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Forecasting banking crises with dynamic panel probit models

António Antunes [a,b], Diana Bonfim [a,c], Nuno Monteiro [a], Paulo M.M. Rodrigues [a,b,*]

[a] *Banco de Portugal, Portugal*
[b] *Nova School of Business and Economics, Universidade Nova de Lisboa, Portugal*
[c] *Católica Lisbon School of Business and Economics, Universidade Católica de Lisboa, Portugal*

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ABSTRACT

Banking crises are rare events, but when they occur, their consequences are often dramatic. The aim of this paper is to contribute to the toolkit of early warning models that is available to policy makers by exploring the dynamics and exuberances embedded in a panel dataset that covers 22 European countries over four decades (from 1970Q1 to 2012Q4). The in- and out-of-sample forecast performances of several (dynamic) probit models are evaluated, with the objective of developing common vulnerability indicators with early warning properties. The results obtained show that adding dynamic components and exuberance indicators to the models improves the performances of early warning models significantly.

1. Introduction

Predicting banking crises is certainly a difficult endeavor. Econometrically, these rare events ares very challenging to predict, given that they can have a range of different causes and consequences. The aim of this paper is to help to improve the early warning tools that are available to policymakers. Recent decades have seen many and diverse contributions attempting to help identify the main drivers of financial crises and to aid policymakers in forecasting crises. A large part of this literature has focused on currency crises, most notably in emerging market economies (Burnside, Eichenbaum, & Rebelo, 2004; Chang & Velasco, 2001; Krugman, 1979; Obstfeld, 1986). Often, currency crises go hand in hand with banking crises (Kaminsky & Reinhart, 1999). The negative effects on the economy usually last longer and are more pronounced when a financial crisis is also characterized by serious disruptions and losses in the banking system (Cecchetti, Kohler, & Upper, 2009; Jordà, Schularick, & Taylor, 2011, 2013). Schularick and Taylor (2012) explored over more than a century of data for developed economies and showed that financial crises are usually credit booms gone wrong. More recently, Davis, Mack, Phoa, and Vandenabeele (2016) showed that credit booms that are financed by foreign borrowing are significantly riskier than those that are financed domestically.

Although every crisis is different and unique (Reinhart & Rogoff, 2011), we explore the commonalities of these rare events in a dataset of European systemic banking crises. Our main contribution relies on an exploration of the dynamics and exuberant behavior of the variables considered in the analysis. A wide range of methodologies have been used in the literature for forecasting banking crises.[1] For example, Demirgüç-Kunt and Detragiache (2005) and Davis and Woutersen (2008) used a signal approach and a multivariate binary model, building on the important contribution of Estrella and Hardouvelis (1991), who were among the first to show that binary models can be used successfully for forecasting. Bussière and Fratzscher (2006)

* Corresponding author at: Banco de Portugal, Portugal.
E-mail addresses: aantunes@bportugal.pt (A. Antunes), dbonfim@bportugal.pt (D. Bonfim), nmmonteiro@bportugal.pt (N. Monteiro), pmrodrigues@bportugal.pt (P.M.M. Rodrigues).

[1] For recent and comprehensive reviews, see for instance Frankel and Saravelos (2012) and Kauko (2014).

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and Caggiano, Calice, and Leonida (2014) used a multinomial logit approach, which allows one to distinguish between more than two states (for instance, tranquil, crisis and post-crisis periods). Duttagupta and Cashin (2011) explored the contribution of a joint deterioration in several variables by using binary classification trees, while, more recently, Alessi and Detken (2011) used a random forest method, which bootstraps and aggregates a multitude of decision trees.

None of the contributions listed above model the dynamic and exuberance dimensions explicitly when forecasting banking crises. However, these two features are crucial for explaining the emergence of financial distress in the banking system. Berger and Udell (2004) were the first to show evidence supporting the institutional memory hypothesis. Their analysis showed that loan officers' ability to measure risk deteriorates through the credit cycle: the farther away they are from a recession or a crisis, the less they are able to assess the risks correctly. Bassett, Chosak, Driscoll, and Zakrajek (2014) and Bonfim (2009) present further evidence of changes in the lending behavior and in credit risk through the cycle. All of this evidence lays the groundwork for investigating the potential relevance of a dynamic component in early warning models.

These dynamic effects are often intertwined with amplification mechanisms that originate from the behaviors of banks. For instance, Uchida and Nakagawa (2007) and Bonfim and Kim (2017) show that banks engage in herding behavior and collective risk-taking strategies. This type of behavior could potentially become stronger immediately before a crisis occurs, when banks in distress may try to gamble for resurrection (Rochet, 2008). Such strategic interactions between banks may foster volatility and increase the amplitude of the instability (Dungey & Gajurel, 2015). Thus, an exuberant behavior may reflect some amplified negative macroeconomic outcomes as a result of bank distress (Babecký et al., 2014). Hence, macroeconomic variables may contain useful information that can help to anticipate increases in the risk of future banking turmoil (e.g., when the ratio of domestic private credit to GDP exceeds its trend trajectory). Along these lines, Cumperayot and Kouwenberg (2013) and Pozo and Amuedo-Dorantes (2003) show how extreme values in statistical distributions may be relevant for the prediction of rare events such as banking crises.

The advantage of the dynamic models considered in this paper is that, in addition to a set of macroeconomic variables, which to a certain extent comprehend exogenous sources of crisis persistence and potentially useful information for anticipating negative events, they also include sources of the endogenous persistence of crises through the lags of the binary crisis variable, thus allowing us to assess the impact of the regime prevailing in previous periods on the crisis probability[2] and/or the lags of the index associated with the probability of being in a crisis regime (Candelon et al., 2014). Finally, exploring extreme values in time series allows us to capture the sorts of exuberant behaviors that are common ahead of crises (Shiller, 2015).

Overall, we find that using dynamic probit specifications helps to enhance the forecast accuracy of early warning models significantly. Exploring the dynamics that are intrinsic to the panel dataset allows us to improve the forecasting power of the models substantially, relative to static binary models. This is true for both in- and out-of-sample exercises, when looking at a wide array of metrics for assessing the performances of the models.[3]

Despite the ever-growing body of literature on early warning tools and the variety of methodologies used, the dynamics embedded in the dependent variable have not been explored extensively. Falcetti and Tudela (2006) were perhaps the first to study the determinants of currency crises in emerging markets using a maximum smoothly simulated likelihood approach on a lagged dependent variable model, thereby explicitly modeling the existence of inter-temporal links between crisis episodes. Methodologically, our paper is closer to the estimation technique used by Kauppi and Saikkonen (2008), who estimate a dynamic binary probit model for predicting US recessions, using the interest rate spread as the leading variable. They observe that dynamic probit models outperform static probit models both in- and out-of-sample. Bismans and Majetti (2013) use a similar methodology for forecasting recessions. Candelon, Dumitrescu, and Hurlin (2012) and Candelon et al. (2014) generalize the univariate dynamic probit model developed by Kauppi and Saikkonen (2008) to a panel setting (which is the framework that we consider in this paper) and apply it to the forecasting of crises.

We explore the information content of the time series under analysis further by extending the previous literature and investigating the signaling power of exuberance indicators. Our approach is simple and intuitive. Given that systemic banking crises are rare events of large magnitudes, we try to explore the signaling properties that are embedded in the distribution of the explanatory variables used in our early warning models. The intuition behind this approach is that usually imbalances are being built up in the run-up to crises. This may be apparent in the non-linear behaviors of some variables, which may take extremely high or low values before crises occur. We label these non-linearities as exuberance indicators. These are captured by exploring the extreme percentiles of the distribution of the leading indicators used in the models recursively. This is the first paper to use this approach. Our results show that placing more weight on specific values of the distribution of the variables may allow for further improvements in the performances of dynamic models as early warning tools.

This paper is organized as follows. Section 2 provides a detailed description of the methodology used (models and parameter estimation) and its relationship with the existing literature. Section 3 presents the empirical analysis, discusses our main results, analyzes the forecasting accuracy of the models and performs robustness checks. Finally, Section 4 summarizes our main findings.

2 Note that there is an implicit threshold effect in this case, since a crisis is identified only if the index goes beyond ao certain threshold; see Candelon, Dumitrescu, and Hurlin (2014).

3 In a recent paper, Vasicek et al. (2017) showed that many early warning tools perform well in-sample but rather poorly out-of-sample, thus highlighting the importance of showing the results for both cases.