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Models of Economic and Financial Crises

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1.0 Introduction

The decade of the 1990s was certainly marked by a rather unusual number of financial and economic crises with the Asian Crisis of 1997 as perhaps the most prominent such case. These crises naturally renewed interest in the study of the relevant causes, consequences, and cures for such episodes. In the wake of these recent events, one very important question has been the need and the feasibility of predicting such crises. The objective of this paper is to focus on this last issue.

In terms of the structure of the remaining paper, following an overview of the relevant methodologies employed by the existing studies of the Early Warning Systems, this paper argues for Markov Switching Modeling as a new methodological approach to the issue of predicting financial and economic crises. A prototype Markov Switching Model is then applied to the case of Turkey and its empirical results are then presented.

2.0 Review of the Relevant Literature

While the different types of crises could range from "garden variety" currency crises to rather esoteric real estate bubbles, studies of such crises exhibit empirical and theoretical commonalities which will be highlighted below (for types of crises, see IMF World Economic Outlook, 1998). Also, these crises can have significant social costs as noted in Shabbir (1999).

1. Review of Empirical Literature

There are essentially two alternative methodologies that have been employed in the empirical studies of the Early Warning Systems for different kinds of crises: (a) The relatively more popular approach is to use probit or logit models. (As illustrated by Eichengreen and Rose (1998) for currency crisis and Demirguc-Kunt and Detragrache (1998) for prediction of banking crises.); (b) Alternatively, the methodology adopted by Kaminsky and Reinhart (1996), and Kaminsky, Lizondo and Reinhart (1998) is known as the "signals" approach which essentially optimizes the signal to noise ratio for the various potential indicators of crisis.

The above noted two approaches are discussed in some detail later on in the section on 'Methodology' (For additional related studies see Goldstein (1996), Klein (1998), Lau and Park (1995) and Mishkin (1998)).

2.1.1 Determinants of Currency Crises - Empirical Regularities
In an attempt to note possible empirical regularities, Kaminsky et al (1998) reviews about twenty-five relevant studies. Due to the disparate nature of the studies in terms of their methodologies and specifications, the overall empirical results do not provide "a clear-cut answer concerning the usefulness of each of the potential indicators of currency crisis". However, on the positive side, Kaminsky et. al (1998) favor drawing the following tentative conclusions from these group of studies:

1. Given the fact, that the currency crises may be preceded by multiple economic and even political problems, the modeling of currency crisis prediction should involve a relatively broad range of indicators.

2. The variables that receive 'ample' support as useful predictors of currency crises include: international reserves, the real exchange rate, credit growth, credit to the public sector and domestic inflation. The results also lend support for including the trade balance, export performance, money growth rate, M2/International reserves, real GDP growth and the fiscal deficit as potential early warning indicators. On the other hand, the variables associated with the external debt profile or the current account balance did not fare well.

Besides presenting a relatively comprehensive review of the earlier work, Kaminsky et al (1998) also presents an extension of previous work which employs the 'signals' approach to identifying and predicting currency crises. Based on empirical results for a sample of fifteen developing countries and five industrial ones during 1970-95, the authors report that the variables with the best track record in anticipating crises include output, exports, real exchange rate deviations, equity prices and the ratio of broad money to gross international reserves.

Incidentally, Sami (1999) uses a variant of the Kaminsky et al signaling approach in order to analyze the Egyptian case for the period 1961:01 to 1999:03.

2.1.2 Determinants of Banking Crises - Empirical Regularities

The representative study that uses the logit/probit framework is by Demirguc-Kunt and Detragiache (1996) and it deals with predicting banking crises. Based on observations for 1980-94 for a large sample of developed and developing countries, it reports that banking crises tend to occur when the macroeconomic environment is weak especially when growth rate of GDP is low and inflation is high. Also, high real interest rates, balance of payment deficits and presence of deposit insurance scheme were found to be significant precursors of banking crises.

2.2 Review of Theoretical Literature

Using the case of the currency crises as an important illustration of the financial crises in general, this section presents a brief overview of the theoretical literature on the causes of currency crises with a special reference to identifying the potential early warning indicators. The historical development of the theoretical literature can be grouped in three "generations" of models --- each reflecting the distinct mechanism that is espoused as the major cause of such crises. We will discuss these models in turn.

Epitomized by Krugman (1979), the First Generation Models tend to focus on the role of economic and financial 'fundamentals' such as the unsustainable fiscal policies in the face of the fixed exchange rate as the major cause of an eventual currency crisis. Given a fixed exchange rate regime, the persistent need to finance government budget deficits through monetization would surely lead to a reduction in the international reserves held by the Central Bank. Since such reserves are finite the speculative attack on the currency is the eventual outcome of this scenario.

This rather simple model suggests certain 'fundamental' imbalances such as the gradual decline in international reserves, growing budget and current account deficits, domestic credit growth, and gradual exchange rate overvaluation as the potential early warning indicators of speculative attacks.
The development of the so-called Second Generation Models of the currency crises were motivated by the EMS currency crisis in 1992-93 where some countries such as the UK and Spain suffered crises despite having adequate international reserves, manageable domestic credit growth and non-monetized fiscal deficits --- characteristics that ran counter to the necessary conditions asserted by the first generation models. Obstfeld (1994) and Krugman (1998) addressed the concerns raised by these counter-examples.

The main innovation of these Second Generation Models lies in identifying the role that the 'expectations' of the market agents may play in precipitating currency crises. These models allow for "multiple equilibria" and, under certain (generally untenable) circumstances of perfect information-based decision making, could argue that predicting crises may not be feasible due to the 'self-fulfilling' nature of the expectations of the crisis.

Finally, the Third Generation Models are based on the notion of 'contagion' where the mere occurrence of a crisis in one country increases the likelihood of a similar crisis elsewhere As described in Masson (1998), three related scenarios can be identified to represent the paradigm of contagion: 'monsoonal effects', 'spillover effects' and 'pure contagion effects'

3.0 Methodology

As mentioned earlier, the recent efforts at devising an early warning system for an impending financial crisis have taken the form of two related approaches. The first approach estimates a probit or logit model of the occurrence of a crisis with lagged values of early warning indicators as explanatory variables. This approach requires the construction of a crisis dummy variable that serves as the endogenous variable in the probit or logit regression. Classification of each sample time point as being in crisis or not depends on whether or not a specific index of vulnerability exceeds an arbitrarily chosen threshold. For example, for currency crises, the index of vulnerability is sometimes based on a weighted average of percentage changes in nominal exchange rates, gross international reserves and short-term interest rate differentials (e.g. local versus US rates when dealing with crises in the Philippines). Explanatory variables typically would be variables in the real sector of the economy, financial variables, external sector and fiscal variables. This approach has the advantage of providing a framework for statistically measuring the magnitude and significance of the effects of various potential explanatory variables on the onset of a crisis. The estimated model also allows the estimation of the probability of occurrence of a crisis in the future given projected or anticipated values of the explanatory variables. Negative aspects of the approach partly derive from the following:

1. The model does not address the independence of crisis occurrence from period to period - except indirectly through serial correlations that exist in the explanatory variables.

2. Additional serial correlations may even be introduced inadvertently through the explicit manner in which the crisis dummy variable is constructed. For example, the use of exclusion windows (where the crisis variable automatically is set to zero for k periods immediately following a time point rated to be in crisis) establishes perfect correlation between a crisis time point, and the next k periods following it. In general, any serial correlation in the crisis dummy variable which is not taken into account in the probit or logit regression would cause the estimates of the model to be inconsistent.

3. Another source of inconsistency: errors in the construction of the crisis dummy variable leading to misclassification of time points - either a false signal of a crisis or a missed reading of a crisis.

4. The method does not provide a direct measure of the weakness or intensity of the signal of each explanatory variable regarding the onset of a crisis.

The second method uses a signaling approach to get a more direct measure of the importance of each candidate explanatory variable. The approach constructs a similar binary variable from each explanatory variable - thus imputing a one (for crisis) or a zero (no crisis) signal from each explanatory variable at each
point in time in the sample. A signal-to-noise is then computed for each explanatory variable over the whole
sample period - as a quantitative assessment of the value of the variable as a crisis indicator. This signal-to-
noise ratio is defined as the ratio of the success rate of crisis predictions relative to the false alarm rate. More
specifically, let \( n_{ij} \) be the sample frequencies (for each explanatory variable) defined as follows:

<table>
<thead>
<tr>
<th>Actual</th>
<th>No Crisis</th>
<th>Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Crisis</td>
<td>( n_{11} )</td>
<td>( n_{12} )</td>
</tr>
<tr>
<td>Crisis</td>
<td>( n_{21} )</td>
<td>( n_{22} )</td>
</tr>
</tbody>
</table>

Then, the signal-to-noise ratio for the indicator variable is

\[
\frac{n_{22}/(n_{21} + n_{22})}{n_{21}/(n_{11} + n_{21})}.
\]

This approach allows a direct ranking of variables as crisis indicators and provides a quick focus on the
source of the crisis (assuming an encompassing set of indicators). But the approach does not take into
account strong correlations among indicators, provides no framework for statistical testing or calculation of
crisis probabilities in the future, and is still open to misclassification errors that can bias the conclusions of
the analysis.

In this paper we propose the Markov Switching Model as the new approach to predicting financial crisis and
apply it to the case of Turkey. This methodology avoids the potential misclassification errors in the probit
data, addresses the serial correlations inherent in crisis occurrence, allows for measuring and testing
significance of indicator variables, delivers forecast probabilities of future crises conditional on projected
future values of indicator variables, and short-run forecasts of key macroeconomic variables.

Our proposed approach constructs a quantitative prediction model that consists of two parts:

1. A Markov chain model of the unobservable financial health of a country, say, \( S_t \). We argue that what we
   observe are indicators of this latent attribute of the country. Initially, we assume two states: normal (\( S_t=1 \)),
   and critical (\( S_t=0 \)). We further assume that this Markov chain is of order 1, with transition probabilities that
   are time varying through dependence on observable indicator variables. Part of our empirical analysis will
deal with identifying the appropriate set of indicator variables, thus identifying early warning indicators of a
crisis. Experimentation starts with the indicator variables suggested by earlier studies.

2. A vector autoregressive (VAR) model of key macroeconomic variables such as GDP or industrial
   production, inflation, interest rate and exchange rate. This VAR model differs from the usual one in the sense
   that it includes the unobservable state variable, \( S_t \), as an additional endogenous variable. With the inclusion
   of \( S_t \), we introduce the notion that the VAR system behaves in a different fashion depending on whether
   financial conditions are normal (\( S_t=1 \)) or critical (\( S_t=0 \)). We reflect this in our model by allowing VAR
   parameters to change in value over time as financial conditions become normal or critical.

In summary, we are proposing a Markov Switching VAR Model that allows intercepts, lag coefficients and
error variances in the VAR model to stochastically switch over time according to the value taken by the
Markov chain.

The model is described in further detail below.

Let \( S_t \sim \text{Markov chain of order 1} \) with transition probabilities \( p_t \) and \( q_t \). Thus, at any given time \( t \), \( S_t = 0 \) or \( S_t = 1 \), and

\[
\Pr(S_t=1 \mid S_{t-1}=1) = p_t, \quad \text{and} \quad \Pr(S_t=0 \mid S_{t-1}=0) = q_t
\]

Further, let

\( Y_t = \) the vector of endogenous variables that we want to forecast

\( X_t = \) the vector of exogenous variables to be used to explain the movements in \( Y_t \),

\( Z_t = \) the vector of exogenous variables to be used as indicators of a financial crisis; this may overlap with \( X_t \)

Then we also assume that

\[
p_t = F(\lambda'Z_t), \quad q_t = F(\delta'Z_t),
\]

where \( F(\cdot) \) is a cumulative distribution function such as for a standard unit normal distribution.

Finally, we complete the model with the specification of the VAR model for \( Y_t \) variables:

\[
Y_t = \Pi_{1,\text{st}} Y_{t-1} + \Pi_{2,\text{st}} Y_{t-2} + \ldots + \Pi_{r,\text{st}} Y_{t-r} + B X_t + \varepsilon_t
\]

Note that the lag coefficient matrices \( \Pi \) are subscripted by \( S_t \). This says that values are shifting between two sets of possible parameter values: \( \{\Pi_{j,0}\} \) and \( \{\Pi_{j,1}\} \) depending on whether the Markov chain is equal to zero or one.

An initial set of explanatory variables (\( X_t \) and \( Z_t \)) is determined and data are collected for them and for \( Y_t \) for a specific country. The Markov Switching Model specified above is then estimated by recursive maximum likelihood methods. Our empirical analysis proceeds from there to assess the statistical significance and relative importance of each explanatory variable as an early warning indicator of a crisis. Diagnostic tests are performed to validate the forecasting ability of the estimated model and to assess its performance in comparison with the earlier approaches.

### 4.0 Prediction of Financial Vulnerability: The Case of Turkey

There are a handful of studies which try to predict economic and/or financial crises in Turkey (for a detailed and descriptive analysis of Turkish crises, see Celasun (1998), Gultekin (1994), Mariano, Gultekin, Ozmucur & Shabbir (1999), Onis & Ozmucur (1989a,1989b), and Ozatay (1996)).

Neftci & Ozmucur (1991a, 1991b) try to find coincident and leading indicators of economic activity based on monthly data for the period 1980 to 1990. Their coincident indicators are: index of manufacturing production, imports, newly established firms, and railway freight. Real M1 and real M2, real central bank credits to banking sector, the ratio of central bank credits to M2, real value of capital reinvested, total surface area of buildings in new building permits, real value of government's consolidated budget expenditures, and demand for jobs as reported by Government employment bureaus are eight variables which make up the
index of leading indicators. Leading indicators perform well in capturing cycles in economic activity during the 1980-1990 period.

Ozmucur (1991) uses logit and probit models to predict "need for IMF programs" and "bottlenecks" in the economy. Using 1950 to 1991 annual data, it was possible to predict seven out of eight years with "bottlenecks". Real exchange rate, real interest, external terms of trade, excess demand (money supply growth- real GDP growth), and share of current account balance in GNP, all with one or two lags, are used as explanatory variables in the model.

Ucer, VanRijckeghem, Yolalan (1998) examine currency crisis of 1994, and conclude that the crisis was a result of deterioration of economic fundamentals, and not only macroeconomic mismanagement. They use quarterly data and apply the methodology of Kaminsky, Lizondo and Reinhart (1998) and propose some new indicators. In addition to 12 indicators used by KLR, they conclude that ratio of exports to imports, real exchange rate, short-term external debt/GNP, debt maturity, reserves to M2Y plus debt stock, government deficit/GNP, short-term advances to the treasury/GNP.

Our methodology (Markov switching with varying transition probabilities) indicates the importance of following variables on selected indicators (exchange rate, industrial production and stock prices): current account, inflation, export/import, direct investment, reserves/money supply, reserves/imports, foreign debt service/exports, and short-term capital.

In the next step, these variables will be used as a group in a VAR system to improve the predictive power of the model.

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