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An Early Warning Model for Predicting Credit Booms Using Macroeconomic Aggregates☆

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ABSTRACT

In this paper, we propose an alternative methodology to determine the existence of credit booms, which is a complex and crucial issue for policymakers. In particular, we exploit the Mendoza and Terrones's (2008) idea that macroeconomic aggregates contain valuable information to predict lending boom episodes. Specifically, our econometric method is used to estimate and predict the probability of being in a credit boom. We run empirical exercises on quarterly data for six Latin American countries between 1996 and 2011. In order to capture simultaneously model and parameter uncertainty, we implement the Bayesian model averaging method. As we employ panel data, the estimates may be used to predict booms of countries which are not considered in the estimation. Overall, our findings show that macroeconomic variables contain relevant information to identify and to predict credit booms. In fact, with our method the probability of detecting a credit boom is 80%, while the probability of not having false alarms is greater than 92%.

Un modelo de alerta temprana para la predicción de *booms* de crédito usando los agregados macroeconómicos

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RESUMEN

En este documento se propone una novedosa metodología para determinar la existencia de *booms* de crédito, el cual es un tema bastante complejo y de crucial importancia para las autoridades económicas. En particular, se explota la idea de Mendoza y Terrones (2008) que señala que los agregados macroeconómicos contienen información valiosa para predecir los episodios de *boom*. El ejercicio econométrico realiza la estimación y predicción de la probabilidad de estar en un *boom* de crédito. El trabajo empírico se lleva a cabo a partir de datos trimestrales de seis países latinoamericanos entre 1996 y 2011. Para capturar simultáneamente la incertidumbre en la elección del modelo y el valor de los parámetros, se emplea la técnica Bayesian Model Averaging. Como se hace uso de datos panel, los resultados econométricos podrían ser empleados para predecir *booms* de países que no se consideran en la estimación. En conjunto, los resultados muestran que las variables macroeconómicas contienen información importante para identificar y predecir los *booms* de crédito. De hecho, con nuestro método la probabilidad de detectar un *boom* de crédito es 80% mientras la probabilidad de no tener falsas alarmas es mayor al 92%.

1. Introduction

In general, a credit boom is defined as an excess of lending above its long-run trend. Credit booms tend to make economies more volatile and vulnerable, and are often associated with increases in inflation, declines in lending standards, instability in the banking sector and increases in the probability of financial crisis (Reinhart and Kaminsky 1999; Gourinchas et al., 2001; Barajas et al., 2007, Dell'Ariccia et al., 2012, and Williams, 2012). Consequently, the identification of episodes of credit boom and their early prediction is a crucial problem for policymakers.

Nevertheless, the correct determination of these booms is a complex problem that is far from being straightforward in practice. Recent literature on credit booms characterizes these latter as periods where the cyclical component of lending exceeds a specific

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threshold, and associates these episodes with the dynamics of macroeconomic aggregates (e.g. Gourinchas et al., 2001; Cottarelli et al., 2005; Kiss et al., 2006, and Mendoza y Terrones, 2008). However, these works do not focus on the construction of early warning indicators of credit booms.

The main objective of this paper is the construction of a quantitative tool that allows the identification and early prediction of credit boom episodes by exploiting the relationship between these latter and the macroeconomic aggregates. Our indicator is based on two elements: the probability of being in a credit boom at time $t+h$ for $h \geq 0$ conditioned on the set of data available at time t, and second, on an estimated threshold value that establishes the probability at which the model defines the existence of a credit boom.

The probabilities of credit boom are computed through a Bayesian average of many logistic regression models applied to panel data. The Bayesian model averaging (BMA) methodology deals with both parameter and model uncertainty. In our case, model uncertainty is related to the selection of the macroeconomic aggregates that should be included as explanatory variables in the logistic regression. The BMA runs a large number of estimates on different combinations of covariates, and then, takes the weighted average of all the results. The weights are given by the model posterior probability.

The econometric analysis is applied on quarterly data of six Latin American countries between 1996 and 2011. Our findings show that macroeconomic aggregates hold valuable information to identify lending boom episodes and to provide early warning signals about future booms. The estimated probabilities of being in a credit boom at time $t+h$ with $h \geq 0$ show an outstanding performance. For instance, in our sample of Latin American countries, we estimate a threshold probability of 38%, which implies a probability of detecting a credit boom of 80.3% and a probability of not having false alarms greater than 92%.

In order to test whether macroeconomic variables provide additional information to the credit growth rate in the identification of credit boom episodes, we run the BMA algorithm on two sets of covariates. The first set only considers macroeconomic aggregates as explanatory variables in the model while the second set additionally includes the credit growth rate.

We also carry out a cross-validation exercise across countries to check the reliability of our results. Our findings indicate that the determinant factors of credit booms are similar across countries, and that those factors can be captured with standard macroeconomic variables. These results also suggest that our algorithm may be used to predict lending booms of countries in the region that are not considered in the estimation and that may have short time series data.

Overall, this paper provides a valuable tool to quantify the probability of being in a credit boom, or having a boom in the future. To the best of our knowledge, this is the first paper that performs the estimation and prediction of credit boom probabilities using macroeconomic data. In this sense, both the methodology and the empirical results for our sample of Latin American countries represent a new contribution to the burgeoning literature on credit booms.

The reminder of this paper is organized as follows. Section 2 presents the econometric methodology. Section 3 goes into the details of the data set used in the empirical exercise. In Section 4 we perform the empirical exercises. Finally, Section 5 brings some conclusions.

2. Econometric Methodology

In order to estimate the probability of credit boom, we use the logistic regression model with panel data and fixed effects

$$y_{i,t+h} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \varepsilon_{it} \qquad i = 1, \dots, I \quad t = 1, \dots, T \tag{1}$$

where $y_{i,t+h} = 1$ if there is a credit boom for country i at quarter $t+h$, $h \geq 0$ and $y_{i,t+h} = 0$ otherwise, $\boldsymbol{\beta}$ is a $R \times 1$ parameter vector, ε_{it} is the error term and $\mathbf{x}_{it} = (x_{1,it}, \dots, x_{R,it})$ is a set of R covariates, α_i with $i = 1, \dots, I$ are the fixed effects.

Our aim is to estimate the probability of being in a credit boom at time $t+h$ with $h \geq 0$ conditioned on the information at time t through the following equation

$$p(y_{i,t+h} = 1|\theta; \mathbf{x}_{it}) = F(\alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it}). \tag{2}$$

where F is the cumulative logistic distribution function and $\theta = [\boldsymbol{\alpha}'\boldsymbol{\beta}']'$ with $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_I]'$.

In order to deal simultaneously with the model and the parameter uncertainty, we apply the BMA methodology (see Raftery, 1995, and Raftery et al., 1997). We assume that $\mathcal{M} = [M_1, \dots, M_k]$ is the set of all models, where M_k is the k-th model, which is defined by the subset of covariates included in the model, and whose size is less or equal to R.

The BMA probability of being in a credit boom at time $t+h$, $h \geq 0$ is given by

$$p^{BMA}(y_{i,t+h} = 1 | D) = \sum_{k=1}^{k} \int p(y_{i,t+h} = 1 | \theta^k; D) p(\theta^k, M_k | D) d\theta^k \tag{3}$$

where $p(\theta^k, M_k | D)$ is the joint posterior probability, θ^k is its associated parameter vector and D denotes the data set. As can be seen, the BMA probability in equation (3) is a weighted average of equation (2) where the weights are given by $p(\theta^k, M_k | D)$. Since the joint posterior probability is unknown, we approximate equation (3) using the reversible jump Markov chain Monte Carlo (RJMCMC) algorithm introduced by Green, 1995 (see also Hoeting et al., 1999; Brooks et al., 2003, and Green and Hastie, 2009, for additional details).

Even though the probability $p^{BMA}(y_{i,t+h} = 1 | D)$ is informative, it is interesting to determine a value of this probability at which we have a clear warning of the existence of a credit boom. In other words, how large does this probability need to be before calling for a credit boom? To answer this question, we define a threshold value, $\tau \in [0,1]$, over which the methodology defines the warning. This estimation is carried out through a variable $\hat{y}_{i,t+h}(\tau)$ defined as

$$\hat{y}_{i,t+h}(\tau) = \begin{cases} 1 & \text{if } p(y_{i,t+h} = 1 | \theta^k; D) \geq \tau \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Note that for a given probability $p(y_{i,t+h} = 1 | \theta^k; D)$, the number of estimated credit booms depends on the threshold τ. If this latter is very small, then we will have many warnings of credit boom which could be false alarms. On the contrary, if τ is very large, then we will have few warnings, and the probability of having undetected booms would be larger.

In order to define a threshold probability, we compute the value τ that

$$\text{Min } \phi(\tau) \text{ subject to } \gamma(\tau) \leq \overline{\gamma}$$

$$\tau \in [0,1] \tag{5}$$

where $\phi(\tau)$ is the proportion of credit boom's false alarms, $\gamma(\tau)$ is the proportion of undetected credit booms and $\overline{\gamma}$ is the maximum value of γ admitted by the policymaker. The values of $\gamma(\tau)$ and $\phi(\tau)$ are estimated as

$$\gamma(\tau) = \frac{\sum_{i=1}^{I} \sum_{t=1}^{T} 1_{\{(\hat{y}_{i,t+h}(\tau)=0) \wedge (y_{i,t+h}=1)\}}}{T \times I} \tag{6}$$

$$\phi(\tau) = \frac{\sum_{i=1}^{I} \sum_{t=1}^{T} 1_{\{(\hat{y}_{i,t+h}(\tau)=1) \wedge (y_{i,t+h}=0)\}}}{T \times I} \tag{7}$$