A cautious note on the use of panel models to predict financial crises

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ABSTRACT

Panel data framework has often been used to build Early Warning Systems for financial crises. This paper questions the implicit assumption that crises are homogenously caused by identical factors. It suggests a preliminary step aiming at forming optimal country clusters.

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JEL classification:
Financial crisis
Early warning system
Panel data

1. Introduction

The recent financial turmoil has stimulated researchers in explaining and predicting crises. As a consequence, academic literature on financial crises has soared. One of the first to address the causes of a financial crisis were Eichengreen et al. (1995, 1998). Afterwards, the literature focused more on developing countries (Frankel and Rose, 1996; Sachs et al., 1996). Simultaneously, models to predict the occurrence of a financial crisis have been developed. The first idea, proposed by Kaminsky, Lizondo and Reinhart (1998), involves building an Early Warning System (EWS) using a signalling approach. They consider a large set of indicators relating 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 and recommend the use of discrete choice techniques. The endogenous variable (Ch,t) represents the occurrence of a crisis at most h-months ahead. If a crisis occurs within the next h periods Ch,t takes a 1, otherwise a 0. Several major criticisms have been addressed to these models.

First, the results highly depend on the definition of the crisis. It is clear that 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 et al. (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 crises variable is constructed as a binary variable that takes the value one for the periods [t − h, t − 1] when a crisis occurs at time t. Consequently, the standard errors will be biased. This affects all inferences unless a robust HAC covariance matrix or bootstrap method is used.

Third, several studies (in particular Kumar et al., 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 has to be preferred.

Fourth, seminal EWSs such as Berg and Pattillo (1999) exclusively focus on individual countries. Recent papers however (inter alii, Shortland, 2004; Fuertes and Kalotychou, 2007 and Kumar et al., 2003), 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 homogeneous across the cross section dimension. Under these restrictive assumptions, heterogeneity may then simply be captured by fixed effects and all other features of the models may be 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 crises 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 spillover 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 inference.

This paper proposes a deeper analysis of the panel-logit model as EWS. We focus 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 paper is organized as follows: In Section 2, the competing models (full, regional, cluster and individual) are presented. In Section 3, the ability of these models to predict financial crises is investigated.

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 such a case, 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). In a first step, the “Naive Model” is estimated and the poolability tested via a traditional Hausman test. If this test rejects the null hypothesis of poolability, the country, whose contribution to the Hausman statistics is the highest is excluded in a second step. The group of countries is reduced until the poolability is no more rejected. The fourth model, called “Country Model” (CoM) is the logit model estimated for each individual country and constitutes a benchmark. With the exception of the “Country Model”, we encounter a panel-logit model, particular attention is devoted to the correct specification of country-specific terms, which can be fixed or random. Hausman tests are performed to ensure a correct specification.2

2.1. Data, crisis indicator and performance indicators

The dataset covers 13 countries3 from South America and South-East Asia. Data are at monthly frequency, adjusted for seasonality and run from January 1985 to December 2004. They are obtained via Datastream. The sources used are the IMF-IFS database and the national banks of the respective countries. Explanatory variables correspond to those used in Kumar et al. (2003) They are the 1-year growth rate of International Reserves, Imports, Exports, M2 Multiplier, Domestic Credit over GDP, Real Bank Deposits, M2 to Reserves and Industrial Production, as well as the levels of the ratio M2 to Reserves, the Real Interest Rate and the ratio Lending Rate over Deposit Rate. Following Kumar et al. (2003), we reduce the impact of extreme values by dampening every variable via the transformation $y_{it}^{\text{New}} = \text{sign}(y_{it}) \ast \ln(1 + |y_{it}|)$.

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 standard deviation.

In order to assess the respective quality of each of the four models in consideration, three traditional in-sample goodness-of-fit indicators (see Diebold, 2004) are defined as:

$$Q_{PS} = \frac{1}{T} \sum_{t=1}^{T} 2 (P_t - C_{24t})^2,$$

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

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

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

<table>
<thead>
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<th>Table 1</th>
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<td>In-sample performance of the empirical models</td>
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<tr>
<th>Optimal cluster</th>
<th>Goodness of fit</th>
<th>NM</th>
<th>RM</th>
<th>CM</th>
<th>CoM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina Brazil, Peru</td>
<td>QPS</td>
<td>0.2543</td>
<td>0.2424</td>
<td>0.2228</td>
<td>0.1669</td>
</tr>
<tr>
<td>Korea Indonesia</td>
<td>QPS</td>
<td>0.1890</td>
<td>0.1583</td>
<td>0.1184</td>
<td>0.0342</td>
</tr>
<tr>
<td>Malaysia Taiwan, Thailand</td>
<td>QPS</td>
<td>0.1871</td>
<td>0.0994</td>
<td>0.0463</td>
<td>0.0234</td>
</tr>
<tr>
<td>Philippines (none)</td>
<td>QPS</td>
<td>0.1642</td>
<td>0.0593</td>
<td>0.0734</td>
<td>–</td>
</tr>
<tr>
<td>Taiwan Malaysia, Thailand</td>
<td>QPS</td>
<td>0.1642</td>
<td>0.0936</td>
<td>0.1186</td>
<td>–</td>
</tr>
<tr>
<td>Thailand Malaysia, Taiwan</td>
<td>QPS</td>
<td>0.1396</td>
<td>0.3879</td>
<td>0.7023</td>
<td>–</td>
</tr>
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2 Models are estimated by Newton Raphson’s Maximum Likelihood using Stata 9.0 software.

3 In South America: Argentina, Brazil, Mexico, Peru, Uruguay and Venezuela. In South-East Asia: Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand.

4 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.
Fig. 1. Predicted probability of a crisis.
alarms, 0 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.

3. The results

In all cases a panel-logit model with fixed effect is supported by Hausman tests. In Table 1 we present for each country the optimal cluster, obtained via the Kapetanios recursive procedure as well as the performance of each empirical model 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 within-sample and out-of-sample performance is strongly related. Therefore it is sufficient to evaluate only the within-sample performance.

Unsurprisingly, it turns out that the optimal clusters are smaller than the whole set of countries, but also smaller than the set of countries located in the same region. 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. Four optimal clusters are found: a) Argentina, Brazil and Peru, b) Mexico, Uruguay and Venezuela, c) Indonesia and Korea and d) Malaysia, Taiwan and Thailand. These clusters turn out to be very reasonable from an economic point of view. Argentina, Brazil and Peru were in the late 80’s characterized by hyper inflation (Kiguel and Liviatan, 1995). Financial crises match then these periods of extreme inflation rates and end with the stabilization plans established in the early 90’s. Inflation is then the fundamental underlying variable which has affected the EWS in this cluster. The cluster Mexico, Uruguay, Venezuela seems to have less economic basis, even if similar privatisation reforms have been experienced by Uruguay and Venezuela in the early 90s (McCoy et al., 1998). On the contrary, the occurrence of the Asian crisis (the only one which has been detected in our sample for most of the Asian countries) 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 characterized 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 et al., 1999; Kuo, 2001). This outcome is also supported by the goodness-of-fit indicators where it is possible to see that the CM model almost always outperforms NM and RM. Even if the CoM model 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 predicted probability of a financial crisis is plotted in Fig. 1. The results outlined by the goodness-of-fit indicators are confirmed. Nevertheless it turns out that the loss due to the use of panel-logit model is particularly large for Uruguay, Venezuela, Indonesia, Malaysia and the Philippines.

To conclude, this paper 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.

References


The results of these tests are available upon request from the authors.