rate. Notice that Γ_t takes different forms under the different distributions

$$\begin{aligned} \Gamma_t &= \beta_0 && \text{under Exponential Distribution,} \\ \Gamma_t &= \beta_0 + p\ln(t) && \text{under Weibull Distribution,} \\ \Gamma_t &= \beta_0 - \ln(\gamma) + \gamma t && \text{under Gompertz Distribution.} \end{aligned}$$

The likelihood function can be decomposed into the contributions of each of the periods spent consecutively in one state. One such a period is terminated via one of two ways; either because there is a transition into the other state, or because we have reached the end of the dataset before a transition could occur. In the latter situation the period is said to be censored[5], whereas in the former case it is called uncensored. Suppose that country i experiences some period j in the tranquil state which ends in the interval $(t_j - 1, t_j]$. The contribution to the log

[4]Bradburn, Clark, Love, and Altman (2003) show in their paper that the Akaike or Bayesian Information Criterion can be used to determine which of the forms of the parametric baseline hazard function performs best.

[5]A period is right censored when it is cut off at the end of the sample and left censored when cut off at the beginning of the sample.

likelihood made by this period is:

$$
\begin{aligned}
l_{i,j}(\boldsymbol{\beta}, \lambda_0) &= d_j \ln(\lambda_{i,t_j}) + \sum_{u=1}^{t_j-1} \ln(1-\lambda_{i,u}) \\
&= d_j \ln\left(1 - \exp[-\exp(\boldsymbol{\beta}'\mathbf{X}_{i,t_j} + \Gamma_{t_j})]\right) - \sum_{u=1}^{t_j-1} \exp(\boldsymbol{\beta}'\mathbf{X}_{i,u} + \Gamma_u),
\end{aligned}
\tag{3.5}
$$

where d_j is a binary indicator that takes value 1 if the period j is uncensored and 0 if it is censored.

Because a country can experience multiple transitions, we know that it may also have multiple contributions to the likelihood function. Naturally, only the last period of country can be censored. Suppose country i experiences C_i periods of tranquility. Let now $d_i = 1$ if the last period of country i is censored and $d_i = 0$ otherwise. Also, let $\lambda^c_{i,s_{ic},t}$ denote the hazard function at time t of period c for country i that started at time s_{ic}. The elapsed duration of the current period is then $t - s_{ic}$. Suppose that the period c of country i ends in the interval $(t_{ic}-1, t_{ic}]$. A country's contribution to the log likelihood, given that it experiences C_i periods now becomes:

$$
\begin{aligned}
l_i(\boldsymbol{\beta}, \lambda_0) = &\sum_{c=1}^{C_i-1} \left[\ln(\lambda^c_{i,s_{ic},t_{ic}}) + \sum_{u=s_{ic}}^{t_{ic}-1} \ln(1-\lambda^c_{i,s_{ic},u}) \right] \\
&+ d_i \ln(\lambda^{C_i}_{i,s_{iC_i},t_{iC_i}}) + \sum_{u=s_{iC_i}}^{t_{iC_i}-1} \ln(1-\lambda^{C_i}_{i,s_{iC_i},u}).
\end{aligned}
\tag{3.6}
$$

As the above expression is the contribution to the log likelihood of one country, we take the sum of these contributions over all countries to get the overall log likelihood function of our duration model.

From the model description in Equations (3.5) and (3.6) it is clear that the model is estimated jointly for all countries. This implies the undesirable restriction that a crises has the same macro economic causes in each country throughout the sample. This homogeneity assumption is quite heroic, but avoiding it is to face the finite-sample problem (see Chapter 2). Unfortunately the number of crises are not sufficient to have a country by country analysis. To allow for some heterogeneity, we also estimate the duration model for regional subsamples, which as saw in Chapter 2, is a step towards more homogenous samples.

3.3 Data

3.3.1 Dataset

We are interested to find out the difference of the time effect between first generation crisis models on the one hand and crises where the link between macro economic fundamentals and the crisis occurrence is not always clear on the other hand. Our dataset therefore covers 17 countries from the regions Latin-America and Asia: Argentina, Brazil, Ecuador, Mexico, Paraguay, Peru, Uruguay, Venezuela, China, Fiji, India, Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand. We use monthly data from January 1985 to January 2005, obtained from Datastream[6].[7]

The set of explanatory variables we use in this chapter is the same as the set of variables used in Chapter 2. Because the hazard rate is defined as the probability of transition between states of the world, the effect of the variables on the hazard rate is expected to be similar to the effect on the probability of a crisis as discussed in the previous chapter. This section is included here such that it is not necessary for readers to have read Chapter 2 beforehand. The reader that did read the data section of Chapter 2, can feel free to skip ahead to Subsection 3.3.2.

As explanatory variables for the hazard rate we selected several macroeconomic variables relating to different aspects of the economy. We use variables from the external sector, the financial sector and the real sector. Notice that all explanatory variables enter the hazard rate one month lagged. This way, at time t, the probability of a crisis is affected only by variables which are observable at time t.

The external sector can be separated into the current account and the capital account. Because we use monthly data, we cannot use the quarterly data for the current account and capital account directly. We therefore approximate these factors by other variables that are available on a monthly basis. The first variable relating to the current account is the annual growth rate of exports. Because a decrease in exports indicates a loss in international competitiveness, it can lead to a recession and business failures (Dornbusch, Goldfajn, and Valdes, 1995). Hence we expect a decrease in exports to increase the probability of a crisis. The other variable related to the current account is the imports annual growth rate. For imports the theory is not so clear. On the one hand an decrease in imports could be an indication of weakening of economic activity, while on the other hand an increase in imports can be caused by a strong overvaluation of the real exchange rate (Kaminsky and Reinhart, 1999). To proxy the capital account, the real interest rate differential with respect to the United States as well as the growth in international reserves are used. For the latter we expect that a decrease in reserves lowers the leverage of the central bank to deal with speculative attacks and

[6]The sources used are the IMF-IFS database and the national banks of the respective countries.

[7]Due to the limited data availability is was unfortunately not possible to construct a consistent dataset dating further back than 1985.

therefore increases the probability of crisis. A high real interest rate differential is typically associated with a high amount of pressure on the currency as the increased domestic interest rate could be a response to excess supply of the currency (see Eichengreen et al., 1995).

The second aspect of the economy is the financial sector. It has been shown by McKinnon and Pill (1996) that currency crises, most notably those accompanied by a banking crisis (labelled as "twin crises"), have often been preceded by periods of financial liberalisation. Facilitated by the more relaxed reserve requirements for banks, the financial liberalisation tends to make people and banks overconfident in the stability of the currency, leading to excessive (foreign) borrowing. The banking sector now becomes vulnerable to speculative attacks (Krugman, 1979). Overborrowing results in an increase in the M2 multiplier as well as growth of domestic credit relative to GDP (McKinnon and Pill, 1998). For both these variables it holds that a higher ratio indicates higher vulnerability and therefore a higher probability of crisis. To capture the credit risk rating and the willingness of banks to lend, the ratio lending rate over deposit rate is included. An increase in this ratio indicates that banks require a high risker premium on their loans. The higher risk premium is a direct consequence of a lower economic stability. We also include the ratio M2 over reserves. An increase of the ratio is caused both by an increase in M2 money and decrease in reserves. The higher this ratio, the more vulnerable is the economic system to speculative attacks (Calvo and Mendoza, 1996). The ratio M2 over reserves is included both as levels and as growth rate, because not only an increase in the ratio increases the vulnerability, but also a ratio that is simply high. The final financial variable is the growth of bank deposits. A decrease in this variable shows capital flight and bank runs, a clear indicator of an imminent crisis (Goldfajn and Valdes, 1997).

The last aspect of the economy captured by the variables, is the real sector of the economy. As a proxy for output growth we use the industrial production growth rate. A decrease in industrial production growth is the sign of a weakening domestic economy and therefore an increase in the probability of crisis.

The reason for the transformation of most of the explanatory variables to their annual growth rates is not only the benefit that we can have data at a monthly frequency. As a crisis is by definition a sudden change with respect to a previous time period, we believe that we must also use the changes in our explanatory variables instead of the levels. The transformation also makes data for different countries more comparable: Even though the level of, for example, international reserves can differ substantially at any point in time, the percentage changes in reserves will be a lot closer together and are also likely to react in a similar way across countries in case of a crisis. Furthermore, missing values in the middle of the sample are interpolated using cubic splines. Missing values at the beginning or end of the sample are dropped.

Other researchers in this area (e.g. Kumar et al., 2003) claim that the extreme observations should be dampened to lower the relative importance of these outliers in the estimation. The transformation they propose to dampen this effect is: $y_t^{\text{New}} = (\text{sign of } y_t) * \ln(1 + |\, y_t |\,)$. We have checked the robustness of our results against this transformation and see that the differences are only marginal, the qualitative results remain unchanged[8]. As the transformation does not seem to have a significant impact on the results, we decide against the transformation in order to keep the clarity of the model as high as possible.

3.3.2 Definition of a Crisis

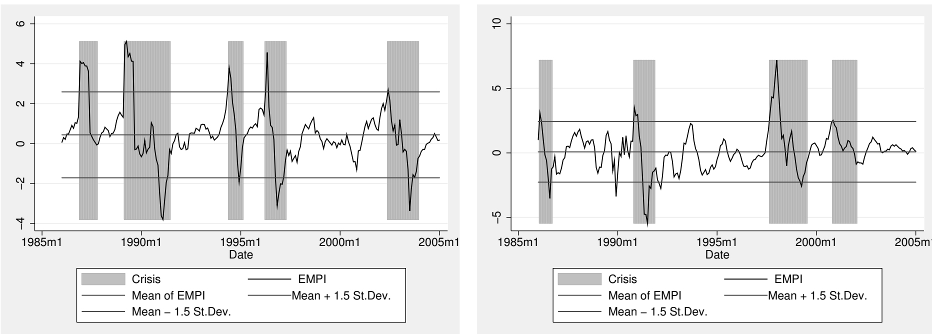
Before we can start modelling any transition from a tranquil state to a state of crisis or vice versa, it must first be decided how a crisis is defined. Since we are interested in the probability of crisis, information about speculative attacks is required. Not all speculative attacks lead to a devaluation or revaluation of the currency. In order to capture both successful and unsuccessful speculative attacks, the periods of crisis are determined via the Exchange Market Pressure (EMP) index (see Eichengreen et al., 1995). This EMP-index is the weighted average between the 6-month change in the exchange rate with respect to the US dollar and (the negative of) the 6-month change in the international reserves. The weights are chosen such that the variance of both factors are standardised to one. A crisis is signalled when the EMP-index exceeds a certain threshold.[9] In our model, a period of crisis is initiated when the EMP-index increases more than one and a half standard deviations above its mean. It might be argued that the threshold of 1.5 standard deviations is not sufficiently high to capture only extreme events. However, we have also tried to estimate the model with more extreme threshold such as 2 or 3 standard deviations. The problem with those higher thresholds is that the number of crises decreases to a level at which we no longer have a sufficient number of observations to conduct sensible inference. The threshold of 1.5 standard deviations seems to be a reasonable compromise between having sufficient observations and capturing only extreme events (crises). Additionally, the volatility of the determinants of the EMP-index tends to be a lot higher in periods of high inflation. To make sure that the periods of high inflation do not crowd out possible crisis events during low inflation, the sample is split into two subsamples. One for periods of high inflation and one for low inflation. The cutoff point is when the 6-month inflation is more than 50%.

It is argued by Bussiere and Fratzscher (2006) that after a crisis period it takes time before the macroeconomic characteristics of a country settle down to normal values. This can be seen for example if we take look at the EMP-index for Venezuela and the Philippines in Figure 3.1. As can be seen from the figure,

[8] The estimation results from the dampened model are available from the author upon request.

[9] As pointed out in Chapter 1, this method of defining periods of crisis has its shortcomings. In the absence of a universal consensus about which dating method is best, we choose the method that comes closest to capturing the fluctuations on the exchange rate market.

most of the time the EMP-index drops well below its normal level in the period right after a crisis has occurred. These huge fluctuations are perfectly in line with the argument of Bussiere and Fratzscher (2006) that after a crisis we first have an adjustment period before the economy returns to its normal, tranquil state. In our model the tranquil state only starts after this adjustment period. Instead of ignoring these periods right after the crisis, which is common practice, we explicitly formulate a duration model for these periods as well to see if we can also predict how long it will take until the economy settles down again.



(a) Venezuela (b) Philippines

Figure 3.1: Exchange Market Pressure Index and Periods of Crisis

In the twenty years that are covered by our database, we classify 46 distinct periods of crisis divided over the 17 countries. We identify slightly more crisis periods than most other studies, which is due to the lower threshold. Because we also have a censored period of tranquility at the end of the sample for each of the countries, the total number of tranquil periods is therefore 63 in the crisis entry model. The model that tries to explain the transition from a state of crisis into a tranquil state, the crisis exit model, covers exactly those 46 periods of crisis. The number of crisis periods per country varies from 5 in Venezuela to only one crisis in Korea, Malaysia and Thailand. Among the crisis periods, we find the 1995 Mexican crisis, the 2002 crisis in Argentina, and of course the Asian crisis. Out of the 9 Asian countries, only China and India do not have a crisis in 1997-98. This is not so strange as these countries were not severely affected by the Asian crisis.

3.4 Estimation and Performance

3.4.1 Estimation Results

When estimating a proportional hazards model with a parametric hazard function, one needs to both choose an appropriate form for the baseline hazard function and determine which explanatory variables should be included. As we take the side to remain agnostic and to impose as little a priori beliefs as possible about the general form of the hazard, the Bayesian Information Criterion (BIC) is estimated to determine the optimal form of the hazard function. As a consequence, we must simultaneously determine which explanatory variables should be included in the model and which is the optimal form for the hazard function. To make sure that our final models are not misspecified due to the decisions made in the estimation procedure, the general-to-specific and specific-to-general methods[10] are applied to decide which are the explanatory variables to include. We do this for each of the three potential forms of the baseline hazard function. It turns out that the optimal choice of explanatory variables is relatively robust to the form of the baseline hazard. Only in two cases[11] there is a slight difference in the variables that are significant. In those cases one of the parametric forms has one or two different significant variables, but most variables are the same. Robustness between the different forms of the hazard was to be expected as the proportional hazards approach explicitly separates the time dependent part of hazard from the part that depends on the explanatory variables.

As mentioned, our sample of countries consists of two main regions, Latin America and Asia. The vast literature on the topic would lead us to suspect that crises in Latin America have different underlying causes than crises in Asia (Berg, 1999; Krugman and Obstfeld, 2003). We therefore estimate the duration model based on the full sample as well as models based on the regional subsamples. Between these models we not only allow for different explanatory variables but also for a different form of the baseline hazard. Ideally, one would also like to allow for country-specific effects but this would mean that we need to estimate at least one additional parameter per country. Given our already limited sample size of 35 and 28 periods of tranquility in Latin America and Asia respectively, the estimation of such a model will not provide reliable results as the number of parameters to be estimated would almost exceed the number of observations.

In Table 3.2 we compare the three different forms of the hazard function for each of the three (sub)samples. The reported statistics correspond to the models with only the significant explanatory variables. The top panel of the table con-

[10]The general-to-specific method starts off with the model that includes all potential explanatory variable and step by step removes the variable that contributes least to the model via the BIC. This procedure is continued until only significant variables are left in the model. The specific-to-general method does exactly the opposite: It starts off with a model that has only a constant. For each of the potential explanatory variables it is checked (with BIC) which variable contributes most to the model. This variable is included in the model and the procedure is repeated step by step until there are no more significant variables to add.

[11]The first difference is in the crisis entry model for the Latin American sample. The model with the Weibull hazard has the growth of international reserves and the level of ratio M2 over reserves as significant variables where both other forms have bank deposits growth as significant variable instead. The second difference is in the crisis exit model for the Asian sample, where the Gompertz hazard model has international reserves growth and industrial production growth as additional significant variables compared to the other two forms of the hazard.

Crisis entry				
Model	LL(null)[a]	LL(model)	df	BIC
Exponential (Full Sample)	-94.95	-53.86	7	164.01
Gompertz (Full Sample)	-94.95	-53.40	8	171.13
Weibull (Full Sample)	-94.71	-53.86	8	172.04
Exponential (Latin America)	-56.27	-40.20	5	116.46
Gompertz (Latin America)	-55.56	-39.93	6	123.14
Weibull (Latin America)	-55.47	-33.45	7	117.40
Exponential (Asia)	-36.61	-5.556	9	70.84
Gompertz (Asia)	-35.34	-1.986	10	63.71
Weibull (Asia)	-36.16	-2.764	10	65.27

Crisis exit				
Model	LL(null)[a]	LL(model)	df	BIC
Exponential (Full Sample)	-49.65	-31.18	4	89.47
Gompertz (Full Sample)	-29.05	-20.18	5	74.26
Weibull (Full Sample)	-24.94	-17.10	5	68.09
Exponential (Latin America)	-29.49	-15.80	4	56.68
Gompertz (Latin America)	-17.83	-10.27	5	51.89
Weibull (Latin America)	-16.27	-9.305	5	49.96
Exponential (Asia)	-20.14	-12.01	5	53.31
Gompertz (Asia)	-10.89	-2.734	8	52.33
Weibull (Asia)	-8.203	-2.129	6	39.41

[a] The null log-likelihood (LL) is the likelihood of the intermediate model in which only the ancillary parameter and the constant are estimated.

Table 3.2: Determining the hazard function for the crisis entry and crisis exit model. (Crisis if *EMP*-index > mean + 1.5 stdev)

tains the model that explains the transition from tranquil to the crisis state. From the Bayesian Information Criterion we see that for the Latin American and full sample the exponential form of the baseline hazard is preferred by a small margin, whereas for Asia the Gompertz form for the hazard is best. These results indicate that for Latin America the hazard to fall into crisis is relatively constant with respect to time, the time dimension therefore plays only a small role in determining the probability to fall into crisis, leaving more room for the macroeconomic explanatory variables. This is consistent with the message for first generation crisis models. For Asia we see that the baseline hazard increases with time exponentially ($\gamma > 0$). Basically this means that the hazard of transition into crisis can increase even without any macroeconomic fundamentals causing it. This shows that in Asia other factors than weak fundamentals also play a role in determining whether a crisis will occur. We may therefore conclude that the forms we find for the baseline hazard corresponds to what we would expect in the respective regions.

The bottom panel of Table 3.2 shows that the Weibull is the optimal form for the baseline hazard function of the model that explains the transition from a state of crisis back into the tranquil state. The Weibull form is optimal for all samples. If we also consider that the estimated value of the parameter p, which determines the form of the Weibull hazard (see Table 3.4), is larger than 1 in all (sub)samples, we can conclude that for all countries the 'hazard' of moving back into the tranquil state increases as time passes. This is a sensible result as the panic that is associated with the outbreak of a crisis eventually will settle down as time passes. Interestingly it is the same for both regions.

Tables 3.3 and 3.4 shows the estimation results of the models with the optimal form of the baseline hazard and the explanatory variables that are significant at a 10% significance level. A first glance at the tables reveals that for both the crisis entry and crisis exit model the results of the full sample are very close to those of the Latin American Sample. This indicates that the estimation of the full sample model is dominated by the Latin American countries. This could mean that the macroeconomic fundamentals change more severely in Latin America. This is in line with the general consensus about having first generation models in Latin America and second generation models in Asia. Note also that the standard errors are calculated using a robust estimator for cluster correlation (see Williams, 2000). This variance estimator does not only allow for heteroscedasticity, it also corrects for serial correlation of the observations within one country, whereas independence is assumed between countries.

Taking a closer look at the results of the crisis entry model, we see that the majority of the parameters has the expected sign. In total, 10 macro economic variables have a significant effect on the hazard rate in at least one of the three samples. Only 3 of them exhibit an unexpected sign; the M2 multiplier growth, the lending rate over deposit rate ratio and the growth of the M2 over reserves. Interesting differences between the two regional samples emerge. For example the

Variable	Full Sample	LA Sample	Asian Sample	Exp. Sign
Exports Growth$_{t-1}$			-2.873	-
			(1.608)	
Imports Growth$_{t-1}$			3.199	+/-
			(1.522)	
Reserves Growth$_{t-1}$	-3.701		-16.97	-
	(1.197)		(3.408)	
Real Int. Rate Differential$_{t-1}$	0.199	0.218	16.71	+
	(0.016)	(0.015)	(4.081)	
M2 Multiplier Growth$_{t-1}$	-2.554	-3.133		+
	(0.729)	(0.825)		
Lending/Deposit Rate$_{t-1}$	-0.595	-0.653	-0.378	+
	(0.235)	(0.344)	(0.125)	
M2/Reserves$_{t-1}$	0.096		0.130	+
	(0.023)		(0.077)	
M2/Reserves Growth$_{t-1}$			-6.313	+
			(1.343)	
Bank Deposits Growth$_{t-1}$	-1.197	-2.354		-
	(0.608)	(0.610)		
Industrial Prod. Growth$_{t-1}$			-3.937	-
			(2.085)	
Constant	-3.310	-3.121	-4.741	
	(0.409)	(0.588)	(0.647)	
γ			0.016	
			(0.005)	

LL Full Sample = -53.86, LL Latin American Sample = -40.20,
LL Asian Sample = -1.986

Table 3.3: Estimation Results Crisis Entry Models

Variable	Full Sample	LA Sample	Asian Sample	Exp. Sign
Reserves Growth$_{t-1}$	0.643	0.807		+
	(0.127)	(0.129)		
Real Int. Rate Differential$_{t-1}$			7.040	-
			(0.881)	
M2 Multiplier Growth$_{t-1}$	0.034	0.044	3.661	-
	(0.008)	(0.005)	(1.442)	
Lending/Deposit Rate$_{t-1}$			0.600	-
			(0.069)	
M2/Reserves$_{t-1}$			-0.188	-
			(0.063)	
Industrial Prod. Growth$_{t-1}$	1.396	1.367		+
	(0.246)	(0.226)		
Constant	-7.690	-7.290	-11.17	
	(0.777)	(0.905)	(1.503)	
ln(p)	0.878	0.801	1.185	
	(0.104)	(0.117)	(0.158)	
Implied p	2.41	2.23	3.27	

LL Full Sample = -17.10, LL Latin American Sample = -9.305,
LL Asian Sample = -2.129

Table 3.4: Estimation Results Crisis Exit Models

current account variables, the imports and exports growth rates, are not significant for Latin America, but both enter the Asian model. This indicates that Asian countries are more vulnerable when their external position weakens, whereas for Latin American this does not seem to be the case. We also see that in contrast to Latin America, crises in Asia are preceded by a decrease in international reserves. This might be an indication that the Asian central banks are more involved in trying to keep the exchange rate stable, whereas in Latin America the currency is on average allowed to float a bit more freely. Further, the decrease in the growth rate of bank deposits is a precedent of a crises in Latin America, but not in Asia. This difference could indicate that people in Latin America have less faith in the banking sector and are more likely to withdraw their money at the first signs of distress. Also, industrial production growth has a significant negative effect on the hazard rate of transition into crisis in the Asian sample, but not in the Latin American or the full sample. Finally, we see that the ancillary parameter γ of the Gompertz baseline hazard in the Asian sample is positive such that the hazard function increases with time. From the vast amount of differences in the significant variables between the two regional subsamples we may conclude that pooling both regions together probably does not yield the most desirable model.

The results for the crisis exit model show us first of all that there are less significant explanatory variables across the samples. This supports the view that a country automatically recovers from a crisis irrespective of the macro economic fundamentals. Once more, the estimates for the Latin American sample and the full sample are close together whereas the Asian sample has different significant variables. Just like in the crisis entry model, the M2 multiplier growth and the lending over deposit rate ratio have the sign opposite from expected. We see that the real interest rate differential has a positive effect on the hazard rate of ending the crisis period in the Asian sample. This effect is opposite from the expected negative sign which comes from the observation of Eichengreen et al. (1995) that a high real interest rate differential is typically associated with a high amount of pressure on the currency and hence a low real interest rate should be associated with an increased probability of exiting the crisis. However, in a period of crisis the government can try to shorten the crisis by making the domestic currency more attractive to investors through a higher real interest rate. Following this argument we should find a positive sign and that is indeed the case. The remaining variables show the expected signs. Finally, notice that for all three samples, the ancillary parameter p is larger than 1, which means that the probability of going back to a tranquil state increases as the duration of the crisis increases.

3.4.2 Prediction Performance

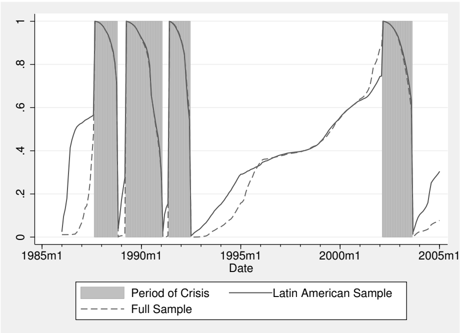
The goal of an Early Warning System is of course to signal crises before they actually happen. The performance of the model should therefore also be measured in terms of how well it predicts the currency crises. We measure this performance by the behaviour of the probability to go into a crisis right before crises occur, where the forecast horizon is varied between 6 and 24 months. Unlike in the logit and probit models, the probability of a crisis is not directly estimated in the duration model. Before we can proceed, we must therefore first define this probability.

At any point t in time, we measure the probability of going into a crisis as the inverse of the probability of surviving longer than time t given that the current period of tranquility started at some time t_0. This survival probability is defined as the product of the $t - t_0$ probabilities to survive one more period conditional on reaching the previous period. The estimated probability of crisis is shown in Figures 3.2-3.4. Ideally we would like to have a model for which the probability of crisis is low when no crisis is at hand and jumps up some time before a crisis. In the figures the periods of crisis are denoted by the grey areas. The probability of transition for the full sample is depicted as the dashed line, whereas the solid line denotes the probability constructed from the regional subsample. We can see that especially for the Latin American countries the two curves are close together. This result follows directly from the fact that the estimated model for the full sample is strongly dominated by the Latin American sample. For the Asian countries, we see a more profound difference in the two probability lines. The figures show a generally lower probability of crisis. This is desired as the estimated probability based on the full sample is very high, even in periods where it should not be. From the figures it also seems that the probability of crisis from the Asian sample performs better than the probability from full sample because the increases in probability are more focussed on the months before the crises.

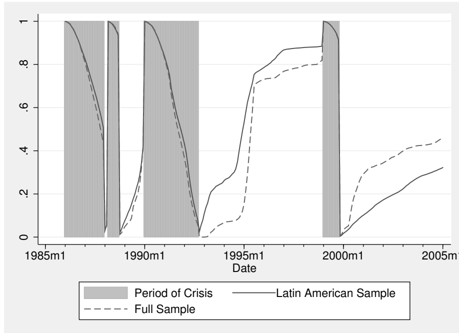
Note that also the crisis exit models are included in the figures. As they try to explain the exit out of the crisis into the tranquil state, their probabilities ‘live’ on the grey areas in the figures. To keep the crisis entry and exit model in one figure, we plotted the probability to stay in the crisis state for the exit model instead of the transition probability. This means that the estimated probability is transformed into the cumulative survival probability to remain in a state of crisis.

Because we would like to have a more formal measure of prediction performance, we also examine the probability of transition into crisis numerically. To do this, we use the signalling method as originally used by Kaminsky (1999). In this approach we compare the cases when the model signals a crisis to those when we would like it to signal a crisis. The model is said to signal a crisis if the probability of a crisis crosses a certain threshold percentage. This signalling threshold is determined individually per country. Following Fuertes and Kalotychou (2007), we try to find the optimal threshold level by minimising a loss function of a policy-maker that is a weighted average of the type I and type II errors[12]: $LF = \theta * (\%\ \textit{Type I Errors}) + (1 - \theta) * (\%\ \textit{Type II Errors})$. As a missed crisis typically brings larger costs to a policy-maker than a false alarm, the weight θ most likely will be larger equal than 0.5. To check the sensibility of the results we use three different weights: 0.5, 0.67 and 0.8. This way minimising type I errors

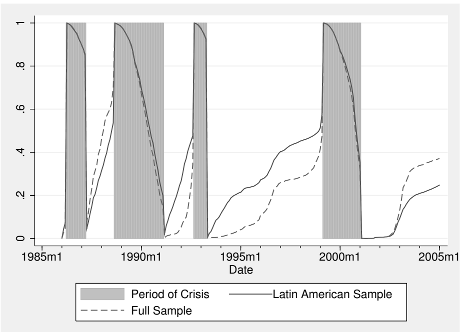
[12] A type I error means failing to signal a crisis. A type II error means giving out a false alarm.



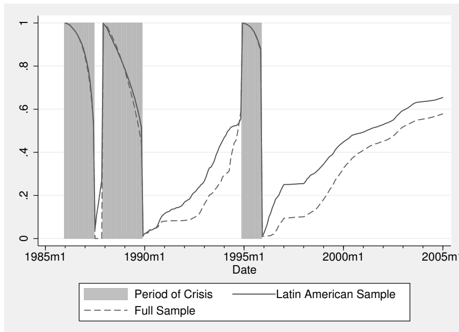
(a) Argentina (+ Exit)



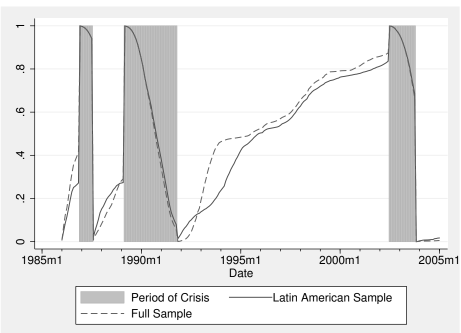
(b) Brazil (+ Exit)



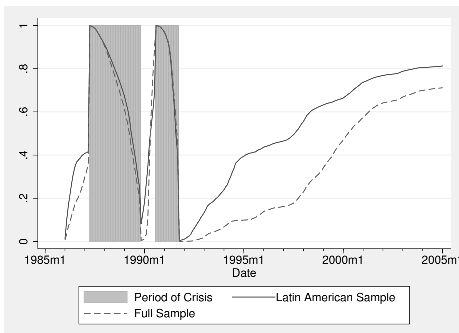
(c) Ecuador (+ Exit)



(d) Mexico (+ Exit)

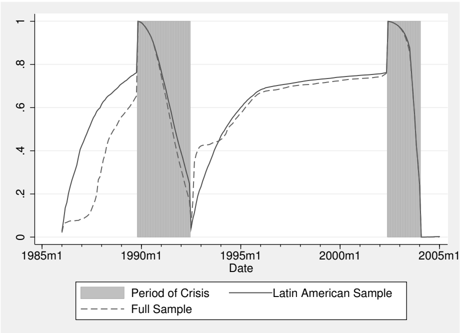


(e) Paraguay (+ Exit)

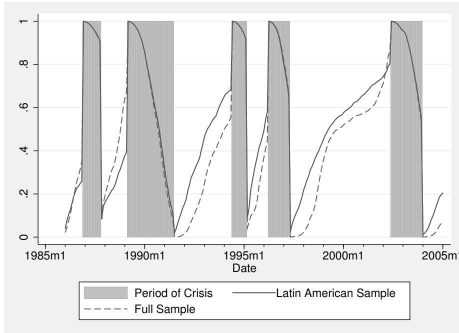


(f) Peru (+ Exit)

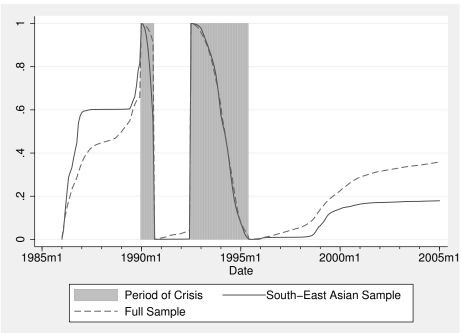
Figure 3.2: Predicted Probability of a Crisis in the Next Period (1)



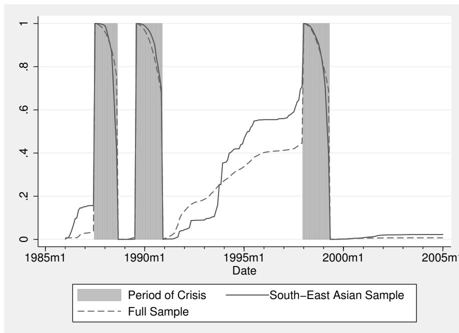
(a) Uruguay (+ Exit)



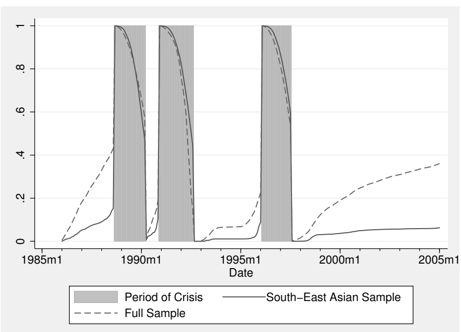
(b) Venezuela (+ Exit)



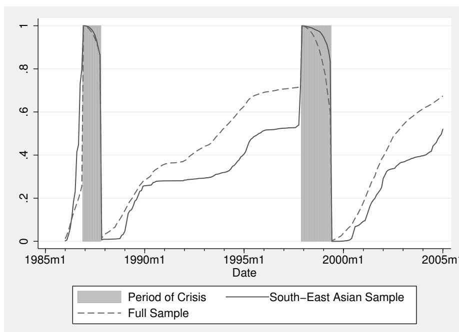
(c) China (+ Exit)



(d) Fiji (+ Exit)

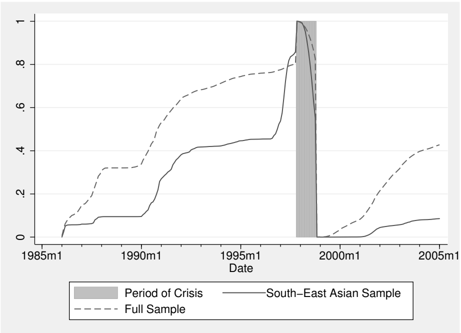


(e) India (+ Exit)

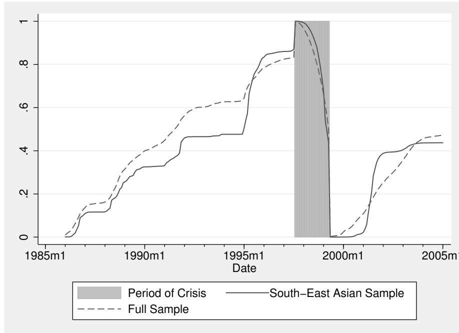


(f) Indonesia (+ Exit)

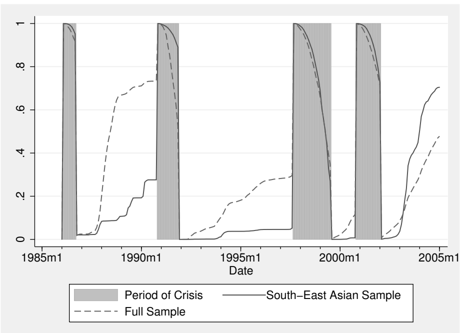
Figure 3.3: Predicted Probability of a Crisis in the Next Period (2)



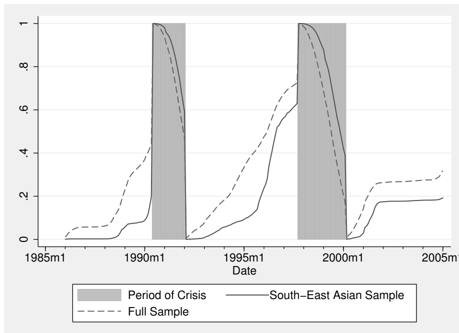
(a) Korea (+ Exit)



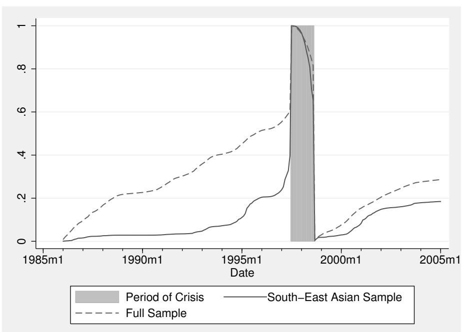
(b) Malaysia (+ Exit)



(c) Philippines (+ Exit)



(d) Taiwan (+ Exit)



(e) Thailand (+ Exit)

Figure 3.4: Predicted Probability of a Crisis in the Next Period (3)

Prediction Horizon = 24 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	36.3%	24.0%	32.6%	30.6%
0.67	22.3%	46.8%	20.1%	48.5%
0.8	20.3%	49.9%	17.5%	53.4%

Prediction Horizon = 18 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	42.1%	22.3%	40.4%	30.2%
0.67	24.0%	46.0%	22.8%	48.0%
0.8	22.8%	47.5%	20.5%	53.6%

Prediction Horizon = 12 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	38.2%	27.6%	32.3%	29.8%
0.67	24.8%	42.4%	20.9%	45.3%
0.8	19.3%	54.2%	16.9%	54.6%

Prediction Horizon = 6 Months)

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	36.7%	25.6%	30.9%	27.7%
0.67	27.3%	34.6%	18.0%	43.9%
0.8	20.1%	48.0%	18.0%	43.9%

Table 3.5: Prediction performance in Latin America with threshold levels based on different weights in the loss function. Type I error: Missed Crisis. Type II error: False Alarm.

Prediction Horizon = 24 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	24.9%	9.8%	28.9%	11.4%
0.67	24.3%	10.4%	18.2%	20.9%
0.8	19.0%	19.2%	17.4%	22.4%

Prediction Horizon = 18 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	27.2%	11.5%	28.5%	13.9%
0.67	23.2%	15.9%	19.8%	22.3%
0.8	21.8%	19.1%	19.1%	23.3%

Prediction Horizon = 12 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	29.9%	10.8%	29.4%	14.4%
0.67	24.6%	15.2%	20.9%	23.4%
0.8	24.2%	16.3%	20.9%	23.4%

Prediction Horizon = 6 Months

	Full Sample		Regional Sample	
θ	Type I Error	Type II Error	Type I Error	Type II Error
0.5	39.4%	4.8%	26.6%	15.9%
0.67	22.9%	15.6%	21.1%	21.0%
0.8	22.9%	15.6%	21.1%	21.0%

Table 3.6: Prediction performance in Asia with threshold levels based on different weights in the loss function. Type I error: Missed Crisis. Type II error: False Alarm.

is respectively equally important, twice as important or four times as important than minimising type II errors. For the moments at which the model ideally should signal a crisis we also take different values. We require that the model should start signalling a crisis respectively 6, 12, 18 or 24 months ahead of a crisis. The perfect fit would be if the signal of the model coincide exactly with the required signals. We therefore count the number of correct signals (A), the number of times the model did not give a signal when it actually should have (C), the number of false alarms (B) and the number of correct no-signals (D). In Tables 3.5 and 3.6 we provide per region the percentage of type I errors $[C/(A+C)]$ and the percentage of type II errors $[B/(B+D)]$ that are obtained using the different combinations of the type I error weights and prediction horizons.

For both regions the performance of the full and the regional sample models is similar. In general, the regional models have a slightly lower percentage of type I errors at the expense of a slightly higher percentage type II errors. We do find a difference in performance between the two regions. Whereas the model performance is average for the Latin American countries, the results for the Asian countries are pretty good. As existing Early Warning Systems traditionally have troubles picking up the Asian crisis, this result is confirmation that the duration model can capture causes of a crisis other than macro economic fundamentals.

Even though the numerical prediction performance measures do not show a great difference between the full sample model and the regional models, the estimation results show that the underlying causes of a crisis differ greatly between the two regions here under examination. It is therefore wise to allow for heterogeneity between the countries, for example by estimating regional models. In contrast to existing early warning systems, we find that the duration model works well for Asian countries.

3.5 Concluding Remarks

In this chapter parametric proportional hazards models are estimated to explain and predict currency crises in Latin America and Asia. Our model is an addition to existing work because our fully parametric proportional hazards model allows us to use the time dimension of the duration model more explicitly than the semi-parametric Cox-PH model.

A duration model was fitted to the full sample of countries as well as to the two regional subsamples. We found that the crises in Latin America can be explained by changes in macroeconomic fundamentals in the periods preceding the crises. The resulting model has an exponential baseline hazard function and therefore does not depend on the time passed since the last crisis. In the Asian sample, the time dimension of the duration model plays a much more prominent role in the prediction of a crisis. This can be seen from the Gompertz distribution for the baseline hazard that increases exponentially as the time spent in the tranquil state lengthens. This supports the theory that it was not only weak macroeconomic fundamentals that was at the basis of and caused the spreading of the crises in Asia. We can therefore conclude that in order to predict all crises we need a model that also includes factors other than macroeconomic variables. The prediction performance measures show that the duration model works well especially for the Asian countries. The duration model thereby appears fit to model crises for which weak fundamentals are not necessarily the sole cause.

Next to modelling the transition dynamics of going into a crisis, we also modelled the process that gets an economy out of a crisis. The most interesting finding of this exit model is that the duration of the crisis plays an identical role in all countries. The Weibull distribution of the baseline hazard shows that the probability to get back into the tranquil state increases as time progresses. This shows that even if the governing bodies do not act to accelerate the recovery process, the probability that the crisis will end in the next period increases with time.

In this chapter we perform in-sample forecasts. As the survival probability up to time t depends on the values of the economic fundamentals until time $t-1$, it is not possible to come up with sensible multi-step out-of-sample forecasts without simulating the future realisations of the fundamentals. We could extend the baseline hazard multiple steps ahead to get an indication, but then we would only have the average hazard for all countries (within the subsample) as the best estimate. A solution to this problem could be to use a technique from the financial literature, autoregressive conditional duration (ACD). This method might be helpful because here the duration of the current spell is defined as a function of past durations and conditional durations. Additionally, one could merge the crisis entry and crisis exit together as the current setup assumes independence between the duration of the tranquil and crisis periods.

Another aspect to our model that can be improved in the future, is the inclusion of contagion. Currently, we model regional dependence by simply taking regional subsamples. It is safe to assume that the dependence between the countries within those regions also differs per country-pair. Neighbouring countries are probably more closely related than countries that are further apart. Spatial econometrics could be a good way to model this effect.

Chapter 4

Modelling Exchange Rate Tensions: A Dynamic Duration Approach

This chapter aims at modelling tension on the exchange rate market. A dynamic duration model is estimated for 19 countries from Latin America and Asia over the period 1985-2005 to explain the occurrence and duration of this tension. A modified version of the autoregressive conditional hazards model (Hamilton and Jordá, 2002) is used to allow for time dynamics as well as macroeconomic explanatory variables in the duration model. The results indicate that the probability of transition into and out of tension increases with time spent in the current state. Moreover, as our model has its roots in the high-frequency data domain, our number of observations is relatively small. A Monte Carlo exercise is performed to check the behaviour of the ACD component of our model in a small sample.

4.1 Introduction

A large branch of literature has been devoted to financial distress ever since the theoretical framework was laid down by Krugman (1979) and Flood and Garber (1984). As financial crises became more frequent, the need for predicting the occurrence of turmoil increased and so did the literature on it.[1] Throughout the literature, many different definitions of crisis have been used, ranging from extreme periods of depreciation of the currency (e.g. Frankel and Rose, 1996; Flood and Marion, 1997; Kumar, Moorthy, and Perraudin, 2003) to extreme values of a pressure index (e.g. Eichengreen, Rose, and Wyplosz, 1995, 1998; Sachs, Tornell, Velasco, Calvo, and Cooper, 1996; Kaminsky, Lizondo, and Reinhart, 1998; Berg

[1] For an extenstive overview of the literature please refer to Chapter 1.

and Pattillo, 1999; Tudela, 2004). Naturally, the decision on what is the best index to use as a basis to proxy the crisis periods is open for debate. Even disregarding this issue, two problems can be distinguished that are common to all. Both problems are inherently related to the fact that a crisis is by default an extreme event. The first problem lies indeed with the definition of an extreme value. How to detect an extreme value? Typically some ad hoc threshold level is chosen and a crisis is identified when the index to proxy the crisis exceeds this threshold. The second problem is a data availability problem. Because crises are extreme values, they occur by default only very infrequently. As a result, one only has only very little information to work with. In order to circumvent these problems, we consider tension on the exchange market in this chapter instead of crisis episodes.

We define tensions on the exchange market as periods in which there is a depreciating pressure on the currency of interest. The pressure is measured via a version of the Exchange Market Pressure (EMP)-index of Eichengreen et al. (1998). Under a flexible exchange rate regime this pressure causes a depreciation of the currency. In a fixed regime the depreciating pressure has to be fended off by the central bank through the sale of foreign currency. The decrease in international reserves and/or depreciation of the currency could lead to further investors withdrawing their investments thereby further increasing the pressure on the currency. When the pressure starts to decrease, we know that the investors' confidence in the currency is reestablished. This turning point defines the end of the tension.

In addition to the modelling benefits, we believe that it is of importance to model all tensions on the exchange market instead of only the tensions that leads to a crisis, because we know that any increase in the EMP-index is the direct consequence of increasing pressure on the currency. Under floating exchange rates it results in a depreciation, while under fixed rates it is detectable via either a loss in international reserves or an increase of the interest rate. Either way, the increased tension on the exchange market has at the very least an psychological effect on investors, irrespective of the size of the adjustments. If we model crises instead of tension periods, this effect is missed completely if the effect on the pressure index is not large enough for it to exceed the threshold level.

Following the binary nature of a crisis or tension indicator, the popular choices for modelling crises or tension have been limited dependent variable models such as probit and logit. These types of models traditionally have problems to capture crises that are not preceded by weak macroeconomic fundamentals. By means of a duration model Tudela (2004) moves a step closer to capturing the hidden factors causing the crises. The idea behind the duration model is that the time since the last crisis influences the expectation of the probability of crisis. However, the standard duration model does not allow for any time dynamics. As shown by Candelon, Dumitrescu, and Hurlin (2010), time dynamics can play an important role in the Early Warning System however. Thus it may be expected that the expectation of the duration of the current period depends the strongest on the most recent durations. Therefore, we use a modified version of the Autoregressive Conditional Hazard (ACH) model by Hamilton and Jordá (2002) to introduce these dynamics. In the ACH model the dynamics of the Autoregressive Conditional Duration (ACD) approach by Engle and Russell (1997) is combined with time-varying economic fundamentals into a model for the hazard rate of transition into and out of tension.

Because we use macroeconomic data, the time series dimension of our sample is significantly shorter than the high-frequency datasets to which the ACD and ACH techniques are usually applied. For this reason we perform a simulation study to examine the behaviour of the estimators in the ACD model when the sample size decreases.

The remainder of the chapter is organised as follows. In Section 4.2 it is explained how we model tension on the exchange market. The methodology of the ACH framework is presented in Section 4.3. Section 4.4 contains the results of the Monte Carlo simulations on the small sample performance of the model. The empirical results are presented in Section 4.5, and Section 4.6 concludes.

4.2 Exchange Rate Tension

The variable to be analysed in this paper is the duration of periods of increasing and decreasing pressure on the exchange market. Unlike most other studies, we focus on explaining tension on the exchange market rather than the occurrence of currency crises. One of the main reasons for this different approach is the fact that when modelling crises, one only takes into account very strong attacks on the currency that lead to a crisis whereas with tension also the smaller attacks are taken into account. Under the assumption that investors are risk-averse, they will be more reluctant to invest in a currency that is tending towards a depreciation than investing in a currency that is tending to appreciate. A tendency to depreciate hence creates reluctance to invest or tension on the market that cannot be disregarded.

The impact of the market fluctuations is modelled using the chartist fundamentalist approach (e.g. Day and Huang, 1990; Huang and Day, 1993; Chiarella, Dieci, and Gardini, 2004; Farmer and Joshi, 2002; Wieland and Westerhoff, 2005; Manzan and Westerhoff, 2007). In this approach we distinguish two types of agents on the exchange market. On the one hand there are the fundamentalists who base their investment decisions on the relative position of the exchange rate with respect to its fundamental value. The chartists on the other hand, operate based on their beliefs about market fluctuations. If they perceive a bullish or bearish market, they trust that the current tendency on the market is a good predictor for the immediate future and thus trade accordingly. As a result, the overall exchange rate market dynamics could be quite different depending on the market's trend.

We define tension on the exchange market as periods of increasing pressure on the currency. We use a version of the Exchange Market Pressure (EMP)-index originally proposed by Eichengreen et al. (1998) as a measure of that pressure. The version of the EMP-index that we use is a weighted average between the percentage change in the nominal exchange rate and the (negative of the) percentage change in international reserves, where the weights are chosen such that the variances of the two terms are equal.[2] The index for exchange market pressure then becomes:

$$EMP_{i,t} = (\%\Delta \mathrm{exr}_{i,t})/\sigma_i^{\mathrm{exr}} - (\%\Delta \mathrm{res}_{i,t})/\sigma_i^{\mathrm{res}}, \tag{4.1}$$

where $\mathrm{exr}_{i,t}$ denotes the price of a US dollar in country i's currency at time t; $\mathrm{res}_{i,t}$ denotes the amount of international reserves of country i at time t; and σ_i^{exr} and σ_i^{res} are the respective country-specific standard deviations. The EMP-index goes up when either the exchange rate starts to depreciate or when the amount of international reserves starts to decrease. The latter event occurs under fixed exchange rates when the currency is suffering from excess supply and the central bank intervenes through the sale of its international reserves. The former is the result of excess supply under a pure floating exchange rate. Intermediate exchange rate regimes lead to a mixture of the events, unambiguously leading to an increasing EMP-index.

The periods of tension are defined as the periods in which the general direction (slope) of the EMP-index is upward. To identify the turning points of the slope of the EMP index, we employ a technique that is closely related to the dating algorithm of Bry and Boschan (1971).[3] As we apply the technique to the EMP-index, the intuition of the peaks and troughs and hence of the bears and bulls deviates from the traditional stock market intuition. In the stock market index the period from a trough to a peak embodies a booming (bullish) market. In our case, the period from a trough to a peak entails a period in which the pressure is increasing, hence a period of tension and vice versa.

4.3 The Modelling Framework

Tudela (2004) shows that the duration of the time spent in a spell of tranquility has an effect on the probability of a crisis occurrence. As tension is a related

[2]The EMP-index as originally proposed in Eichengreen et al. (1998) is a weighted average of three terms: Exchange rate changes, reserve changes and changes in interest rate difference. The interest rate differential is not included in our index because unfortunately it is not possible to find the same interest rate for all countries. If different interest rates were to be used for different countries in the construction of the pressure index, the dependent variable of our model would be not be same for all countries. Pooling across such a panel is not recommended.

[3]The exact implementation of the dating algorithm and the associated issues about window length will be tackled in Section 4.5.

phenomenon on the same market, a duration model can also be useful in our case. Tudela's duration model is completely static, it is therefore very difficult to make any statements about expected future durations. The Autoregressive Conditional Duration (ACD) framework of Engle and Russell (1997, 1998) allows for these dynamics. In the ACD the expected duration of the next period conditional on the past durations is modelled as a function of lagged observed durations and of lagged conditional expected durations.

Our setup with monthly observations differs from the high frequency data to which the ACD framework usually is applied. As the length of the durations is measured in months as opposed to seconds, the number of observations will be substantially lower in our tensions model than in common applications by default. Our dataset offers only up to 10 durations per country. By pooling all countries, the total number of durations can be increased to almost 150. This amount remains well below the number of observations in more common applications. For further discussion about the small sample behaviour of the ACD estimation, we refer to the simulation in Section 4.4. To pool data over different countries means that an implicit assumption is made that dynamics of the duration process are homogenous across the countries. Van den Berg, Candelon, and Urbain (2008) note that one should construct clusters that find the balance between allowing for enough heterogeneity and having sufficient observations. We will use the simulation study in Section 4.4 to get an indication about the minimum number of observations required within a cluster to perform sensible inference.

Let $\{z_{i,1} \ldots z_{i,N_i(T)}\}$ denote the durations of all spells of tension for country $i = 1, \ldots, K$, where $N_i(t)$ is a counting process that counts the number of spells up to date $t = 1, \ldots, T$. Also, let $\psi_{i,n}$ denote the expectation of $z_{i,n}$ conditional on the past durations:

$$\psi_{i,n} = E(z_{i,n}|z_{i,n-1} \ldots z_{i,1}). \tag{4.2}$$

Because the $\psi_{i,n}$ cannot be negative, the estimation of the standard ACD model is subject to some nonnegativity constraints. To circumvent these constraints, Bauwens and Giot (2000) proposed the Logarithmic ACD (LACD) model[4] that is based on the logarithm of the conditional expected duration:

$$\ln(\psi_{i,n}) = \omega + \sum_{j=1}^{q} \alpha_j \ln(z_{i,n-j}) + \sum_{j=1}^{p} \beta_j \ln(\psi_{i,n-j}). \tag{4.3}$$

[4]The version of the LACD model that is used here is the LACD_1 model of Bauwens and Giot (2000). Alternatively one could use the LACD_2 model in which the log expected duration depends on its lagged value and on the lagged 'excess duration' instead. As the two LACD models yield very similar results, only the LACD_1 version is employed here.

In this model there is only the constraint that $|\alpha_j + \beta_j| < 1$ for all j. This is to ensure covariance stationarity of $\ln(\psi_{i,n})$.

The standardised durations, $\epsilon_{i,n} = (z_{i,n}/\psi_{i,n})$, are assumed i.i.d. with some density f_0, such that all time dependence comes from the process described in Equation (4.3). We allow the density of the standardised durations to be either Exponential (ELACD) or Weibull (WLACD). Under the Exponential density the hazard rate, i.e. the probability of ending the current period, is constant with respect to the time spent in the current period. The Weibull density is a generalisation of the Exponential density; conditional on the value of the shape parameter γ the hazard rate can increase or decrease with time spent in the period. A hazard rate increasing with time means that investors believe an already long period between transitions is going to end sooner rather than later. This is consistent with the principle of business cycles. A decreasing hazard rate with time would mean in contrast that investors do not believe in cyclicality of the market.

From Engle and Russell (1997) we know that the log likelihood function of the LACD model is simply the sum of (the logarithm of) the densities of the standardised durations $(z_{i,n}/\psi_{i,n})$. As our pooled regression implies common parameters across countries, the sum of the likelihood does not run only over all durations in one series, but also over all countries. Let θ denote $(\omega, \alpha', \beta')'$. The log likelihood (LL) functions of the ELACD and WLACD models are then given by:

$$\begin{aligned}
\mathrm{LL}_{ELACD}(\theta) &= -\sum_{i=1}^{K} \sum_{n=1}^{N_i(T)} \left[\ln(\psi_{i,n}) + \frac{z_{i,n}}{\psi_{i,n}} \right], \\
\mathrm{LL}_{WLACD}(\theta, \gamma) &= -\sum_{i=1}^{K} \sum_{n=1}^{N_i(T)} \left[\ln\left(\frac{\gamma}{z_{i,n}}\right) + \right. \\
&\qquad \left. \gamma \ln\left(\frac{\Gamma(1+\frac{1}{\gamma})\, z_{i,n}}{\psi_{i,n}}\right) - \left(\frac{\Gamma(1+\frac{1}{\gamma})\, z_{i,n}}{\psi_{i,n}}\right)^{\gamma} \right].
\end{aligned} \tag{4.4}$$

It is shown by Engle and Russell (1998) and Grammig and Maurer (2000) that a maximum likelihood estimator with a correctly specified density is a consistent and efficient estimator of the LACD model.

4.3.1 The Autoregressive Conditional Hazard Model

From the ACD model, an expected duration is found for each of the periods of tension as well as for each of the periods of decreasing pressure. As one such period progresses, information about the macroeconomic situation of the respective country comes available. We would like to include this information into the determination of the probability that the period ends. Because the ACD model is only able to handle information that is constant throughout a period, a modified version of the Autoregressive Conditional Hazard (ACH) model developed by

Hamilton and Jordá (2002) is used here.

The ACH model is based on the ACD model, but it has its focus on the hazard rate instead of on the duration. Because the hazard rate is defined in calendar time, the ACH allows us to include monthly observations of explanatory variables. The hazard rate then depends on both the a priori expected duration of the current period and the explanatory variables.

The hazard rate of the ACH model is found by writing up the hazard rate of the ACD in calendar time and adding the explanatory variables. Because we are interested in the probability of a period of (non-)tension ending in the next month, the hazard rate should be expressed not as an instantaneous transition rate in continuous time, but in discrete form as the rate of transition between time $t+1$ and time t.[5] Whereas Hamilton and Jordá (2002) propose to incorporate the explanatory variables into their model as a modifier of the expected duration in an additive way, we let the variables enter in a multiplicative way. More precisely, the expected duration is divided by the exponent of the explanatory variables. This setup is chosen in order to ensure positivity of the hazard rate and achieve the intuitive interpretation that a positive (negative) estimated coefficient for a variable means that an increase in that variable leads to an increase (decrease) in the hazard rate. Let $X_{i,t}$ denote the set of explanatory variables for country i at time t and let $\mathcal{I}_{i,t-1}$ be the complete information set available up to time $t-1$. Depending on the assumption of Exponential or Weibull distributed durations, the discrete time hazard rate for country i at time t conditional on information available at time $t-1$ is given by:

$$\begin{aligned} \lambda_{ELACH}(i,t|\mathcal{I}_{i,t-1}) &= 1 - \exp\left(-\frac{\exp(\delta' X_{i,t-1})}{\psi_{i,N(t)+1}}\right), \\ \lambda_{WLACH}(i,t|\mathcal{I}_{i,t-1}) &= 1 - \frac{\exp\left[-\left(\frac{\Gamma(1+\frac{1}{\gamma})\exp(\delta' X_{i,t-1})}{\psi_{i,N(t)+1}}(t^*+1)\right)^{\gamma}\right]}{\exp\left[-\left(\frac{\delta' X_{i,t-1}\cdot\Gamma(1+\frac{1}{\gamma})}{\psi_{i,N(t)+1}}t^*\right)^{\gamma}\right]}, \end{aligned} \tag{4.5}$$

where t^* stands for the time already spent in the current period.

Because the hazard rate is defined as the probability that the current period ends within one unit of time, it is fairly straightforward to build the log-likelihood function using this hazard rate. Consider a dummy variable $D_{i,t}$ that takes the

[5] In discrete form, the hazard function is defined as the probability of failure before or at time $t+1$ given survival up to time t (Lancaster, 1990). In a formula this is given by:

$$P[T_f \le t+1|T_f > t] = \frac{F(t+1)-F(t)}{S(t)} = 1 - \frac{S(t+1)}{S(t)}$$

where T_f, $F(t)$ and $S(t)$ denote respectively the time of failure, the distribution function and the survival function.

value 1 whenever a period ends and 0 otherwise. The probability of observing $D_{i,t}$ is then

$$P[D_{i,t} \,|\, \mathcal{I}_{i,t-1}; \Theta] = (\lambda_{XLACH}(i,t))^{D_{i,t}} (1 - \lambda_{XLACH}(i,t))^{1-D_{i,t}}, \tag{4.6}$$

with Θ representing all parameters to be estimated[6]. The Log-Likelihood function follows immediately:

$$\begin{aligned} LL_{XLACH}(\Theta) = \sum_{i=1}^{K} \sum_{t=1}^{T} \{ & D_{i,t} \ln[\lambda_{XLACH}(i,t)] \\ & + (1 - D_{i,t}) \ln[1 - \lambda_{XLACH}(i,t)] \}, \end{aligned} \tag{4.7}$$

which can be maximised numerically with respect to Θ.

4.4 Small Sample Performance of the ACD

In this section we examine the properties of the ACD model in a small sample. It has already been shown by Grammig and Maurer (2000) that a misspecification of the distribution of the durations has serious consequences for the consistency of the estimation. We therefore focus on the case in which we know the true form of the distribution.

The expected durations ($\psi_{i,n}$) in the ACH model are not updated as a period progresses, they are therefore essentially only identified by the information that is also used in the pure ACD model. As the ACD model has originally been developed for high frequency data and as our durations are measured in terms of months, we have a rather small amount of observations to estimate the expected durations. To cope with the finite sample we pool the series of all countries. A large drawback of pooling is that one implicitly assumes homogeneity among the countries. As a compromise between having a larger number of observations and still having a panel that does not violate the homogeneity assumption, Van den Berg et al. (2008) propose to pool only clusters of similar countries. In our sample, this means that the number of durations in such a cluster would be around 50 or even lower. As we will find from the simulation study below, at this amount of observations the ACD estimations do not give reliable results even under the strongly simplifying assumptions of homogeneity and independence of the series.

4.4.1 Setup of the Simulations

In our simulation we mimic a LACD(1,1) model. In the LACD(1,1) we have from equation (4.3) the following relationships between the actual durations $z_{i,n}$, the

[6]Specifically, for the Exponential-LACH, $\Theta = (\delta', \theta')'$, and for the Weibull-LACH, $\Theta = (\delta', \theta', \gamma)'$,

expected durations $\psi_{i,n}$, and the innovations $\epsilon_{i,n}$:

$$\ln(\psi_{i,n}) = \omega + \alpha \ln(z_{i,n-1}) + \beta \ln(\psi_{i,n-1}), \tag{4.8}$$

$$z_{i,n} = \psi_{i,n}\epsilon_{i,n}. \tag{4.9}$$

In our simulations we assume the $\epsilon_{i,n}$ i.i.d. and distributed either Exponential(1) or Weibull(1,γ). The errors are standardised such that their asymptotical mean equals 1. For given individual-specific starting values $\psi_{i,0}$, the durations $z_{i,n}$ and expected durations $\psi_{i,n}$ can then be built iteratively.

We focus on two different data generating processes (DGP) based on equations (4.8)-(4.9). The first DGP is an Exponential-LACD(1,1) process. The parameters ω, α and β are chosen such that they roughly mark the process of our empirical application. The second DGP is a Weibull-LACD(1,1) where the parameters ω, α and β are chosen similarly and $\gamma = 2$. Notice that for the Weibull(1,2) density the first moment of the innovations $\epsilon_{i,n}$ is not equal to one. In order to keep the expected value of the simulated durations $x_{i,n}$ at the intended value $\psi_{i,n}$, we need to rescale the innovations such that their first moment is equal to one. For each of the DGPs we simulate an $N * K$ panel of durations and expected durations with four different sample sizes. The number of individuals is kept constant at $K = 10$, whereas the number of durations per individual is set at $N = 5, 10, 100$ or 1000. The simulation study is based on 1000 replications per series.

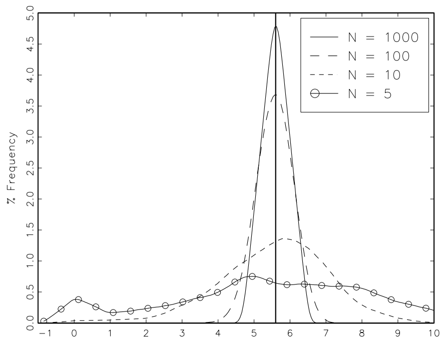
4.4.2 Simulation Results

Figures 4.1 and 4.2 show the distribution of the estimated parameters. The tables containing the numerical results corresponding to the figures can be found in the appendix to this chapter.

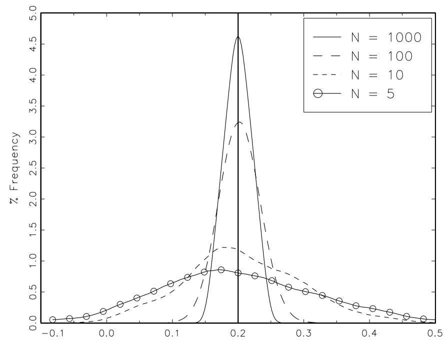
Figure 4.1 contains the results of the Exponential-LACD for the varying sizes of N. We can see that the estimation works fine if the sample is large enough, i.e. $N = 100$ or $N = 1000$ per individual. Also, the estimation of the α coefficient appears remain consistent even if the sample size decreases. The two other coefficients however, suffer from consistency problems when N becomes smaller. At $N = 10$ (i.e. 100 observations in total), the estimation of ω is slightly skewed to the left, whereas the for the β coefficient it is skewed to the right. When the sample decreases further, to $N = 5$, both distributions even have a second local maximum, ω at around 0 and β slightly below 1. The observations that are located in these hump are from the same replications. In these replications the sum of the α and β coefficient is very close to one, a sign of a high degree of persistence in $\ln(\psi_{i,n})$. It follows that the value of ω needs to be close to zero in order to keep the expected value at a reasonable level.

For the Weibull-LACD(1,1) model (Figure 4.2), the results in the very small samples are very similar to those of the ELACD model. Additionally, the shape coefficient of the distribution, γ, shows a right tail that is a little too heavy, resulting in an upward bias that disappears as the sample size grows.

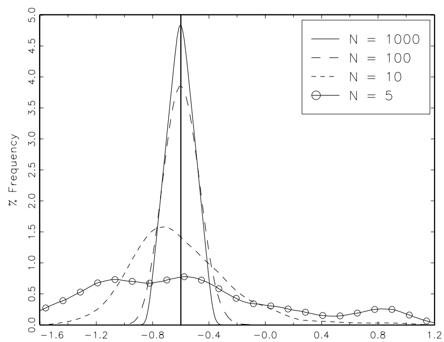
From this small simulation exercise we may conclude that even under the simplifying assumptions of homogeneity, knowing the correct distribution as well as independence of the innovations with respect to both dimensions of the panel, the LACD model suffers from convergence problems in small samples (50 observations). When the sample size is doubled however, the problems in the ELACD and the WLACD are within reasonable bounds. These results indicate that one must be very careful when estimating an ACD in small samples, especially when the number of observations is below 100.



(a) ω, value = 5.6



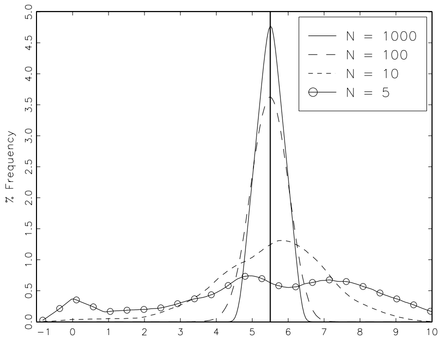
(b) α, value = 0.2



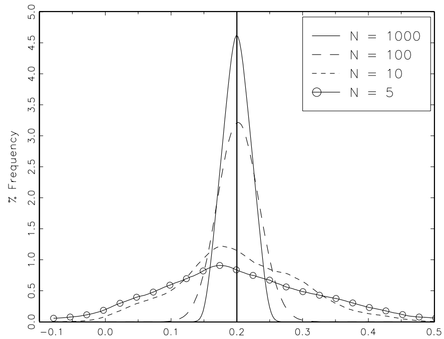
(c) β, value = -0.6

Note: $K = 10$. The vertical black line represents the true value of the parameter.

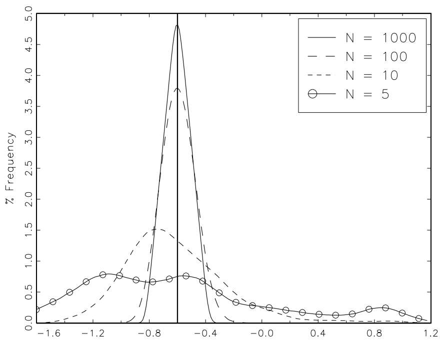
Figure 4.1: Simulated ELACD estimation results when the innovations are Exponential.



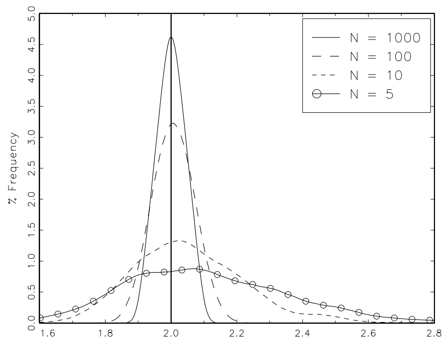
(a) ω, value = 5.5



(b) α, value = 0.2



(c) β, value = -0.6



(d) γ, value = 2.0

Note: $K = 10$. The vertical black line represents the true value of the parameter.

Figure 4.2: Simulated WLACD estimation results when the innovations are Weibull.

4.5 Empirical Application

4.5.1 Data

Our dataset consists of monthly data from January 1985 to January 2005. It covers 19 countries from the regions Latin America and Asia: Argentina, Bolivia, Brazil, Chile, Ecuador, Mexico, Paraguay, Peru, Uruguay, Venezuela, China, India, Indonesia, Korea, Malaysia, Philippines, Sri Lanka, Taiwan and Thailand. The data is obtained via Datastream[7]

In order to identify the periods of increasing and decreasing pressure, we employ a technique closely related to the dating algorithm of Bry and Boschan (1971) to the Exchange Market Pressure index. This procedure aims to identify periods in which the trend is generally increasing, named bulls, and periods in which the trend generally decreases, named bears. The main purpose of the algorithm is to locate the turning points i.e. the local maxima (peaks) and minima (troughs). These turning points signify the points in time when the general trend switches from upward to downward, or vice versa. Let $Y_{i,t}$ denote the exchange market pressure index for country i at time t. In the series for country i, a peak (trough) then occurs when Y_{it} is a local maximum (minimum) in a window of 12 months. In a formula it looks as follows.

$$\begin{cases} \text{peak at } t & \text{if } Y_{i,t} > Y_{i,t-j} \text{ and } Y_{i,t} > Y_{i,t+j} \quad \text{for } j = 1\ldots 6, \\ \text{trough at } t & \text{if } Y_{i,t} < Y_{i,t-j} \text{ and } Y_{i,t} < Y_{i,t+j} \quad \text{for } j = 1\ldots 6. \end{cases}$$

In case of more than one consecutive peaks (troughs), the highest peak (lowest trough) remains whereas the others are removed such that the series constitutes a alternating sequence of peaks and troughs.

Applying the Bry and Boschan (1971) based algorithm described above, we identify a total of 246 peaks and 240 troughs in our sample. These turning points give us 250 separate periods of tension (trough-to-peak) of which 9 are left-censored and 4 are right-censored[8]. The average length of these periods is approximately 9 months. The average time from a peak to a trough is slightly shorter: 8 months. There are a total 255 of such periods without tension, 10 of which are left-censored and 15 are right-censored. The exact dates of the turning points are provided in Tables 4.1 and 4.2.

The set of explanatory variables we use in this chapter is almost the same as the set of variables used in the previous chapters. The economic reasoning behind the inclusion of these variables remains the same. The effect on the hazard rate is slightly different than in Chapter 3 however. This difference comes from the

[7] Sources are the IMF-IFS database and the national banks of the respective countries.

[8] A period is called to be censored if not the entire period in included in the sample. A left-censored period is a period that started some time before the first observation in the sample. A right-censored period is a period of which the end is not observed.

	ARG	BOL	BRA	CHI	ECU	MEX	PAR	PER	URU	VEN
Peak		86/03								
Trough		86/07	86/08	86/05			86/05		86/10	86/03
Peak	87/10	87/08	87/05	87/05	86/04	86/08	87/02	87/04	87/04	86/12
Trough	88/08	88/10	88/09	89/05	87/03	87/04	87/07		88/08	87/10
Peak	89/04			89/09	88/11	88/01	89/03		89/11	89/04
Trough	90/08			90/10		90/09		89/08		
Peak	91/06	90/05	90/03	91/09				91/05		
Trough	91/12	90/11			90/12		91/06			91/02
Peak		92/01			92/09	92/10	92/12			
Trough		92/06	92/05	92/06	93/02	93/04			93/02	
Peak		93/02	94/06	93/12					94/09	94/06
Trough		94/08		95/04			94/07	94/08		94/12
Peak	95/03	95/11		96/01	96/02	95/03	96/02	95/06		96/05
Trough	96/02		95/10			95/07	96/08	96/08		96/11
Peak	96/10									
Trough	98/09	97/09		97/06	97/05				98/04	
Peak	99/09	98/05	99/02	98/04		98/09	98/04	99/02	98/10	98/09
Trough	99/12	98/12	99/09	98/12		99/05	99/09	00/05	99/05	00/11
Peak		00/07		99/06	00/02	00/09	00/11	01/02		
Trough		01/07		01/03	00/11	01/05	01/09	01/11		
Peak	02/06	02/07	02/12	02/02	03/02	02/09	02/07	02/06	02/09	02/06
Trough	03/07		03/06	03/03	03/08	03/05	03/07	03/03	03/08	03/07
Peak	04/01		04/05	03/08	04/03	04/07		03/09	04/07	04/10
Trough		05/01			04/09					

Table 4.1: Dates of the Peaks and Troughs Identified for Latin America

definition of tension compared to periods of crisis. When an increase in one of the variables is expected to increase the tension on the market, the hazard rate for transitioning out of tension should decrease, whereas in the model for moving into tension the hazard rate is expected to increase. The included explanatory variables relate to different aspects of the economy. We use variables from the external sector, the financial sector and the real sector. Notice that all explanatory variables enter the hazard rate one month lagged. This way, at time t, the probability of a turning point within the next month is affected only by variables which are observable at time t.

Within the external sector the current account and the capital account can be distinguished. Because we use monthly data, the quarterly data for the current account and capital account cannot be used directly. We therefore include monthly variables as approximation. The first variable relating to the current account is the annual growth rate of exports. Because a decrease in exports indicates a loss in international competitiveness, it would lead to a recession and business failures (Dornbusch, Goldfajn, and Valdes, 1995). Hence we expect a decrease in exports to add to the tension on the market. Secondly, we have the imports annual growth rate. For imports the theory is not so clear. On the one hand an decrease in imports could be an indication of weakening of economic activity, while on the other hand an increase in imports can be caused by a strong overvaluation of the real exchange rate (Kaminsky and Reinhart, 1999). The overall impact on the durations of the tension depends on which of these two effects is strongest. It is also examined if the ratio trade balance over GDP has an impact on the hazard rate. A lower trade balance (more imports, less exports) could indicate that the domestic currency is overvalued. This creates additional tension and as such is expected to extend its duration. To capture the capital account, the real interest rate differential with respect to the United States as well as the growth in inter-

	CHN	IND	INO	KOR	MAL	PHI	SRL	TAI	THA
Peak	86/11	86/11	87/01	86/05	86/07				86/07
Trough	87/10	87/05	87/07		87/03	86/08		87/01	
Peak		88/09			88/05	88/02		88/08	
Trough				88/06			88/06	89/05	89/05
Peak	90/01		90/06	90/04			89/09	90/06	
Trough	90/07	90/03	91/03		90/10	89/12	90/03		
Peak		91/07			91/04	90/11			
Trough		92/02		93/03	92/09	91/07		92/01	
Peak	94/01	93/03	94/07	94/05	93/05	93/09	93/01	93/07	92/08
Trough	94/12	94/03			94/01	94/04	93/07	95/04	93/10
Peak	96/04	96/02			95/03	95/05	95/11	95/11	95/03
Trough	97/01	97/07	97/04	95/11	96/07	96/08	97/11	97/01	95/09
Peak	98/12	98/01	98/01	98/01	98/01	98/01	98/11	98/01	97/12
Trough			99/03	98/07	99/02	99/04			98/07
Peak				99/10					
Trough		00/03		00/04			99/12	00/02	
Peak		00/10	01/02	01/04	01/03	00/11	01/02	00/12	00/10
Trough	02/02			02/07	02/02	02/01		02/07	02/07
Peak	02/08			03/03	03/01	02/11		03/01	03/02
Trough	03/11	04/04	03/04	03/10		04/08	03/09	04/04	
Peak	04/05	04/10	04/10	04/10			04/10	04/10	

Table 4.2: Dates of the Peaks and Troughs Identified for Asia

national reserves are used as proxies. For the latter we expect that a decrease in reserves will extend the duration of the tension period. A high real interest rate differential is typically associated with a high amount of tension of the market (see Eichengreen et al., 1995). The argument behind this could be that the interest rate has been increased in a response to an excess supply of the currency.

The second aspect of the economy is the financial sector. It has been shown by McKinnon and Pill (1996) that currency crises, most notably those accompanied by a banking crisis (labelled as twin crises), have often been preceded by periods of financial liberalisation. Facilitated by the more relaxed reserve requirements for banks, the financial liberalisation tends to make people and banks overconfident in the stability of the currency, leading to excessive (foreign) borrowing. The banking sector now becomes vulnerable to speculative attacks (Krugman, 1979). Overborrowing results in an increase in the M2 multiplier as well as growth of domestic credit relative to GDP (McKinnon and Pill, 1998). For both these variables it holds that a higher ratio indicates higher vulnerability and therefore more tension for the investors. To capture the credit risk rating and the willingness of banks to lend, we include the ratio lending rate over deposit rate. An increase in this ratio indicates that banks require a high risker premium on their loans. This signal that investments are more insecure, creates tension for the investors on the market. We also include the ratio M2 over reserves. An increase of the ratio is caused both by an increase in M2 money and decrease in reserves. The higher this ratio, the more vulnerable is the economic system to speculative attacks (Calvo and Mendoza, 1996). The ratio M2 over reserves is included both as levels and as growth rate, because we believe that tension is created not only by an increasing ratio, but also by a ratio that is simply high. The next variable is the ratio foreign liabilities over GDP. A high ratio means more outstanding debt and hence a weaker position of the economy. The duration of a tension period is expected to increase with this ratio. The final financial variable is the growth of bank deposits. A decrease in this variable shows capital flight and bank runs (Goldfajn and Valdes, 1997). The loss of confidence in the banking sector increases tension on the market.

The last aspect of the economy included, is the real sector of the economy. As a proxy for output growth we use the industrial production growth rate. A decrease in industrial production growth is the sign of a weakening domestic economy and therefore a more vulnerable economy. As a result we expect the period of tension to last longer as the industrial production growth rate decreases.[9]

4.5.2 Estimation Results

In this section we report the estimation results of the Autoregressive Conditional Hazard models and compare them with results from static duration models. Notice that this static duration model is the model we developed in Chapter 3. We have a separate model for the periods of tension and for the periods without tension. As shown in the simulation study, we are only able to produce consistent results when we use the complete panel of countries. Notice that next to the implied homogeneity of the countries, we also make the assumption that the countries' series are mutually independent. In order to have some country specific effect, we allow for a different starting value of the expected duration in equation (4.3) for each country. Because the starting value used is the mean of all durations of that country, it acts like a fixed effect to capture the difference in stability of the economies. This then results in a different baseline risk that is assigned to a country by the investors. Model specifications with regional dummies in both the ACD part and the explanatory variables part were also estimated. In all cases the regional dummy was highly insignificant. This might seem surprising. It is likely however that the country specific effects already capture the differences between the regions. The section ends with an analysis of how well the models can predict the transitions into and out of tension.

The estimation results of the models for the probability of transition from tension periods to non-tension periods are presented in Table 4.3. The table contains the parameter estimates of both the Exponential- and Weibull-LACH model.[10] The results of the two models are qualitatively very similar. The signs of the coefficients are the same for all explanatory variables and also the ACD parameters are very close to each other. From the values of the ACD parameters we see that the log expected duration depends negatively on its own lag. The lagged observed durations have no significant effect. This indicates that expectations about durations are pretty constant over time. Additionally, the shape parameter $\gamma = 1.768$ of the Weibull distribution supports the idea that the hazard rate increases as the time spent under tension lengthens. It also indicates that the true distribution of the durations most likely is not Exponential, for then γ should have been close to 1.

[9] Note that most explanatory variables enter the model as the one-month lag of the annual growth rate.

[10] The ACH version of the Gompertz duration model did not converge properly making a comparison with the static duration model impossible.

Two variables related to the external sector have a significant effect on the hazard rate. First there is the exports growth for which the expected positive sign is found. The positive coefficient indicates that an increase in probability of the end of the tension period is associated with a rise in exports growth. This supports the theory that an increase in exports is a sign of a strong economy. The second significant variable is the growth rate of international reserves. The coefficient is negative in both models whereas a positive coefficient was expected; an increase in the reserves growth should decrease tension. This counter-intuitive finding can be explained by the fact that currency crises are in fact extreme peaks of the EMP-index and therefore coincide with some of the peaks that signal the end of a tension period. Huge reserves losses are a sign that a crisis (= peak) is near, leading to a negative coefficient. The final significant variables relates to the financial sector. The ratio M2 over reserves has the expected negative sign; a decrease in the growth rate of the ratio increases the probability of transition out of tension.

Table 4.4 shows the results of the static duration models for the transition out of tension. In the estimation of these static models, the ACD part of the model is disregarded. The expected durations, $\psi_{i,N(t)+1}$, in Equation (5.2) are replaced by the simple country by country means of the observed durations to allow for a country-specific scaling effect. Comparing the estimated coefficients of the static models with those of the dynamic duration models, we see that the same variables are significant with the same signs. These results of the static duration models confirm therefore the findings of the LACH models.

Table 4.5 contains the estimation results of the ELACH and WLACH models for the probability of transition from periods without tension into periods of tension. The dependence structure of the durations of periods without tension is completely different from the tension periods. The expected duration depends heavily on the previous expected duration, indicating strong persistence[11] in the expected duration length. Surprisingly, it depends negatively on the last observed duration. This might indicate that market agents expect that short and long periods of tension alternate over time. Even though the model suffices the conditions for stationarity, the sum of α and β is very close to the bound which might hamper the convergence. As the shape parameter of the Weibull distribution is larger than one, the hazard rate of transition out of a period without tension increases proportionally to the time spent in the period.

As we are now modelling the transition into a period of tension instead of the transition out of the period of tension, we expect the explanatory variable to affect the hazard rate opposite than before. We see however that different variables are significant. This time around there is also a difference between the Exponential- and Weibull-LACH model.

[11] Fernandes and Grammig (2006) show that necessary and sufficient conditions for covariance stationarity are $|\alpha + \beta| < 1$ and $E(\epsilon_{i,n}^{m})$ exists.

Variable	ELACH	WLACH	Expected Sign
ω	4.042	4.040	
	(0.666)	(0.337)	
α	-0.016	-0.016	
	(0.064)	(0.032)	
β	-0.811	-0.812	
	(0.324)	(0.163)	
γ		1.768	
		(0.083)	
Exports Growth$_{t-1}$	0.417	0.275	+
	(0.241)	(0.130)	
Reserves Growth$_{t-1}$	-1.953	-0.739	+
	(0.272)	(0.138)	
M2/Reserves Growth$_{t-1}$	-0.641	-0.332	-
	(0.241)	(0.110)	
Constant	0.144	-0.033	
	(0.073)	(0.044)	

Log-Likelihood ELACH = -8614.1, Log-likelihood WLACH = -8113.1

Table 4.3: Estimation results of LACH models for transition out of tension.

Variable	Expon.	Weib.	Expected Sign
Exports Growth$_{t-1}$	0.438	0.317	+
	(0.243)	(0.132)	
Reserves Growth$_{t-1}$	-1.964	-0.751	+
	(0.275)	(0.141)	
M2/Reserves Growth$_{t-1}$	-0.582	-0.275	-
	(0.198)	(0.105)	
Constant	0.140	-0.038	
	(0.073)	(0.044)	

Log-L. Exponential Model = -8592.6, Log-L. Weibull Model = -8060.2

Table 4.4: Estimation results of the static duration models for transition out of tension.

Variable	ELACH	WLACH	Expected Sign
ω	0.015	0.014	
	(0.064)	(0.032)	
α	-0.115	-0.114	
	(0.032)	(0.016)	
β	1.098	1.098	
	(0.034)	(0.017)	
γ		1.951	
		(0.090)	
Reserves Growth$_{t-1}$		0.485	-
		(0.111)	
M2/Reserves$_{t-1}$		-0.029	+
		(0.012)	
M2/Reserves Growth$_{t-1}$	-0.648	0.229	+
	(0.221)	(0.126)	
Industrial Production Growth$_{t-1}$	0.454		-
	(0.055)		
Constant	-0.140	-0.138	
	(0.066)	(0.047)	

Log-Likelihood ELACH = -7566.3, Log-likelihood WLACH = -6706.7

Table 4.5: Estimation results of LACH models for transition into tension.

As in the opposite model, the growth of international reserves is significant with the wrong sign for the WLACH model. Also, the growth rate of M2 over reserves is significant with the expected sign like before. The level of this ratio now is significant as well, but with the opposite from expected sign. As the point of transition into tension lies in the trough of the EMP-index the level of reserves has been increasing in the periods just before the turning point. Since an increase in the level of reserves lowers the M2/reserves ratio, the negative sign could be caused by this effect. In the ELACH model only the growth rates of the ratio M2 over reserves and of the industrial production are significant. Both have the wrong sign even though M2/reserves growth had the expected sign in the opposite model. The poor performance is evidence that the exponential form for the hazard function is not adequate to explain this transition process. This is supported by the fact that the shape parameter of the Weibull is significantly larger than 1. In the static duration models (see Table 4.6), none of the explanatory variables show any expected signs. That the Exponential duration model behaves like its dynamic counterpart is not entirely unexpected, but the static Weibull model now also fails.

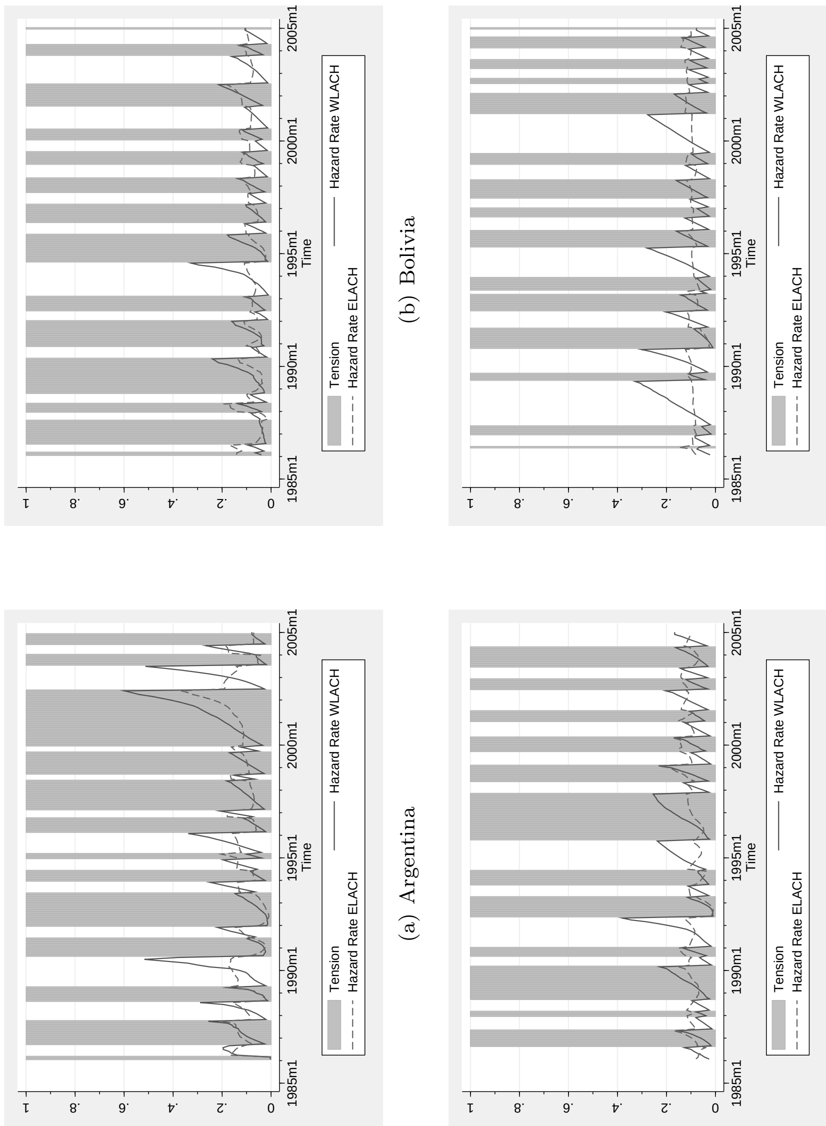
Variable	Expon.	Weib.	Expected Sign
Reserves Growth$_{t-1}$		0.343	-
		(0.087)	
M2/Reserves Growth$_{t-1}$	-0.667		+
	(0.222)		
Industrial Production Growth$_{t-1}$	0.474	0.233	-
	(0.055)	(0.130)	
Constant	-0.152	-0.222	
	(0.066)	(0.040)	

Log-L. Exponential Model = -7576.5, Log-L. Weibull Model = -6823.2

Table 4.6: Estimation results of the static duration models for transition into tension.

From Tables 4.3 and 4.5 it turns out that the macroeconomic variables have very similar impacts in the ELACH model and WLACH model. Nevertheless, from the estimated values of the shape parameter γ, we can conclude that the Weibull-LACH model should be preferred. This view is confirmed by the graphs of the implied probabilities of transition as presented in Figures 5.1-5.3. These graphs show the probability that the current period will end from both types of models. The grey-shaded areas denote the periods of tension and the white areas are the periods without tension. If we notice that the probability of transition should increase when a period is approaching its end and remain low before that time, we see that almost everywhere the Weibull-LACH does a better job than the Exponential-LACH in predicting this probability.

Because a more formal comparison of prediction performance is desirable, the probability of transition into and out of tension is examined numerically as well. To do this, we use the signalling method as originally used by Kaminsky (1999). In this approach we compare the cases when the model signals a turning point to those when we would like it to signal one. The time window ahead of the turning points at which the model ideally should start signalling, is varied between 1 and 6 months in advance. The model signals a turning point if the probability of a crisis crosses a certain threshold percentage. This signalling threshold is determined per country. It is set at the level that minimises missed turning points and false signals. The perfect fit would be if the signals of the model coincide exactly with the required signals. We therefore count the number of correct signals (A), the number of times the model did not give a signal when it actually should have (C), the number of false alarms (B) and the number of correct no-signals (D). These numbers are presented in Tables 4.7 and 4.8 for the different model specifications and prediction horizons. The goodness-of-fit of the model is calculated as the average of the percentages of missed turning points and false alarms. As such, a



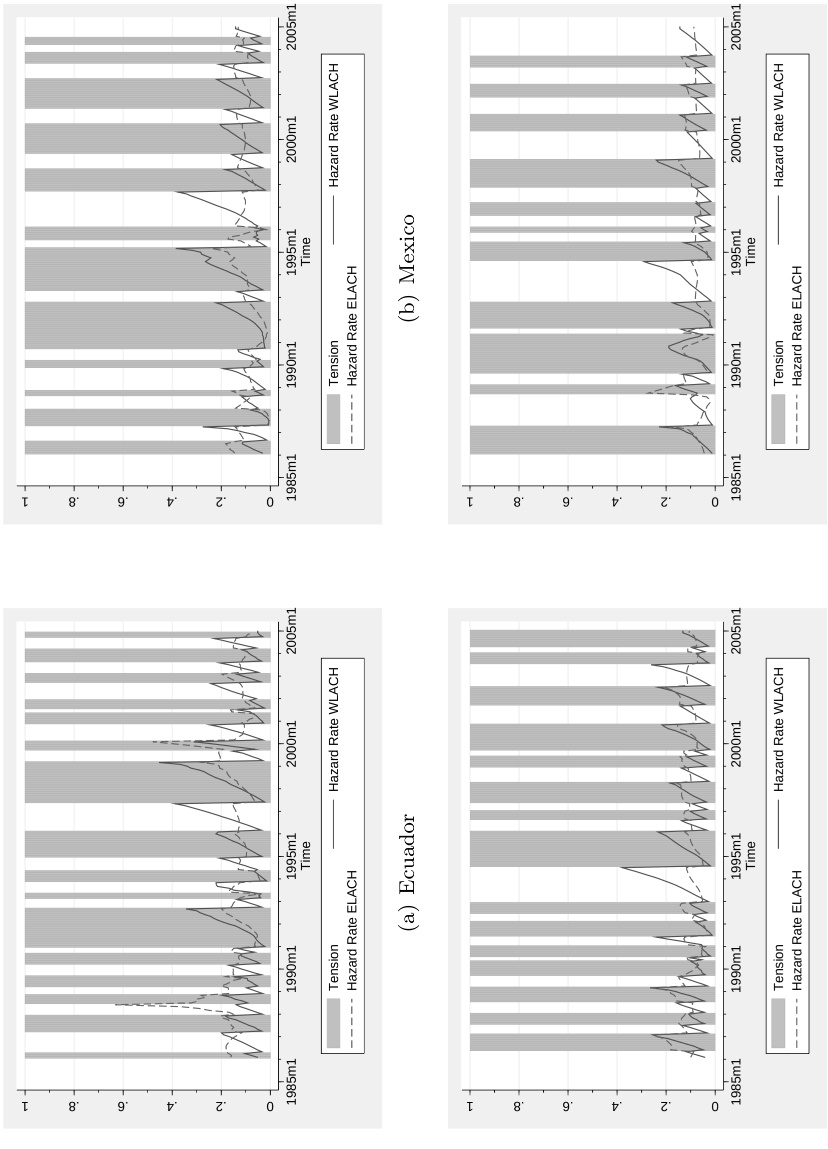
(a) Argentina

(b) Bolivia

(c) Brazil

(d) Chile

Figure 4.3: Probability of transition from period of tension to period without tension and vice versa (1)



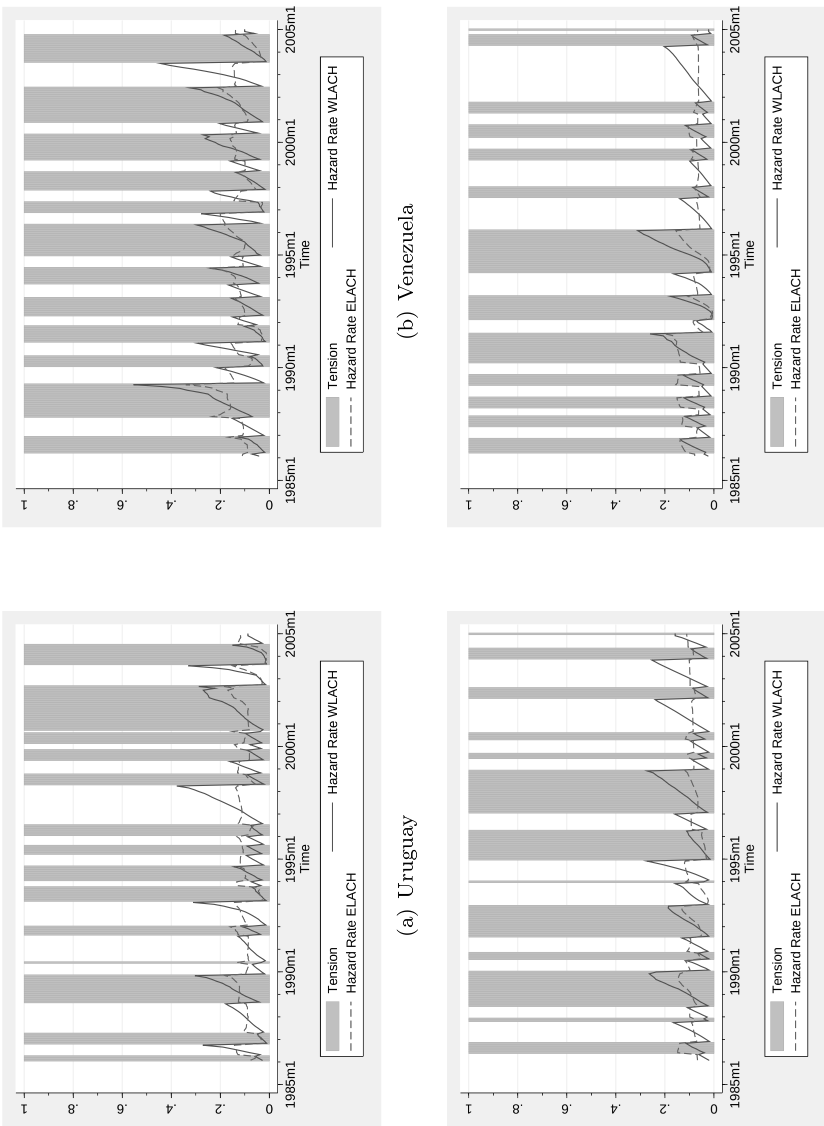
(a) Ecuador

(b) Mexico

(c) Paraguay

(d) Peru

Figure 4.4: Probability of transition from period of tension to period without tension and vice versa (2)



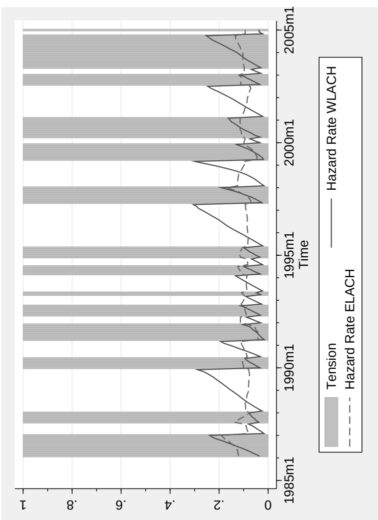
(a) Uruguay

(b) Venezuela

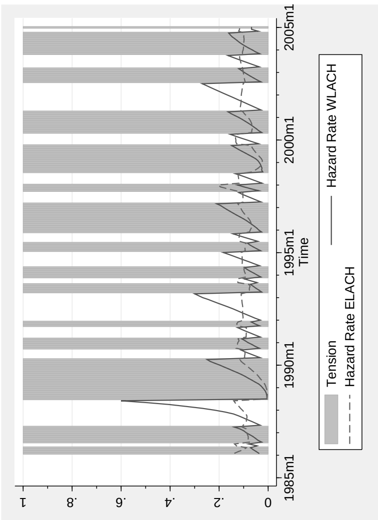
(c) China

(d) India

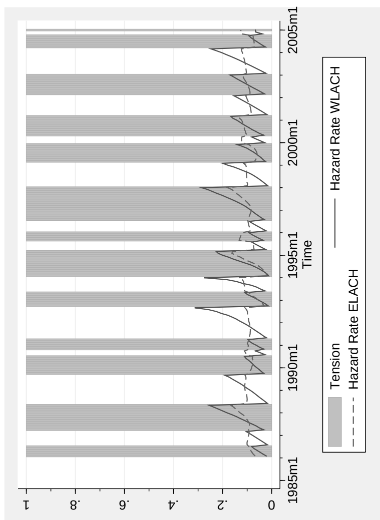
Figure 4.5: Probability of transition from period of tension to period without tension and vice versa (3)



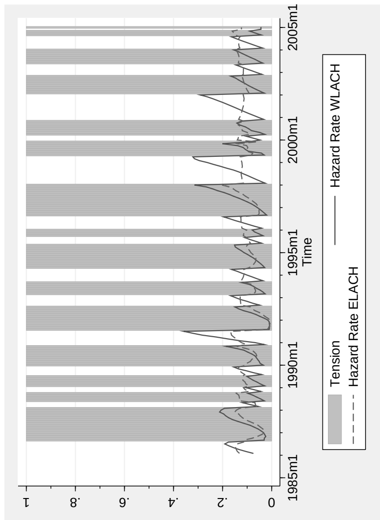
(a) Indonesia



(b) Korea

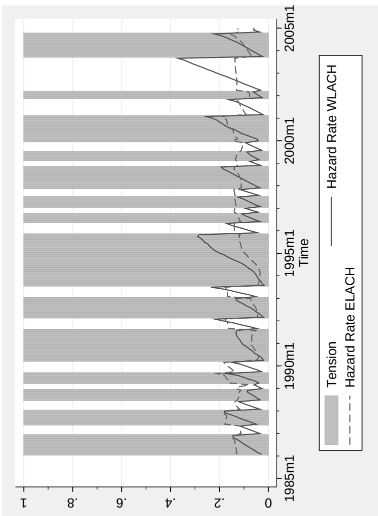


(c) Malaysia

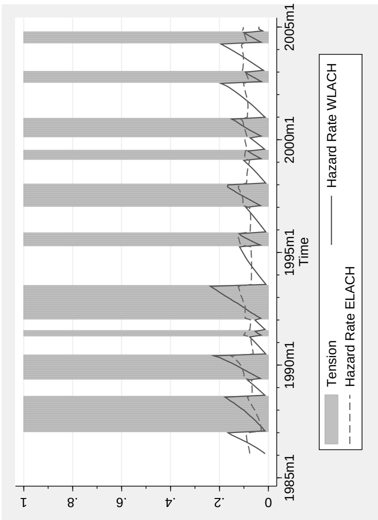


(d) Philippines

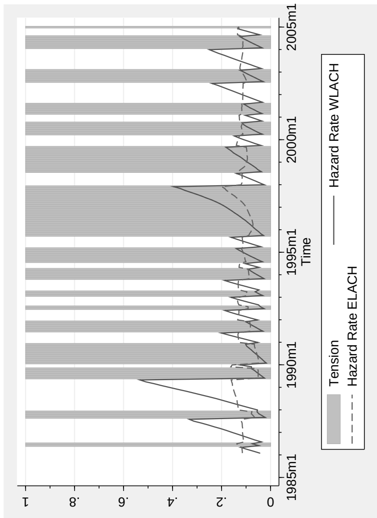
Figure 4.6: Probability of transition from period of tension to period without tension and vice versa (4)



(a) Sri Lanka



(b) Taiwan



(c) Thailand

Figure 4.7: Probability of transition from period of tension to period without tension and vice versa (5)

Model	I[a]	II[a]	III[a]	IV[a]	GoF[a]
Prediction Horizon = 6 Months					
Exponential-LACH	65.5%	34.5%	31.4%	68.6%	0.3296
Static Exponential	61.0%	39.0%	33.1%	66.9%	0.3605
Weibull-LACH	61.7%	38.3%	28.1%	71.9%	0.3320
Static Weibull	57.4%	42.6%	30.7%	69.3%	0.3668
Prediction Horizon = 5 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	65.7%	34.3%	33.5%	66.5%	0.3392
Static Exponential	61.0%	39.0%	35.9%	64.1%	0.3743
Weibull-LACH	64.1%	35.9%	27.9%	72.1%	0.3186
Static Weibull	59.5%	40.5%	30.2%	69.8%	0.3534
Prediction Horizon = 4 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	67.4%	32.6%	38.0%	62.0%	0.3533
Static Exponential	60.1%	39.9%	38.1%	61.9%	0.3901
Weibull-LACH	68.3%	31.7%	29.0%	71.0%	0.3034
Static Weibull	62.1%	37.9%	31.5%	68.5%	0.3469
Prediction Horizon = 3 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	64.1%	35.9%	37.1%	62.9%	0.3648
Static Exponential	56.2%	43.8%	37.1%	62.9%	0.4044
Weibull-LACH	71.8%	28.2%	30.1%	69.9%	0.2917
Static Weibull	63.7%	36.3%	32.4%	67.6%	0.3435
Prediction Horizon = 2 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	68.6%	31.4%	41.5%	58.5%	0.3646
Static Exponential	58.8%	41.2%	41.1%	58.9%	0.4114
Weibull-LACH	71.5%	28.5%	29.4%	70.6%	0.2894
Static Weibull	63.2%	36.8%	30.0%	70.0%	0.3339
Prediction Horizon = 1 Month					
Model	I	II	III	IV	GoF
Exponential-LACH	66.5%	33.5%	36.9%	63.1%	0.3517
Static Exponential	52.5%	47.5%	35.7%	64.3%	0.4161
Weibull-LACH	77.6%	22.4%	33.9%	66.1%	0.2815
Static Weibull	67.7%	32.3%	33.4%	66.6%	0.3287

Table 4.7: Prediction performance of the different model specifications in Latin America.

[a] I is the number of signals for a turning point (A) as a percentage of the total number of periods in which a signal should be given ($A + C$). II is the percentage of non-signals ($C/(A+C)$). III is the percentage of times a signal is given by the model (B) when none is desired ($B+D$). IV is the percentage of correct non-signals ($D/(B+D)$). The Goodness-of-Fit (GoF) is calculated as (II+III)/2.

Prediction Horizon = 6 Months					
Model	I[a]	II[a]	III[a]	IV[a]	GoF[a]
Exponential-LACH	68.0%	32.0%	32.2%	67.8%	0.3214
Static Exponential	66.8%	33.2%	38.5%	61.5%	0.3584
Weibull-LACH	63.8%	36.2%	29.1%	70.9%	0.3261
Static Weibull	61.7%	38.3%	30.6%	69.4%	0.3444
Prediction Horizon = 5 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	71.1%	28.9%	39.0%	61.0%	0.3395
Static Exponential	69.8%	30.2%	45.6%	54.4%	0.3792
Weibull-LACH	67.4%	32.6%	30.9%	69.1%	0.3177
Static Weibull	65.4%	34.6%	33.2%	66.8%	0.3392
Prediction Horizon = 4 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	71.1%	28.9%	41.6%	58.4%	0.3525
Static Exponential	69.2%	30.8%	47.6%	52.4%	0.3920
Weibull-LACH	74.2%	25.8%	37.9%	62.1%	0.3187
Static Weibull	71.0%	29.0%	39.4%	60.6%	0.3422
Prediction Horizon = 3 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	66.9%	33.1%	40.0%	60.0%	0.3657
Static Exponential	65.7%	34.3%	46.1%	53.9%	0.4021
Weibull-LACH	74.6%	25.4%	37.3%	62.7%	0.3133
Static Weibull	70.7%	29.3%	39.4%	60.6%	0.3434
Prediction Horizon = 2 Months					
Model	I	II	III	IV	GoF
Exponential-LACH	64.0%	36.0%	38.9%	61.0%	0.3747
Static Exponential	62.9%	37.1%	44.1%	55.9%	0.4059
Weibull-LACH	80.4%	19.6%	42.8%	57.2%	0.3119
Static Weibull	73.9%	26.1%	44.4%	55.6%	0.3525
Prediction Horizon = 1 Month					
Model	I	II	III	IV	GoF
Exponential-LACH	60.3%	39.7%	37.1%	62.9%	0.3840
Static Exponential	58.3%	41.7%	42.8%	57.2%	0.4225
Weibull-LACH	83.5%	16.5%	44.0%	56.0%	0.3025
Static Weibull	75.2%	24.8%	44.9%	55.1%	0.3486

Table 4.8: Prediction performance of the different model specifications in Asia.

[a] I is the number of signals for a turning point (A) as a percentage of the total number of periods in which a signal should be given ($A + C$). II is the percentage of non-signals ($C/(A+C)$). III is the percentage of times a signal is given by the model (B) when none is desired ($B+D$). IV is the percentage of correct non-signals ($D/(D+D)$). The Goodness-of-Fit (GoF) is calculated as (II+III)/2.

perfect fit would yield a goodness-of-fit measure of 0 whereas the worst possible fit would yield 1. If we now compare the performance of the four models we see that the Weibull models do better than their Exponential counterparts on the all forecasting horizon except the 6-month horizon. This result is expected as the estimated values for the shape parameter γ are well above 1. When comparing the dynamic duration models with the static models, there is clear evidence that the dynamic model works better. In all cases the dynamic model has a goodness-of-fit measure closer to 0 than the static version.

4.6 Concluding Remarks

In this chapter a dataset of 19 countries from Latin America and Asia is used to estimate Autoregressive Conditional Hazard models to explain the occurrence and duration of tension on the exchange rate market. Our model is an addition to existing work for several reasons. First, we model periods of tension instead of periods of crisis in order to overcome the problems that are commonly encountered when modelling crises. Second, we extend the static duration model of Tudela (2004) to allow for time dynamics. To achieve this a modified version of the ACH model as originally proposed by Hamilton and Jordá (2002) is considered. As the time series dimension is too short to properly estimate the time dynamics, pooled panel estimations are performed. Third, we perform a Monte Carlo experiment to examine the behaviour of this model to see what happens to the estimation when applied to a panel with a short time dimension relative to the traditional high-frequency single series datasets to which the ACH usually is applied.

When pooling data, one should wonder whether the data actually is poolable (Van den Berg et al., 2008). The simulation study showed however, that we need the complete panel of countries in order to get reliable estimation results. We found that a single country or clusters of similar countries do not provide sufficient durations to consistently estimate the time dynamics in the ACH model, thereby rendering it impossible to perform any subsample analysis. As regional dummies turned out to be highly insignificant and a model with country dummies is unfeasible, a country specific effect is incorporated into the model by allowing the starting value of the expected duration to be different for each country. This way, every country has its own baseline risk.

In the empirical application we used Exponential-LACH and Weibull-LACH models. Both the probability of transition from periods of tension to periods without tension and the probability of transition from non-tension periods to tension periods are subject to analysis. It results that assuming a Weibull density for the durations works better than assuming an Exponential density in terms of predicting the probability that the current period will end in the next month. This finding holds for both directions of transition. The estimation of the time dynamics reveals that the expected duration of the period of tension depends negatively on the expectation for the previous period, but not on the lagged observed duration. In contrast, the expectation of the duration of the periods without tension shows very high persistence in the expectations and depends negatively on the lagged observed duration. Overall, the lagged expected durations have a stronger impact on the current expectation than the lagged observed durations. Comparison of the dynamic with the static duration models shows that the inclusion of dynamics definitely helps in the prediction of the turning points between periods of tension and non-tension. This finding warrants the use of ACH techniques despite its shortcomings in the finite sample.

4.A Appendix: Monte Carlo Results

This appendix contains the Monte Carlo simulations results that were used to examine the small sample performance of the ACD model.

ELACD(1,1), N=5, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.6	5.5206	5.5796	2.8770	2.1004	[-0.0129; 10.774]
α	0.2	0.2006	0.1907	0.1323	0.1224	[-0.0440; 0.4716]
β	-0.6	-0.5929	-0.6622	0.7132	0.5106	[-1.8084; 0.9229]
ELACD(1,1), N=10, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.6	5.5350	5.6964	1.5240	1.1400	[2.1663; 8.2926]
α	0.2	0.2069	0.2001	0.0883	0.0798	[0.0398; 0.3881]
β	-0.6	-0.5946	-0.6539	0.3587	0.2627	[-1.1569; 0.2754]
ELACD(1,1), N=100, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.6	5.5711	5.5959	0.3528	0.3429	[4.8478; 6.1862]
α	0.2	0.2022	0.2022	0.0243	0.0242	[0.1563; 0.2496]
β	-0.6	-0.5950	-0.6019	0.0800	0.0776	[-0.7357;-0.4271]
ELACD(1,1), N=1000, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.6	5.6040	5.6092	0.1044	0.1054	[5.3920; 5.7932]
α	0.2	0.2000	0.1999	0.0074	0.0076	[0.1857; 0.2151]
β	-0.6	-0.6012	-0.6026	0.0237	0.0237	[-0.6451;-0.5518]

Table 4.9: Estimation results of the ELACD when the innovations are Exponential.

WLACD(1,1), N=5, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.5	5.5911	5.7213	2.8166	1.9059	[-0.0181; 10.622]
α	0.2	0.2010	0.1912	0.1344	0.1145	[-0.0496; 0.4843]
β	-0.6	-0.6304	-0.7074	0.6989	0.4586	[-1.7718; 0.9203]
γ	2.0	2.1136	2.0857	0.2567	0.2314	[1.6832; 2.6727]
WLACD(1,1), N=10, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.5	5.5283	5.6598	1.5388	1.1009	[2.1451; 8.2993]
α	0.2	0.2054	0.1995	0.0890	0.0771	[0.0344; 0.3930]
β	-0.6	-0.6143	-0.6710	0.3584	0.2527	[-1.1890; 0.2069]
γ	2.0	2.0539	2.0373	0.1663	0.1599	[1.7705; 2.4433]
WLACD(1,1), N=100, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.5	5.4727	5.4967	0.3546	0.3433	[4.7547; 6.1093]
α	0.2	0.2022	0.2020	0.0243	0.0241	[0.1562; 0.2494]
β	-0.6	-0.5952	-0.6025	0.0799	0.0774	[-0.7350;-0.4276]
γ	2.0	2.0067	2.0061	0.0496	0.0495	[1.9156; 2.1026]
WLACD(1,1), N=1000, K=10						
Variable	Value	Mean Coeff	Median Coeff	St.Dev. of Est. Coeff	Mean of St.Dev.	95% Conf. Interval
ω	5.5	5.5044	5.5099	0.1045	0.1059	[5.2927; 5.6976]
α	0.2	0.2000	0.1999	0.0074	0.0076	[0.1857; 0.2151]
β	-0.6	-0.6012	-0.6026	0.0237	0.0238	[-0.6451;-0.5519]
γ	2.0	2.0003	2.0003	0.0157	0.0156	[1.9681; 2.0318]

Table 4.10: Estimation results of the WLACD when the errors are Weibull with $\gamma = 2$.

Chapter 5

On the Use of Market Agents' Expectations to Explain Currency Crises

This chapter concludes the thesis. As each chapter contains its own conclusion, we will not go into the details here but rather focus on the general conclusion. Next, we identify some limitations of this work and the currently existing crisis models in general. One of the shortcomings will then be analysed more closely through an exercise with survey data as explanatory variables. A discussion of the findings of the exercise along with possible extensions ends the thesis.

5.1 Overview of previous Chapters

In Chapter 2 we examine the validity of the implied homogeneity assumption that is made when pooling panel data. It is shown that researchers should not naively pool all the data available for a maximum number of countries, because the quality of the prediction severely decreases when homogeneity is wrongfully assumed. We propose to form optimal clusters instead, based on a series of Hausman tests for poolability. Within these optimal clusters the homogeneity assumption is not violated, leading to a better performance of the crisis model in terms of predicting and explaining crisis periods. If feasible with respect to sample size, we suggest a preliminary analysis of optimal country clusters before setting up panel model.

In Chapter 3 we introduce the duration framework as crisis model. The use of the duration model has two advantages over the traditional limited dependent variable models (logit, probit). First, it is not subject to the problem of low variability over time of the dependent variable. And second, the time since the last crisis is added as an additional dimension to capture stability on the exchange rate market. With a fully parametric proportional hazards model it is found that for the Asian countries in the sample, the likelihood of crisis increases as the time since the last crisis episode passes. For the Latin American part of the sample, the time since the last crisis yields no extra information. This is consistent with the consensus (e.g. Berg and Pattillo, 1999; Kumar, Moorthy, and Perraudin, 2003) that the crises in Latin America in the 1980s and 90s can be attributed to misaligned macro-economic fundamentals.

The analysis in Chapter 4 switches the focus to tension on the exchange market. Examining periods of tension instead of crisis episodes has two advantages. First, it is not necessary to define ad hoc measures for finding extreme values that are usually required for identifying times of crisis. Second, it increases the number of useful observations per country. In the chapter we develop a modified version of the Autoregressive Conditional Hazard (ACH) model by Hamilton and Jordá (2002) to allow for time dynamics in the model for expected durations of periods of increasing tension and periods of decreasing tension. The findings indicate that the expected duration of the current period of increasing or decreasing tension depends strongly on previous expected durations and less on previously observed durations. This indicates that once expectations about the stability of a currency are formed, it is difficult to change those expectations. For policymakers this emphasises once more that managing market agents' expectations is of the utmost importance. The ACH model has a drawback as well. In the finite sample convergence is not guaranteed and cross-country pooling is required to produce reliable results. In the process of pooling we are forced to impose the homogeneity assumption across the countries, while from Chapter 2 we would expect that it is unlikely to hold.

One reason for the mixed success of the first-generation crisis models is that not every crisis is necessarily caused by weak macroeconomic fundamentals. Through the expectations of agents, bad news alone about for example future fiscal deficits can already trigger a currency crisis (Corsetti, Pesenti, and Roubini, 1999; Burnside, Eichenbaum, and Rebelo, 2001; Lahiri and Vegh, 2003). If the expectation exists that this deficit will be (partly) financed by printing money, the increase in expected inflation becomes a self-fulling prophecy.

In the previous chapters we attempted to capture the changing expectations indirectly. Either by including macro-economic variables to approximate expectations, or by using the expected duration in the ACH model. In this final chapter we take a more direct approach. In order to explain the phenomena of the self-fulling prophecy[1] and contagion factors more accurately, a number of survey- and forecast-variables are included in the model to measure how agents perceive the market. A contagion effect is incorporated through a weighted index of crisis indicators in other countries where the weights are based on the intensity of the bilateral trade relations.

[1]See Obstfeld (1986)

In the remainder of the chapter we examine whether the inclusion of survey and forecast variables in a duration model provides additional insight in explaining currency crises that cannot be explained by misaligned macro-economic variables. Section 5.2 shortly describes the model. The data and the crisis definition are shown in Section 5.3, while the results are given in Section 5.4. Section 5.5 concludes.

5.2 Model Setup

The multiple equilibria model by Obstfeld (1994, 1996) originated the theory that agents' expectations can trigger a speculative attack. The goal of this chapter is to capture these expectations and utilise them to explain the occurrence of currency crises. We therefore aim to extend the Autoregressive Conditional Hazards (ACH) model of Chapter 4 with a contagion dummy and survey data from the World Economic Survey (WES) as explanatory variables. As these variables are not linked directly to the state of the economy, but rather to the economy as perceived by market agents, we group them as 'sentiment' variables. This section proceeds with a short recap of the modelling framework, followed by a description of the aforementioned variables. For technical details about the model we refer to the previous chapter.

5.2.1 Modelling Framework

The model on which we would like to build, is the dynamic duration model as developed in Chapter 4. The two main equations that define the Weibull Logarithmic Autoregressive Conditional Hazards (WLACH) model are repeated here from the previous chapter. Equation (5.1) shows the ACD aspect of the model as it describes how the expectation of the duration of a tranquil period between two crisis episodes $\psi_{i,N_i(t)}$ depends on the durations of the preceding tranquil periods $z_{i,N_i(t)}$ and on previous expectations. Notice that $N_i(t)$ is a counting process that counts the number of crises in country $i = \{1, \ldots, K\}$ that have occurred up to date $t = \{1, \ldots, T\}$. The expression for the hazard rate is given in equation 5.2. The hazard rate, conditional on information available at time $t-1$, depends on the expected duration of the ongoing tranquil period $\psi_{i,N_i(t)+1}$, the set of explanatory variables $X_{i,t-1}$ and the time passed since the last crisis t^*.

$$\ln(\psi_{i,N_i(t)}) = \omega + \sum_{j=1}^{q} \alpha_j \ln(z_{i,N_i(t)-j}) + \sum_{j=1}^{p} \beta_j \ln(\psi_{i,N_i(t)-j}), \tag{5.1}$$

$$\lambda(i, t|\,\mathcal{I}_{i,t-1}) = 1 - \frac{\exp\left[-\left(\frac{\Gamma(1+\frac{1}{\gamma})\exp(\delta' X_{i,t-1})}{\psi_{i,N_i(t)+1}}\,(t^*+1)\right)^{\gamma}\right]}{\exp\left[-\left(\frac{\delta' X_{i,t-1}\cdot\Gamma(1+\frac{1}{\gamma})}{\psi_{i,N_i(t)+1}}\,t^*\right)^{\gamma}\right]}. \tag{5.2}$$

As shown in Chapter 4, the ACH model suffers from convergence problems in small samples. Effectively, our dataset provides just over 60 periods of tranquility that can be used for estimation. As it turns out, consistent estimation of the ACD parameters is not guaranteed in our setup. We therefore are forced to revert to the duration model without ACD components from Chapter 3. In terms of the model above, this means that Equation (5.1) drops out, and that $\psi_{i,N_i(t)+1}$ in Equation (5.2) reduces to a country-specific constant.

5.2.2 Contagion and Sentiment Variables

In this chapter we develop a second-generation crisis prediction model by incorporating market agents' expectations into the model. From the second-generation crisis model of Obstfeld (1994, 1996) we know that a change in expectations about the currency can act as a self-fulfilling prophecy and possibly cause a country to suffer from a currency crisis without this being caused by misaligned macroeconomic fundamentals. As the market agents' expectations cannot be measured directly, we include several different survey variables to approximate it. Furthermore, a trade-weighted composite variable is included to capture a possible contagion effect that could also influence the stability of the currency through the trade channel.

In order to capture the market agents' sentiments, we use survey data from the IFO World Economic Survey retrieved from Datastream. The dataset covers the agents' opinions about the current economic situation; the expected economic situation 6 months ahead; the stability of the national currency with respect to the US-dollar; the confidence in governments economic policy and the investment climate for foreign investors. All the series are on a continuous scale from 1 to 10, with higher values indicating a more positive opinion. As the survey data is on quarterly basis, it should be transferred to fit the monthly crisis model. We take the quarterly observation as value for all three months in that quarter.[2]

As already discovered by Glick and Rose (1999), close trade relationships are a channel through which a financial crisis could be transferred from one country to another. In order to capture this contagion effect, a weighted variable is included in the model. The variable is based on bilateral trade data. It is constructed as the weighted average of the binary crisis indicator for the other countries in the sample.

$$CD_{i,t} = \sum_{j=1}^{K} w_{i,j} C_{j,t} \qquad i = 1, \ldots, K, \quad t = 1, \ldots, T, \tag{5.3}$$

[2]Alternatively, the missing months were intrapolated using a linear spline. As the estimation results of the crisis model were not affected, the simplest solution was given preference.

where $C_{j,t}$ indicates a crisis in country j at time t; K denotes the total number of countries in the sample; and the weight $w_{i,j}$ for countries i and j is given by the sum of exports and imports between the two countries divided by the total imports and exports of country i:

$$w_{i,j} = \frac{\mathrm{Exp}_{i,j} + \mathrm{Imp}_{i,j}}{\sum_{j=1}^{K}(\mathrm{Exp}_{i,j} + \mathrm{Imp}_{i,j})} \qquad \text{for} \quad i \neq j, \tag{5.4}$$

with $w_{i,i} = 0$ for all i. This definition ensures that the weights per country sum to 1. The trade-weighted variable can therefore take values between 0 and 1. It takes a value of 1 when all other countries (in the sample) are in a crisis and a value of 0 when none of the other countries are suffering from a crisis. Therefore, the closer this variable is to 1, the stronger is the possibility of contagion and the higher is the probability of a speculative attack. Notice that when one (or more) of the country's major trading partners is in a crisis, the impact on the trade-weighted variable is larger than when this is the case for any of the weak trade relations. To avoid the endogeneity problem, this variable is included in the model one month lagged.

5.3 Data

5.3.1 Dataset

Our dataset consists of monthly data from January 1989 to June 2008.[3] It covers 18 countries from the regions Latin America and Asia: Argentina, Bolivia, Brazil, Chile, Ecuador, Mexico, Paraguay, Peru, Uruguay, Venezuela, China, India, Indonesia, Korea, Malaysia, Philippines, Sri Lanka and Thailand. The data is obtained via Datastream and the sources are the IMF-IFS database, the national banks of the respective countries and the IFO World Economic Survey.

The set of macroeconomic explanatory variables is the same as in previous chapters. For a more detailed description, please refer to one of the earlier chapters. It relates to different aspects of the economy. To represent the external sector we use annual growth rate of exports as well as imports; the real interest rate differential with respect to the United States; and the growth rate of international reserves. For the financial sector, we have the M2 multiplier; growth of domestic credit to DGP; and M2 over reserves. The real sector of the economy is proxied by the growth in industrial production.

As described in the previous section, the sentiment variables are survey data on the current economic situation (CES) and the economic situation 6 months ahead (ES 6m); the stability of the national currency with respect to the US-dollar (ERS); the confidence in governments economic policy (CEP) and the investment climate

[3] The starting date of the sample is determined by the availability of the survey data.

	ES 6m	CES	ERS	CEP	IC
Economic Sit. in 6 months (ES 6m)	1				
Current Economic Situation (CES)	-0.001	1			
Exchange rate stability (ERS)	-0.016	0.006	1		
Confidence Economic Policy (CEP)	-0.167	-0.506	0.039	1	
Investment Climate (IC)	0.112	0.240	-0.128	-0.485	1

Table 5.1: Correlation Matrix Survey Variables

for foreign investors (IC). Finally, we also include a trade-weighted variable in order to include a potential contagion phenomenon. Considering that the sentiment variables are retrieved from the same survey while attempting to capture people's feelings about the economy, a concern might be that the variables are highly correlated. Table 5.1 depicts the bilateral correlations between the five sentiment variables. From this table, it can be seen that the bilateral correlations are well within acceptable range with the strongest correlation being -0.5 between the confidence in the current economic situation and the confidence in economic policy. Another interesting fact in Table 5.1, is the near zero correlation between the confidence in the current economic situation and the confidence in the economic situation in 6 months. As the table reports contemporaneous correlations, this results is maybe not so surprising. However, when taking the appropriate lags such that the numbers in the series correspond to the same quarters, the correlation between the series is still only 0.15. This indicates that agents' sentiments about the economy are very changeable over time and perhaps not accurate when the time between the prediction and the period to which is applied is too large. We therefore expect that the sentiment variables work best in the short run, i.e. in a few months leading up to a crisis.

5.3.2 Definition of a Crisis

Before the transition from a tranquil state to a state of crisis can be modelled, it must first be decided how a crisis is defined. Since we are interested in finding the probability of crisis, information about speculative attacks is required. Not all speculative attacks lead to a devaluation or revaluation of the currency. In order to capture both successful and unsuccessful speculative attacks, the periods of crisis are determined via the Exchange Market Pressure (EMP) index (see Eichengreen et al., 1995). As before, this EMP-index is the weighted average between the 6-month change in the exchange rate with respect to the US dollar and (the negative of) the 6-month change in the international reserves. The weights are chosen such that the variance of both factors are standardised to one. A crisis is signalled when the EMP-index exceeds its own mean by more than one and a half standard deviations.[4] This relatively low threshold is chosen to ensure that the

[4]As pointed out in Chapter 1, this method of defining periods of crisis has its shortcomings. In the absence of a universal consensus about which dating method is best, we choose the method

number of crisis episodes does not decrease to such a low amount that any crisis analysis becomes void due to a lack of useful observations.

In the twenty years that are covered by our database, we classify 61 distinct periods of crisis divided over the 18 countries. Because we also have a censored period of tranquility at the end of the sample for each of the countries, the total number of tranquil periods is therefore 79. However, the period leading up to the the first crisis, is left-censored, i.e. we don't know how long ago the last crisis preceding the sample period occurred. For that reason, 18 tranquil periods drop out from the estimation. Post estimation however, when calculating the hazard rate, these periods are included as if the January 1989 is also the first month after the previous crisis. This is done to ensure that each country has at least 1 crisis that can be explained by the model. The number of crisis periods per country varies from 6 in Brazil and Chile to only one crisis in Korea, Malaysia and Thailand. Among the crisis periods, we find the 1995 Mexican crisis, the 2002 crisis in Argentina, and of course the Asian crisis. Of the 9 Asian countries, only China and India do not have a crisis in 1997-98. This is not so strange as these countries were not that severely affected by the Asian crisis.

5.4 Results

This section discusses the estimation results. We first check whether the ACH model converges properly. Because the ACD part indeed does not converge, we proceed with a duration model in the style of Chapter 3. The section proceeds with a comparison of the model including the sentiment variables to a baseline alternative. This comparison is performed based on the estimation results as well as on the performance in terms of predicting crisis episodes.

The estimation results of the WLACH-model can be found in Table 5.2. Before an analysis can be started, it must be checked if the ACD part of the model converged properly. Remember that an ACD(p,q) model as in equation (5.1) is subject to the constraint $\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j < 1$. In our ACD(1,1) model this reduces to $\alpha + \beta < 1$. From the table we find that the estimates for α and β sum up to (almost) exactly 1. This means that the estimates are on the boundary of the constraint. As such, it may be concluded that the estimator has not converged properly. For this reason, we revert to the duration model without ACD components from Chapter 3 for the remainder of the analysis.

The estimation results of the duration models with and without sentiment variables are presented in Table 5.3. The table also includes the results of the model without sentiment variables. For both models we find that of all the macroeconomic variables, only the growth in international reserves and the real interest rate

that comes closest to capturing the fluctuations on the exchange rate market.

Variable	Parameter Estimate	Expected Sign
ω	-0.089	
	(0.107)	
α	-0.122	
	(0.066)	
β	1.122	
	(0.066)	
γ	0.817	
	(0.080)	
Reserves Growth$_{t-1}$	-1.884***	-
	(0.590)	
Real Interest Rate Diff.$_{t-1}$	0.047***	+
	(0.018)	
Trade-weighted Variable$_{t-1}$	2.500***	+
	(0.921)	
Current Economic Situation$_{t-1}$	-0.227***	-
	(0.088)	
Economic Sit. in 6 months$_{t-1}$	-0.179**	-
	(0.084)	
Exchange rate stability$_{t-1}$	-0.225**	-
	(0.091)	
Confidence Economic Policy$_{t-1}$	0.057	-
	(0.099)	
Investment Climate$_{t-1}$	0.136	-
	(0.149)	
Constant	1.756	
	(1.291)	

Note: Fixed effects dummies are not included in the table for brevity. Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%; Log-Likelihood = -4702.9

Table 5.2: Full model with ACH specification.

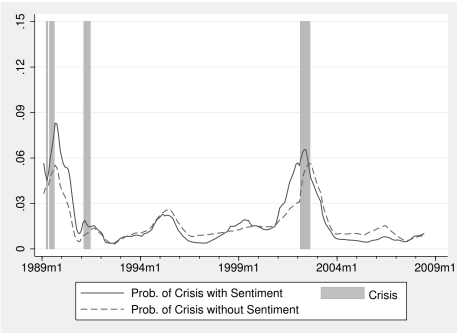
Variable	With Sentiment	Without Sentiment	Expected Sign
Reserves Growth$_{t-1}$	-1.881***	-2.404***	-
	(0.604)	(0.564)	
Real Interest Rate Diff.$_{t-1}$	0.049**	0.060***	+
	(0.020)	(0.018)	
Trade-weighted Variable$_{t-1}$	2.544***		+
	(0.921)		
Current Economic Situation$_{t-1}$	-0.195**		-
	(0.083)		
Economic Sit. in 6 months$_{t-1}$	-0.206**		-
	(0.094)		
Exchange rate stability$_{t-1}$	-0.211**		-
	(0.099)		
Confidence Economic Policy$_{t-1}$	0.047		-
	(0.066)		
Investment Climate$_{t-1}$	0.075		-
	(0.097)		
Constant	1.756	-0.129	
	(1.291)	(0.163)	

Note: Fixed effects dummies are not included in the table for brevity. Standard deviations in brackets; *,** and *** indicate significance at 10%, 5% and 1%; Log-Likelihood with sentiment variables= -4809.7; Log-Likelihood without sentiment variables= -5055.4

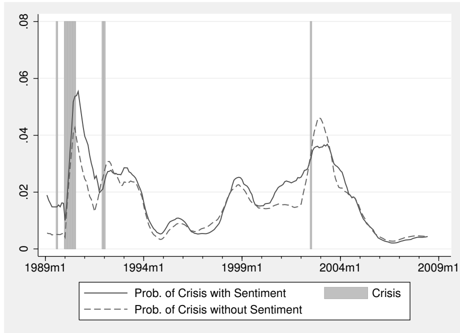
Table 5.3: Comparing models with and without sentiment variables.

differential with respect to the US have a significant impact. The negative coefficient of the reserves growth rate indicates that the probability of a currency crisis increases as the amount of international reserves decreases. This seems a sensible result because a rapidly decreasing pool of reserves means that the central bank has potentially less power to intervene on the exchange rate market in case of a speculative attack. The positive coefficient of the real interest rate w.r.t. the US can be explained via the uncovered interest rate parity (UIP). When the real interest rate of a country is far above the US rate, the UIP asserts that the expected exchange rate of the respective currency vis-à-vis the US dollar is above the actual exchange rate. The fact that a depreciation of the currency is expected, can be a tell-tale sign of an imminent currency crisis. Therefore, a high real interest rate differential should indeed be linked to an increased probability of crisis in our model. The remaining variables in the table relate only to the model with sentiment variables. The trade-weighted variable has the expected positive coefficient. This signifies that the probability of crisis in a country increases when a crisis occurs in a country with which it has close trade relations. The other sentiment variables are defined such that a high value indicates a positive sentiment, while a low value corresponds to a negative sentiment. Therefore the coefficients are expected to be negative. Table 5.3 shows positive but non-significant coefficients for the confidence in economic policy and foreign investment climate variables. For the current economic situation, the economic situation in 6 months and the exchange rate stability we find however that the coefficients are indeed negative and significant. This indicates that the actual probability of a currency crisis will be low when the market agents believe that the economy is and will be strong. Similarly, when the agents believe in a stable exchange rate, the likelihood of a crisis will be small. Basically this means that as long as the market agents have confidence in the economy and the currency, there is little cause for concern about any imminent crisis. That being said, the opposite is also true. When the market agents' confidence declines, a currency crisis could be triggered without misaligned fundamentals; thereby making the self-fulfilling prophecy reality. Based on these results, guidelines for a government to reduce the probability of a currency crisis would be to keep the confidence of domestic market agents high through solid economic growth and a stable currency. On the other hand, the type of economic policy and the climate for foreign investors are less important factors with respect to occurrence of currency crises.

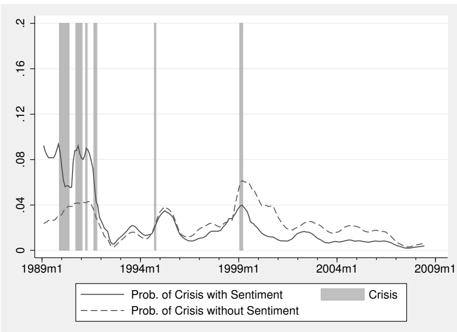
From the estimation results in Table 5.3, we can calculate the probability of crisis for each country at any point in time. These probabilities are shown in Figures 5.1-5.3. The solid line represents the probability from the model with sentiment variables. The dashed line is the baseline model without sentiment variables with which we would like to compare our model. Knowing that the gray areas indicate the times of crisis, the ideal crisis-signalling model would give a high probability in the months leading up to the crisis (to the left of the gray areas) and a low probability otherwise. From the figures however, the difference between the model with and without sentiment variables is not very obvious. A



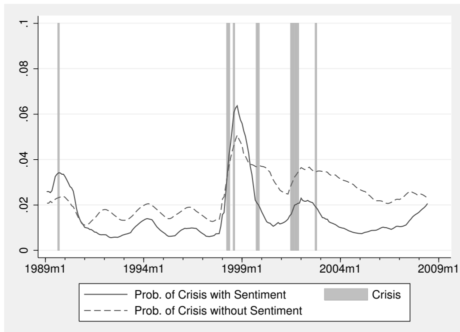
(a) Argentina



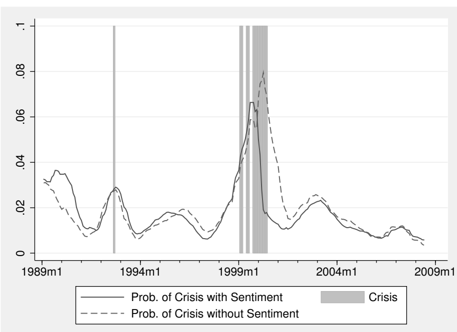
(b) Bolivia



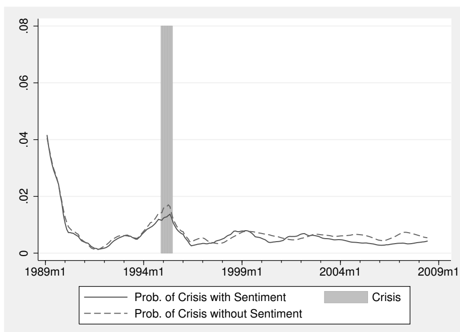
(c) Brazil



(d) Chile

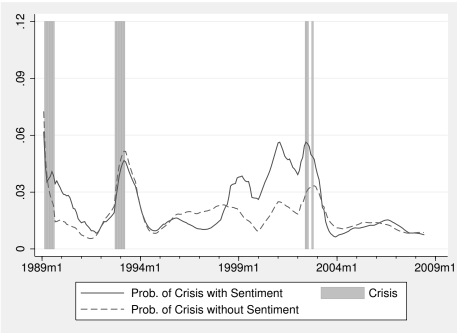


(e) Ecuador

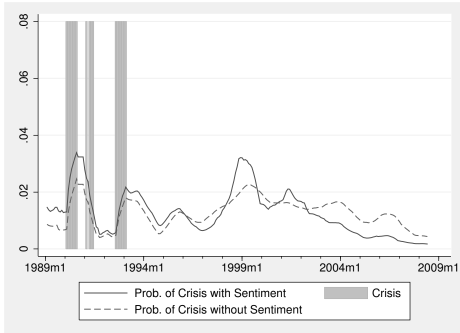


(f) Mexico

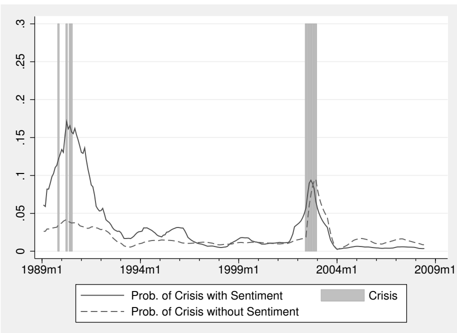
Figure 5.1: Probability of crisis in the next month (1)



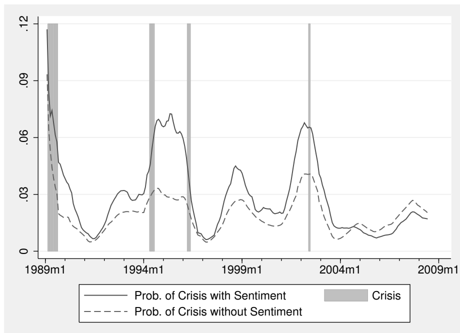
(a) Paraguay



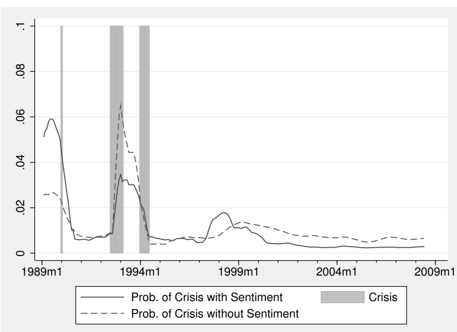
(b) Peru



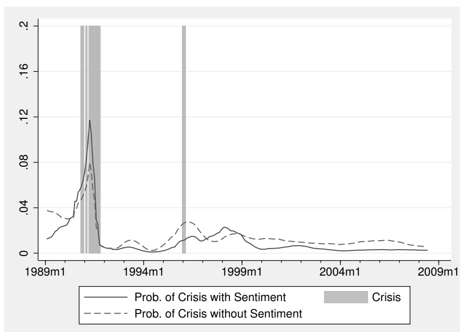
(c) Uruguay



(d) Venezuela

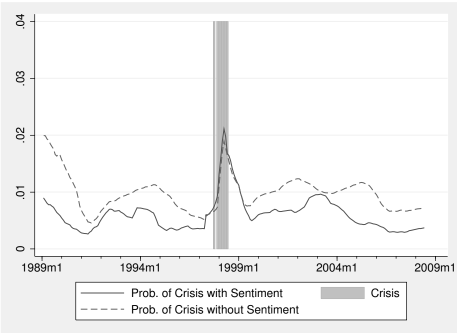


(e) China

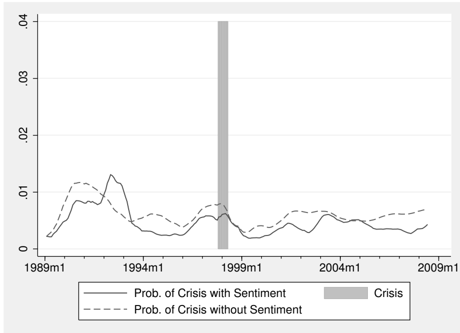


(f) India

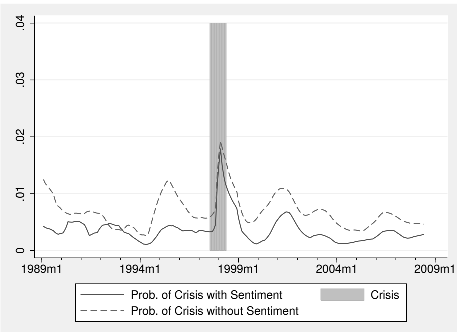
Figure 5.2: Probability of crisis in the next month (2)



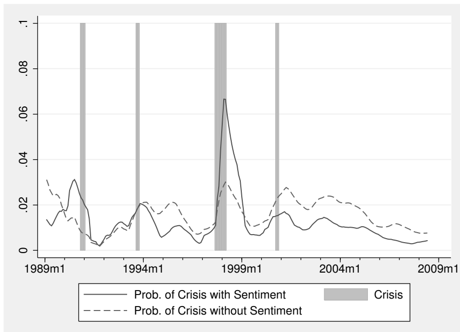
(a) Indonesia



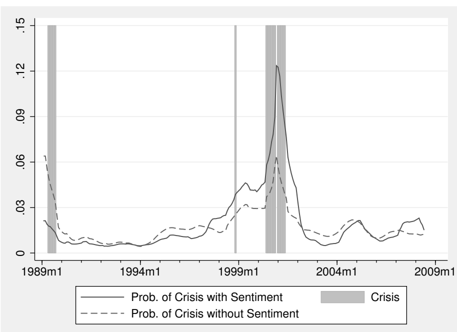
(b) Korea



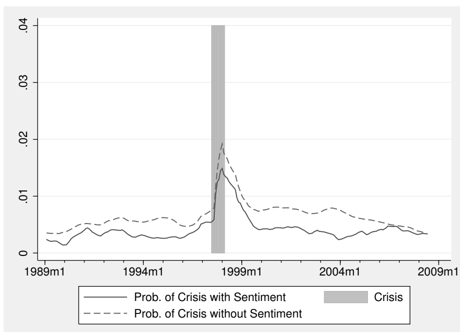
(c) Malaysia



(d) Philippines



(e) Sri Lanka



(f) Thailand

Figure 5.3: Probability of crisis in the next month (3)

more formal comparison of prediction performance is therefore desirable. For this reason, the probability of transition into crisis is examined numerically as well. To do this, we use the signalling method as originally used by Kaminsky (1999). In this approach we compare the cases when the model signals a crisis to those when we would like it to signal one. The time window ahead of the crisis at which the model ideally should start signalling, is varied between 1 and 6 months in advance. The model signals a crisis if the hazard rate crosses a certain threshold. This signalling threshold is determined per country. It is set at the level that minimises missed crises and false signals. The perfect fit would be if the signals of the model coincide exactly with the required signals. We therefore count the number of correct signals (A), the number of times the model did not give a signal when it actually should have (C), the number of false alarms (B) and the number of correct non-signals (D). These numbers are presented in Tables 5.4 and 5.5 for the different model specifications and prediction horizons. The goodness-of-fit of the model is calculated as the average of the percentages of missed crises and false alarms. As such, a perfect fit would yield a goodness-of-fit measure of 0, whereas the worst possible fit would yield 1.

Comparing the performance of the model including the 'sentiment' variables to the baseline model with only macroeconomic fundamentals, we see that the story of the figures is mostly confirmed, as the goodness-of-fit measures are similar between the two models. However, the results indicate slightly lower (better) values for the model with the sentiment variables. For the Latin American countries, this difference is persistent for all prediction horizons. For the Asian countries, the performance of the model with sentiment variables improves relatively to the baseline model as the prediction horizon shortens. This result indicates that market agents' sentiments play the strongest role in the short run, which makes sense as only their immediate and possibly next month's actions are likely to be influenced by their opinion about the economy today.

5.5 Conclusion

In this final chapter our dataset covering 18 countries from Latin America and Asia is used to examine whether survey-variables can be used to improve the quality of explaining the occurrence of currency crisis. The survey data are included as explanatory variables in a duration model along with the more traditional macroeconomic characteristics and a contagion dummy. As expected, the ACH model developed in Chapter 4 is not feasible due to the finite sample. Therefore we use the duration model without time dynamics of Chapter 3.

All in all, the addition of sentiment variables to capture market agents' expectations yielded a mixed bag of results. On the one hand, the model with sentiment variables provided a better fit, but on the other hand, the improvement is not over-

Prediction Horizon = 6 Months					
Model	I[a]	II[a]	III[a]	IV[a]	GoF[a]
With Sentiment	37.7%	62.3%	12.3%	87.7%	0.3729
Without Sentiment	31.6%	68.4%	12.9%	87.1%	0.4065
Prediction Horizon = 5 Months					
Model	I	II	III	IV	GoF
With Sentiment	42.0%	58.0%	15.7%	84.3%	0.3687
Without Sentiment	33.2%	66.8%	13.0%	87.0%	0.3988
Prediction Horizon = 4 Months					
Model	I	II	III	IV	GoF
With Sentiment	42.4%	57.6%	15.7%	84.3%	0.3667
Without Sentiment	34.3%	65.7%	12.8%	87.2%	0.3926
Prediction Horizon = 3 Months					
Model	I	II	III	IV	GoF
With Sentiment	43.2%	56.7%	16.1%	83.9%	0.3643
Without Sentiment	35.4%	64.6%	13.8%	86.2%	0.3919
Prediction Horizon = 2 Months					
Model	I	II	III	IV	GoF
With Sentiment	38.6%	61.4%	11.3%	88.7%	0.3634
Without Sentiment	33.8%	66.2%	12.9%	87.1%	0.3955
Prediction Horizon = 1 Month					
Model	I	II	III	IV	GoF
With Sentiment	40.2%	59.8%	11.5%	88.5%	0.3562
Without Sentiment	30.5%	69.5%	7.7%	92.3%	0.3858

[a] I is the number of signals for a crisis (A) as a percentage of the total number of periods in which a signal should be given ($A + C$). II is the percentage of non-signals ($C/(A+C)$). III is the percentage of times a signal is given by the model (B) when none is desired ($B+D$). IV is the percentage of correct non-signals ($D/(B+D)$). The Goodness-of-Fit (GoF) is calculated as (II+III)/2.

Table 5.4: Prediction performance in Latin America.

Prediction Horizon = 6 Months					
Model	I[a]	II[a]	III[a]	IV[a]	GoF[a]
With Sentiment	29.5%	70.5%	14.5%	85.5%	0.4248
Without Sentiment	26.7%	73.3%	9.5%	90.5%	0.4142
Prediction Horizon = 5 Months					
Model	I	II	III	IV	GoF
With Sentiment	35.5%	64.5%	18.1%	81.9%	0.4129
Without Sentiment	27.0%	73.0%	9.8%	90.2%	0.4139
Prediction Horizon = 4 Months					
Model	I	II	III	IV	GoF
With Sentiment	36.5%	63.5%	17.7%	82.3%	0.4057
Without Sentiment	27.8%	72.2%	9.4%	90.6%	0.4080
Prediction Horizon = 3 Months					
Model	I	II	III	IV	GoF
With Sentiment	34.0%	66.0%	14.4%	85.6%	0.4020
Without Sentiment	33.0%	67.0%	15.5%	84.5%	0.4126
Prediction Horizon = 2 Months					
Model	I	II	III	IV	GoF
With Sentiment	38.9%	61.1%	14.5%	85.5%	0.3778
Without Sentiment	31.9%	68.1%	12.3%	87.7%	0.4017
Prediction Horizon = 1 Month					
Model	I	II	III	IV	GoF
With Sentiment	40.0%	60.0%	10.9%	89.1%	0.3543
Without Sentiment	35.0%	65.0%	12.1%	87.9%	0.3856

[a] I is the number of signals for a crisis (A) as a percentage of the total number of periods in which a signal should be given ($A + C$). II is the percentage of non-signals ($C/(A+C)$). III is the percentage of times a signal is given by the model (B) when none is desired ($B+D$). IV is the percentage of correct non-signals ($D/(B+D)$). The Goodness-of-Fit (GoF) is calculated as (II+III)/2.

Table 5.5: Prediction performance in Asia.

whelming. An explanation for this relatively weak improvement might be that the survey data is available only at a quarterly frequency while the model tries to capture monthly probabilities of crisis. As suggested by the low correlation between the variables capturing the confidence in the current and future economic situation in Table 5.1, the sentiments are likely to be very changeable over time. A more frequent monitoring of market agents' sentiments might therefore be advisable for governing bodies in order to be able to act quickly in case of a drop in confidence.

From this exercise with a direct approach to measuring market agents' sentiments we learn that the use of survey variables could be good step forward to predicting currency crises that occur without any identifiable macro-economic causes. It must be taken into account however, that the explanatory power of the survey data lies in the short run (1, 2 or 3 months ahead). Thus making it difficult for policymakers to intervene on the market to counteract market instability based on survey-data, especially when these data are only updated on a quarterly or even less frequent basis.

In this thesis we used duration analysis to study the likelihood of a currency crisis occurring. The use of fully parametric duration models is an innovative strategy for estimating this probability. This method allows us to include not only economic variables as determinants of the probability of a currency crash, but also the duration of spells of tranquility. This duration is important in assessing currency stability. We found that exchange rate credibility depends not only on macroeconomic fundamentals, but also on the time already spent in a tranquil episode. All things considered we may conclude that a financial crisis can be induced by many different causes. A lot of these causes are not included in models because they cannot (yet) be quantified, think for example about all the channels through which contagion is transmitted. Furthermore, no two crises are exactly the same. This immediately brings up the issue we raised in Chapter 2 about the implicit homogeneity assumption that is made when pooling data across countries. It does not stop there however. It is not just across countries that causes for a crisis may differ, also two different crisis episodes in the same country can have different causes. In order to keep any model tractable and its estimation feasible, some simplifying assumptions must be made however. Furthermore, there exists the possibility of cross-sectional dependence across the countries in our models. Although this is a very important issue that might influence our estimations, we did not take it into account in our models. Tackling this problem could be a good starting point for further research. We must keep in mind however that the art about empirical modelling lies in balancing completeness and accuracy of the model with the limitations and restrictions imposed by the data.

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Nederlandse samenvatting

Sinds de val van het Bretton-Woods systeem van vaste wisselkoersen is het aantal valutacrisissen sterk toegenomen wat geleid heeft tot een stortvloed van literatuur over dit onderwerp. Tot het midden van de negentiger jaren, spitste het onderzoek zich met name toe op het verklaren van valutacrisissen. De eerste empirische modellen benadrukten dat bij inconsistent macro-economisch beleid, de koppeling tussen wisselkoersen niet volgehouden kan worden. Deze onderzoeken richten zich op het gedrag van verschillende macro-economische variabelen tijdens of rond perioden van crisis. Vooral vlak na een financiële crisis is de roep om vroegtijdige alarmsignalen vanuit de overheid vaak erg groot, zoals na de recente grote economische crisis in 2008-2009.

In de praktijk heeft dit geleid tot twee belangrijke richtingen in de ontwikkeling van Vroegtijdige Alarmering Systemen (VAS). De eerste richting is gebaseerd op het monitoren van een groot aantal economische variabelen. Sterke afwijkingen ten opzichte van de gemiddelde tendens worden gekenmerkt als signaal. Hoe meer signalen, des te hoger is dan de kans op een crisis. De andere belangrijke groep van VAS is gebaseerd op een model met een gelimiteerd afhankelijke variabele. Hierbij wordt nog onderscheid gemaakt tussen de probit modellen en de logit modellen. In de probit versie wordt de afhankelijke variabele gemodelleerd op basis van een normale verdeling, terwijl dat in de logit versie gebeurt met een extreme waarde verdeling.

Bovengenoemde modellen zijn in de loop der tijd verder ontwikkeld en verbeterd. Daarnaast zijn diverse alternatieve modellen ontstaan, elk met hun eigen voor- en nadelen. Ondanks de vele inspanningen op dit gebied, vertonen de huidige VAS nog een groot aantal tekortkomingen. In dit proefschrift wordt een poging gedaan een paar van deze tekortkomingen op te lossen.

In een groot deel van de literatuur wordt gebruik gemaakt van panel data waarbij economische gegevens van verschillende landen bij elkaar genomen worden. Dankzij het groter aantal bruikbare waarnemingen dat wordt verkregen door het samenvoegen van gegevens, kan een betrouwbaardere schatting van het model gemaakt worden. Belangrijk hierbij is dat de verschillende landen homogeen genoeg zijn. Met andere woorden, de gegevensreeksen van de landen moeten voldoende overeenkomsten vertonen. Door dit samenvoegen wordt namelijk impliciet aangenomen dat dezelfde factoren voor alle samengevoegde landen de crisis op gelijke wijze voorspellen. Binnen deze beperkende aannames, kan eventuele heterogeniteit tussen de betrokken landen alleen gemodelleerd worden door middel van een zogenoemde fixed effect dummy. Voor alle aspecten waarop deze dummy niet wordt toegepast, wordt dus homogeniteit tussen de landen verondersteld. Deze veronderstelling is echter tegenstrijdig met twee bekende kenmerken van financiële crisissen. Ten eerste hebben niet alle crisissen dezelfde oorzaak. Zo zijn sommige crisissen het gevolg van zwak macro-economisch beleid, terwijl andere juist veroorzaakt worden door psychologische effecten of door een slechte handelsbalans bij de banken. Ten tweede kan onderlinge beïnvloeding ook leiden tot een financiële crisis, zoals geconstateerd is bij de crisis in Azië van 1997-98. Dit betekent dat financiële onrust van het ene land naar een ander land kan overslaan, wat kan leiden tot dynamische cross-sectionele afhankelijkheid. Het middelen en samenvoegen van landen kan tot verlies van informatie leiden. Echter, wanneer cross-sectionele afhankelijkheid niet goed wordt gemodelleerd, heeft dit mogelijk grote gevolgen voor een juiste schatting en inferentie.

In Hoofdstuk 2 wordt de problematiek rond het samenvoegen van gegevens behandeld. Door het toepassen van een panel-logit model op opkomende markt economieën, wordt aangetoond dat onderzoekers niet klakkeloos gegevens van verschillende landen mogen samenvoegen. Er wordt voorgesteld om vooraf een analyse uit te voeren om vast te stellen welke landen wel en niet bij elkaar genomen mogen worden. Op de hierdoor gevormde clusters van homogene landen kan daarna het (panel-)logit model worden toegepast.

Zoals gesteld, vertonen de bestaande Vroegtijdig Alarming Systemen tekortkomingen. In Hoofdstuk 3 wordt een duurmodel ontwikkeld als een alternatief VAS. Door deze benadering is het mogelijk om de kans op een crisis te laten afhangen van de verstreken tijd sinds de vorige crisis. Door middel van de tijdsafhankelijkheid binnen het duurmodel zouden psychologische factoren gesimuleerd kunnen worden. Het gebruik van een duurmodel als VAS is niet nieuw. Het hier voorgestelde model is een uitbreiding waarbij het tijdsafhankelijke onderdeel volledig parametrisch gemaakt wordt. Dit in tegenstelling tot eerdere modellen. Daarnaast wordt het model ook toegepast om het einde van een crisisperiode te voorspellen. Deze informatie kan beleidsmakers inzicht geven hoe te handelen in tijden van crisis.

In het VAS-duurmodel, ontwikkeld in Hoofdstuk 3, is geen plaats voor tijddynamiek. Verwacht mag worden dat de tijdsduur tot een volgende crisis afhankelijk is van de tijdsduur tussen vorige crisissen. In Hoofstuk 4 wordt daarom een aangepaste versie van het Autoregressieve Conditionele Hazards (ACH) model ontwikkeld. In het oorspronkelijke ACH model was het mogelijk dat de kans op een overgang van de ene economische toestand naar de andere negatief zou kunnen worden. Door de voorgestelde aanpassing ligt de kans op overgang wel altijd tussen 0 en 1. Het ACH model combineert de tijddynamiek van het Autoregressieve Conditionele Duurmodel (ACD) met tijdsafhankelijke macro-economische variabelen om zo de kans op overgang tussen twee economische toestanden te bepalen. In tegenstelling tot de andere hoofdstukken, richt de analyse in Hoofdstuk 4 zich op het verklaren van alle spanningen op de wisselkoersmarkt, in plaats van alleen op de spanningen die leiden tot een valutacrisis. Deze benadering heeft twee voordelen. Op de eerste plaats is het niet meer nodig om een (willekeurige) grenswaarde te kiezen op basis waarvan perioden van crisis bepaald worden. Een tweede voordeel is dat het probleem van het hebben van te weinig bruikbare waarnemingen afneemt. Dit komt doordat perioden van toenemende spanning gedefinieerd worden onafhankelijk van de intensiteit van de spanning.

In hoofdstuk 5 worden de conclusies getrokken en de resultaten en beperkingen van de behandelde modellen besproken. Een van die beperkingen is het niet of nauwelijks kunnen modelleren van psychologische invloeden op de markt. Omdat deze invloeden juist ten grondslag liggen aan de self-fulling prophecy en financiële besmetting tussen landen, wordt hier een empirische oefening uitgevoerd met enquête data als verklarende variabelen. Dit wordt uitgevoerd op het VAS van hoofdstukken 3 en 4. Het hoofdstuk sluit af met een aantal aanvullende inzichten gebaseerd op de uitgevoerde oefening, alsmede mogelijke uitbreidingen voor toekomstig onderzoek.

De in dit proefschrift voorgestelde volledig parametrische duurmodellen zijn een innovatieve wijze om het ontstaan van valutacrisissen te voorspellen. Binnen deze methodiek is het mogelijk om naast economische variabelen ook de tijd sinds de laatste crisis mee te nemen als verklarende variabele. De verstreken tijd sinds de vorige crisis is een belangrijke graadmeter van de stabiliteit van de wisselkoers. Alles beschouwende, mogen we concluderen dat financiële crisissen verschillende oorzaken kunnen hebben. Zo ontstaan twee crisissen zelden op een gelijke wijze. Dit impliceert de tegenstrijdigheid van de aanname van homogeniteit zoals deze wordt gemaakt bij het samenvoegen van gegevens over verschillende landen. Dit is echter niet alles. Niet alleen tussen de landen kunnen de oorzaken van een crisis verschillen, maar ook door de tijd. Om het empirisch model bruikbaar en betrouwbaar te houden zijn deze vereenvoudigende aannames echter noodzakelijk. Daarnaast is het mogelijk dat er cross-sectionele afhankelijkheid bestaat tussen de verschillende landen. Hoewel dit een belangrijk punt is dat de schattingsresultaten zou kunnen beïnvloeden, wordt dit niet meegenomen in de modellen binnen dit proefschrift. Het implementeren van deze afhankelijkheid in een VAS, zou een goed beginpunt zijn voor verder onderzoek. We moeten echter niet vergeten dat het ontwikkelen van een goed empirisch model valt of staat bij het vinden van een balans tussen compleetheid en nauwkeurigheid van het model aan de ene kant en de beperkingen opgelegd door de data aan de andere kant.

Curriculum Vitae

Jeroen Johannes Franciscus van den Berg was born on July 25, 1983 in Nieuwegein, The Netherlands. He attended high school (Gymnasium) between 1994 and 2000 at the Trevianum in Sittard. Subsequently, he studied Econometrics at Maastricht University. In October 2004 he obtained his Master's degree.

Just before graduation, Jeroen joined the Department of Economics as a teaching assistant. In April 2005 he became a Ph.D. candidate in the same department under the supervision of Prof. dr. Bertrand Candelon and Prof. dr. Jean-Pierre Urbain. The results of his research are presented in this thesis. Jeroen presented his work at several international conferences and part of this thesis is published in international refereed academic journals. As of January 2010, Jeroen has been working at UWV Werkbedrijf as a labour market analyst.