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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 (2008)'s idea that macroeconomic aggregates other than the credit growth rate contain valuable information to predict credit boom episodes. 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 valuable information 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%.

Keywords: Early Warning Indicator, Credit Booms, Business Cycles, Emerging Markets.

JEL Codes: E32, E37, E44, E51, C53

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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 a financial crisis (Reinhart and Kaminsky (2000), 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. The literature on credit booms has adopted several methodologies to identify periods of credit boom but none of them is fully satisfactory. Accordingly to one of these methods lending boom periods are associated with high credit growth rates. Sachs et al. (1996), Borio and Lowe (2002), Kraft and Jankov (2005), Berkmen et al. (2009) and Frankel and Saravelos (2010) use the credit growth as an early warning indicator for predicting financial crises. However, Terrones (2004) points out that periods with high rates of credit growth can be the result of financial deepening, the economic cycle or the catching up after recession periods. Hence, the dynamics of this rate alone is not a sufficient measure to define boom episodes.

Other strand of the literature characterizes lending booms as periods where the cyclical component of credit exceeds a specific threshold. Moreover, it associates these boom episodes with the dynamics of macroeconomic aggregates (e.g. Gourinchas et al. (2001), Cottarelli et al. (2003), Kiss et al. (2006) and Mendoza and Terrones (2008)). However, these works do not focus on the construction of quantitative early warning indicators of credit booms.

Our main contribution in this paper is the construction of an indicator that allows the identification and the 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 up to 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 parameter and model uncertainty. In our case, model uncertainty is related with 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 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. We run the BMA algorithm on two sets of covariates to test whether macroeconomic variables contain additional information to the credit growth rate to explain credit boom episodes. The first set only considers the macroeconomic aggregates as explanatory variables in the model while the second set additionally includes the credit growth rate.

Our findings show that macroeconomic aggregates hold valuable information to identify the lending boom episodes and to provide early warning signals about future booms. This is the case even if the credit growth rate is included as explanatory variable. The estimated probabilities of being in a credit boom at time $t + h$ with $h \geq 0$ show an outstanding performance. For example, for 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%.

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 empirical tool to give a statistical response on 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 the paper is organized as follows. Section 2 presents the econometric methodology to estimate and predict the probability of being in a credit boom. This section also describes the estimation of the threshold probability. 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

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

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 $\mathbf{x}_{it} = (x_{1,it}, \ldots, x_{R,it})$ is a set of R covariates, α_i with $i = 1, \ldots, I$ are the fixed effects. These latter take into account the effect of omitted variables that are specific to each country and affect the idiosyncratic credit boom probability.

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 up to time t through the following equation

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

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

In order to deal simultaneously with the model and parameter uncertainty, we apply the BMA methodology (see Raftery (1995) and Raftery et al. (1997)). We assume that $\mathcal{M} = [M_1, \ldots, M_K]$ is the set of all models, where M_k is the k-th model, which is defined as a subset of covariates of the set $\mathbf{x}_{it}$ whose size is less or equal to R, θ^k is its associated parameter vector and D denotes the data set.

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

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

where $p(\theta^k, M_k \mid D)$ is the joint posterior probability. As can be seeing, the BMA probability in equation (3) is a weighted average of equation (2) where weights are given by $p(\theta^k, M_k \mid D)$. 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 $p^{BMA}\left(y_{i,t+h} = 1 \mid D\right)$ is informative, it is interesting 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

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

Note that for a given probability $p\left(y_{i,t+h} = 1 \mid \theta^k; D\right)$, 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 large.

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

$$\underset{\tau \epsilon [0,1]}{Min}\, \phi(\tau) \ \text{ subject to } \ \gamma(\tau) \leq \overline{\gamma} \tag{5}$$

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

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

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

for $h \geq 0$, where $\mathbf{1}_{\{\cdot\}}$ is an indicator variable equal to 1 if condition $\{\cdot\}$ is satisfied, and 0 otherwise. Note that the proportion $\{\cdot\}$ is calculated with respect to the total number of observations in the sample, and therefore, $\gamma(\tau)$ and $\phi(\tau)$ are different from the traditional Type I and II errors.

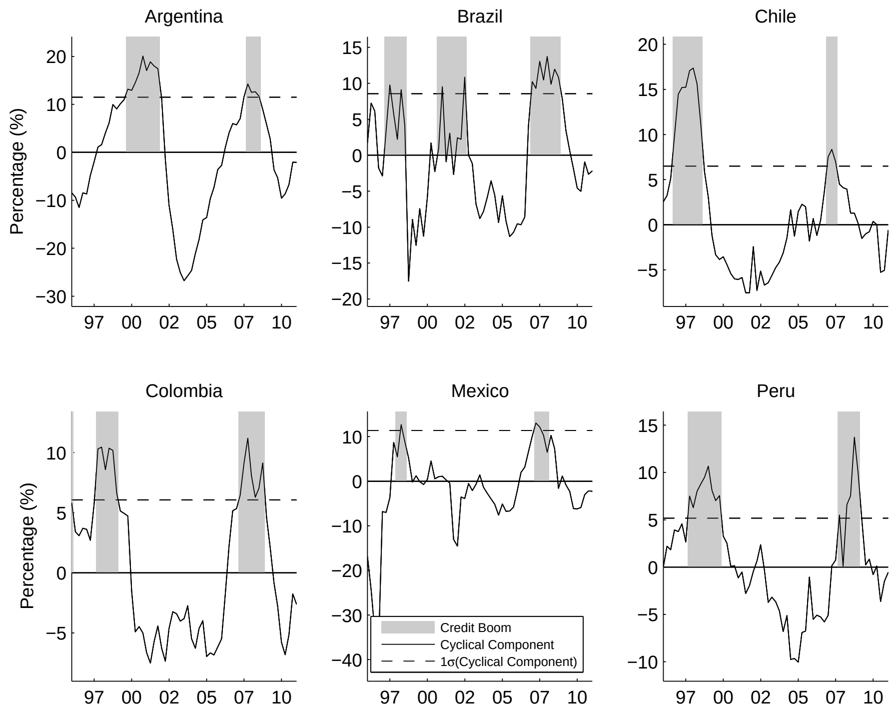
3 Data: Credit Booms and Macroeconomic Aggregates

We use quarterly data from Argentina, Brazil, Chile, Colombia, Mexico and Peru between the first quarter 1996 and the fourth quarter 2011. Our set of covariates includes the macroeconomic aggregates highlighted by Mendoza and Terrones (2008) as relevant to determine credit booms: domestic economic activity variables (Gross domestic product (GDP), investment, private consumption and government spending), international trade variables (terms of trade (ToT), real exchange rate (RER), current account), and financial system variables (asset prices and net capital flows). In specific exercises, we additionally include the quarterly growth rate of the per-capita real credit. We include lagged values of the explanatory variables to capture the build up process of credit booms.

Data come from the International Monetary Found (IMF) and Central Banks websites[1]. The covariates: GDP, investment, private consumption, government spending and asset prices are seasonally adjusted and expressed in real terms through the consumer price index (CPI). The RER corresponds to units of national currency for special drawing rights (SDR) of the IMF basket expressed in real terms with the CPI. The ToT are defined as the ratio between the prices of exportable and importable goods. We compute the

[1] Appendix A summarizes the set of covariates included in this research, the definition of each one and its specific source.

Figure 1. Past Episodes of Credit Boom



cyclical component of these variables with the Hodrick-Prescott filter. Current account and the net capital flows are percentages of the GDP. These variables are smoothed out with a non-centered moving average of order two.

To compute credit boom episodes, $y_{i,t+h}$, we follow Mendoza and Terrones (2008). That is, $y_{i,t+h} = 1$ when the cyclical component of the credit is greater than one standard deviation of its historical measure, and $y_{i,t+h} = 0$ otherwise. We compute the cyclical component of the real credit per-capita using credit data from domestic financial and depositary institutions to the private sector. The credit variable is expressed in per-capita terms using the working age population and deflated with the CPI. The cyclical component of the credit is also calculated with the Hodrick-Prescott filter. Table 1 summarizes the dates of lending booms. Figure 1 shows credit boom episodes (gray areas) for the countries in our sample between 1996 and 2010.

Figure 1 and Table 1 show an average of two credit boom episodes in our sample for each country. In fact, we note that booms are clustered in two well defined periods, but their specific dates and their duration vary across countries. The first period runs between 1997 and 2002. Credit boom episodes of this cluster are generally associated to the process of financial liberalization, privatization, opening to the international competition and the financial deepening of the region during the nineties (see Smith et al. (2008)). Furthermore, these booms preceded the recession periods and financial crises observed in some countries of the region (e.g. Colombia in 1999 and Argentina in 2002). The second cluster includes lending booms detected between 2007 and 2008, which preceded the recent credit crunch and the international financial crisis.

Figure 2 shows the relationship between the dynamics of the annual credit growth rate (black line)

Table 1. Credit Boom Periods

Country	Period 1	Period 2
Argentina	1999 Q4 - 2001 Q4	2007 Q4 - 2008 Q3
Brazil*	1997 Q2 - 1998 Q3	2007 Q1 - 2008 Q4
	2000 Q4 - 2002 Q3	
Chile	1996 Q4 - 1998 Q3	2007 Q1 - 2007 Q3
Colombia	1997 Q4 - 1999 Q1	2007 Q2 - 2008 Q4
Mexico*	1998 Q1 - 1998 Q3	2007 Q2 - 2008 Q1
Peru	1997 Q4 - 1999 Q4	2007 Q4 - 2009 Q1

*We consider that credit booms are economic phenomena that last at least several periods. Hence, episodes defined with only one quarter (e.g. first boom of Mexico and second boom of Brazil) have been extended by adding one period before and after of the specific quarters.

and the periods of credit boom (gray area). As can be seen most of the periods of high growth rates correspond to episodes of catching up after recessions. This is in fact the case in Mexico that experience a large expansion of credit at the end of 2002 and at the beginning of 2003, but does not suffer from a credit boom in those periods. Moreover, most of the time credit booms start once the credit growth rate has reached its maximum value. See, for example, credit booms in Colombia and Argentina that start when credit growth rate was already declining. Figure 2 supports the argument by Terrones (2004) that lending boom episodes happen less often than periods of fast credit growth because these latter are affected by the economic cycle.

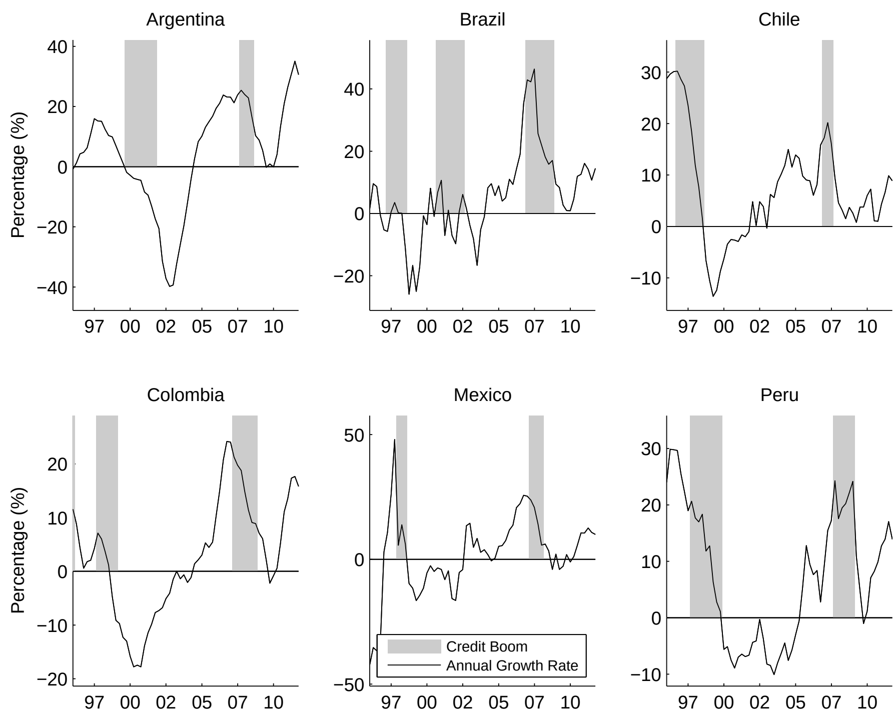
4 Empirical Analysis

This section presents estimated and predicted probabilities of being in a credit boom at time $t+h$ defined in equation (3). The econometric exercises consider $h = 0, 1, 2$. All BMA probabilities are estimated on the set of data $[\mathbf{x}_{it}, y_{i,t+h}]$ defined in Section 3 between the first quarter 1996 and fourth quarter 2010. The BMA estimated parameter and the observations of $\mathbf{x}_{it}$ of 2011 are used to compute the BMA predicted probabilities. For example, with data $\mathbf{x}_{it}$ of the fourth quarter 2011 and $h = 2$, we are able to predict the BMA probability of being in a credit boom at the second quarter 2012. The threshold probability τ is computed by solving the minimization problem (5) with a maximum value of undetected credit booms $\overline{\gamma}$ equal to 5 percent of observations in our sample.

The BMA estimates are performed through a Markov chain with one hundred and twenty thousand draws. The first twenty thousand estimates are burned-up to avoid the noise in the choice of the initial seed. We assume that the prior model probability is $p\left(M_k\right) = \frac{1}{K}$, for all $k = 1, \ldots, K$, and the prior distribution of θ^k is $\mathcal{N}\left(\mathbf{0}^k, 100 \cdot \mathbf{I}^k\right)$ where the zero vector $\mathbf{0}^k$ and the identity matrix $\mathbf{I}^k$ change of size with the model M_k.

The first exercise computes the BMA probabilities described by equation (3) for $h = 0$, when there are no fixed effects, $\alpha_i = \alpha$, and the set $\mathbf{x}_{it}$ does not include information of the credit growth rate. Figure 3 shows the estimated (thin line) and predicted (thick line) probabilities. From now on, the gray areas correspond to periods of credit boom previously identified in Section 3. The threshold probability (dashed line) is estimated at 37%. This figure exhibits an excellent fit of the estimated probability regarding to the established credit booms. The adjustment of the probability is in general quite fast. For instance, periods of boom show high values of the estimated probability. On the contrary, the estimated probability

Figure 2. Real Credit Growth Rate



is close to zero when there is no a boom. In fact, the probability of detecting a credit boom is 79% while the probability of not having false alarms is 90%.

As can be seen in Figure 3, our method captures episodes of credit boom, except for the first episode of Mexico in 1998 and the second boom of Chile in 2007. The model does not find evidence on the macroeconomic aggregates to explain those episodes, which are weakly highlighted in Figure 1. In fact, the first episode in Mexico may be the result of a catching up process after the financial crisis in 1995 rather than a lending boom. On the other hand, there is a weak signal of a credit boom for Mexico in 2001, which is consistent with the first boom of Argentina and the second one of Brazil. The model also provides some early anticipation of Argentina's first boom and Colombia's second one. The outstanding performance of the estimated probabilities suggests that the macroeconomic aggregates of the countries in our sample contain valuable information to identify and to predict credit boom episodes.

Figure 3 shows that the predicted probability of being in a credit boom increases for all countries between the first and fourth quarter of 2011. However, only for Brazil and Peru are the predicted probabilities larger than the threshold value. Our algorithm also yields some lights on the main macroeconomic driving forces of credit booms. Table 2 reports the posterior inclusion probability (PIP) and the sign certainty. We denote the contemporary value and the first three lags of the variable (·) as L0, L1, L2 and L3. The PIP stands for the probability that an explanatory variable is included in the model. The sign certainty presents the probability that the estimated coefficient is positive. Panel A in Table 2 shows the statistics for the covariates with the highest PIP values for the model without credit growth rate as explanatory variable. According to the PIP, the most important variables in the estimation are private consumption (L0, L3, L1), asset prices (L1), RER (L3,L2), capital flows (L3, L1) and current account (L3,L0). The

Figure 3. Probability of Credit Boom at $t+h$, $h=0$: Logit Model with Panel Data

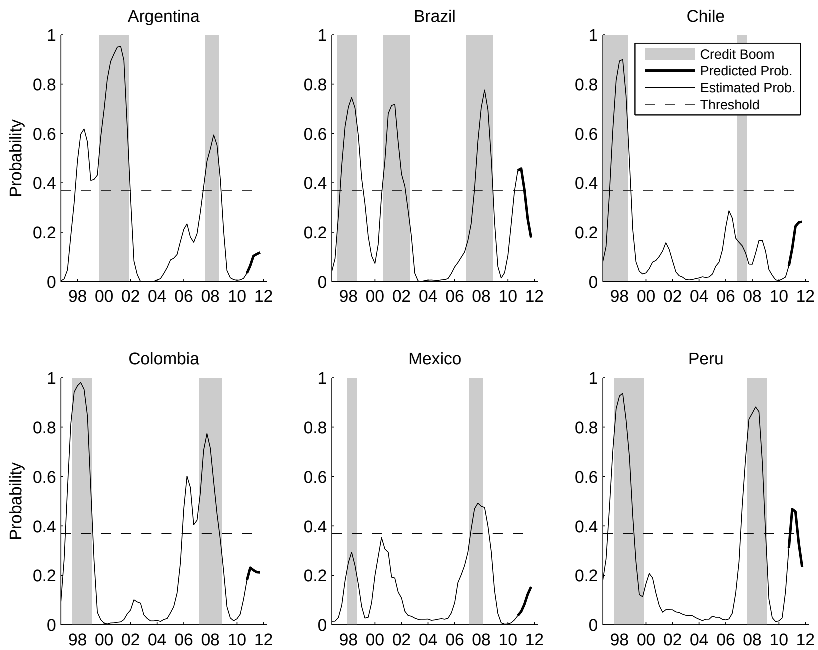


Table 2. Logit Model with Panel Data: Bayesian Analysis

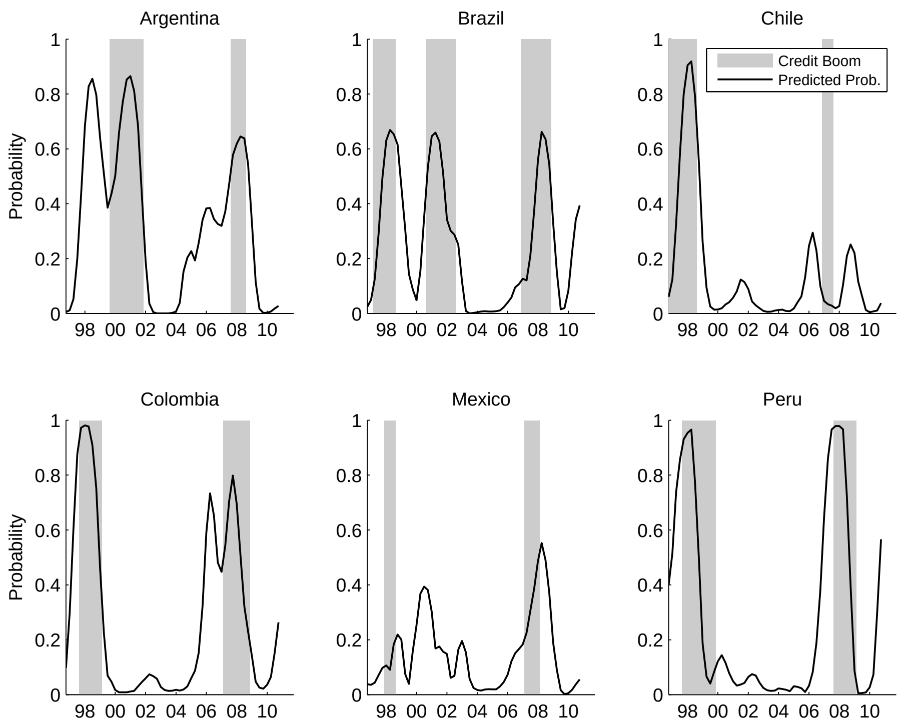
(A) Without the Credit Growth Rate

Variable	PIP	Sign Certainty
Priv. Consumption, L0	0,99	0,99
Asset Prices, L1	0,99	1,00
RER, L3	0,98	0,00
Capital Flows, L3	0,95	0,98
Current Account, L3	0,85	0,08
Investment, L3	0,82	0,98
ToT, L3	0,71	0,98
RER, L2	0,70	0,02
Capital Flows, L1	0,69	0,92
Priv. Consumption, L3	0,68	0,86
Current Account, L0	0,63	0,22
Public spending, L0	0,60	0,93
Current Account, L2	0,56	0,10
Priv. Consumption, L1	0,53	0,97
Public spending, L1	0,51	0,95

(B) With the Credit Growth Rate

Variable	PIP	Sign Certainty
Asset Prices, L2	1,00	1,00
Priv. Consumption, L0	0,99	1,00
Credit Growth, L3	0,99	1,00
RER, L3	0,97	0,00
Current Account, L3	0,95	0,03
Priv. Consumption, L3	0,87	0,92
Investment, L3	0,80	0,96
Public spending, L1	0,80	0,97
Capital Flows, L3	0,79	0,96
Current Account, L0	0,73	0,13
Capital Flows, L1	0,66	0,86
GDP, L1	0,56	0,40
Public spending, L0	0,53	0,92
Capital Flows, L2	0,52	0,86
Current Account, L2	0,50	0,07

Figure 4. Probability of Credit Boom at time $t + h$, $h = 0$: Cross-Validation Exercise

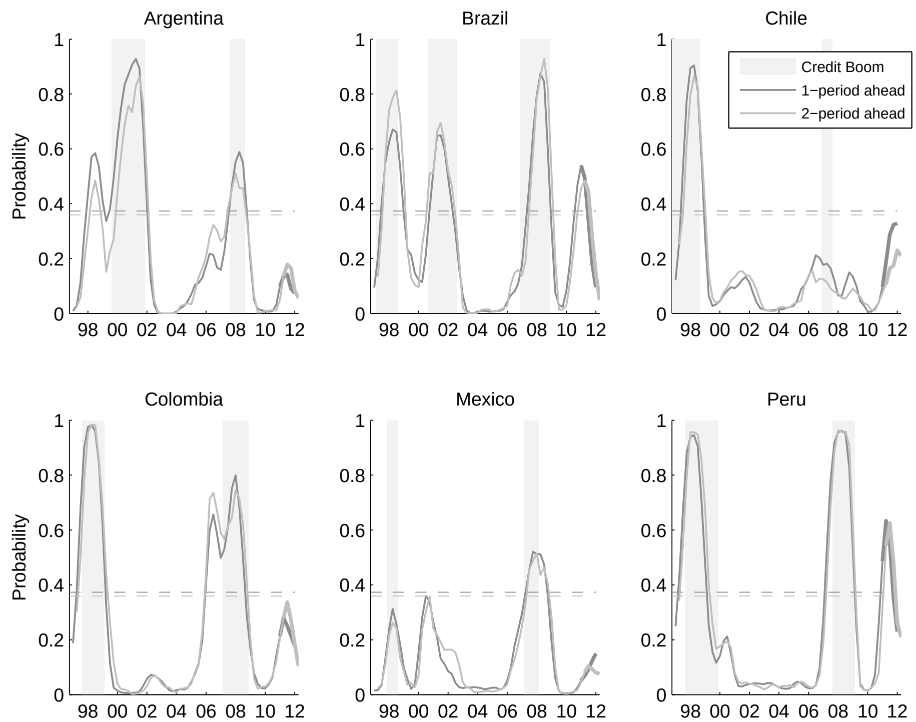


increase of the capital flows to GDP ratio and the cyclical component of private consumption and asset prices have a positive effect on the probability of being in a credit boom. On the contrary, the increase in the cyclical component of the RER and the current account to GDP ratio reduce that probability.

We also carry out a cross-validation exercise across countries to check the reliability and robustness of the estimated probabilities. In this exercise, we take out data of country i (i.e. the dummy variable y_{it} and the covariates $\mathbf{x}_{it}$), and then, estimate the BMA probability described by equation (3) with the remaining data. Once the estimation is performed, we predict the BMA probabilities of being in a credit boom for country i using the observed values of the variables $\mathbf{x}_{it}$ for that country. That is, we perform an out-of-sample forecasting exercise. The prediction is carried out for each t between the first quarter 1996 and the fourth quarter 2010. The routine is performed for each country in our sample.

Figure 4 shows the BMA predicted probability (black line) of the cross-validation exercise. Each panel plots the estimated probability for the country that is not included in the estimation. For instance, the panel with label Argentina contains the predicted probability for Argentina when no data for this country was used in the BMA algorithm. The predicted probabilities in Figure 4 fit very well the episodes of boom already established. Moreover, these predictions agree in general with the estimated probabilities in Figure 3. The results of this exercise suggest that determinant factors of credit booms are similar across countries, and that, those factors can be captured by the evolution of the macroeconomic aggregates. Over the set of estimations, the macroeconomic variables with the highest PIP are private consumption, asset prices, capital flows and current account. The panel data structure in this econometric exercise allows to use the estimated parameters to predict booms in countries of the region which are not considered in the estimation.

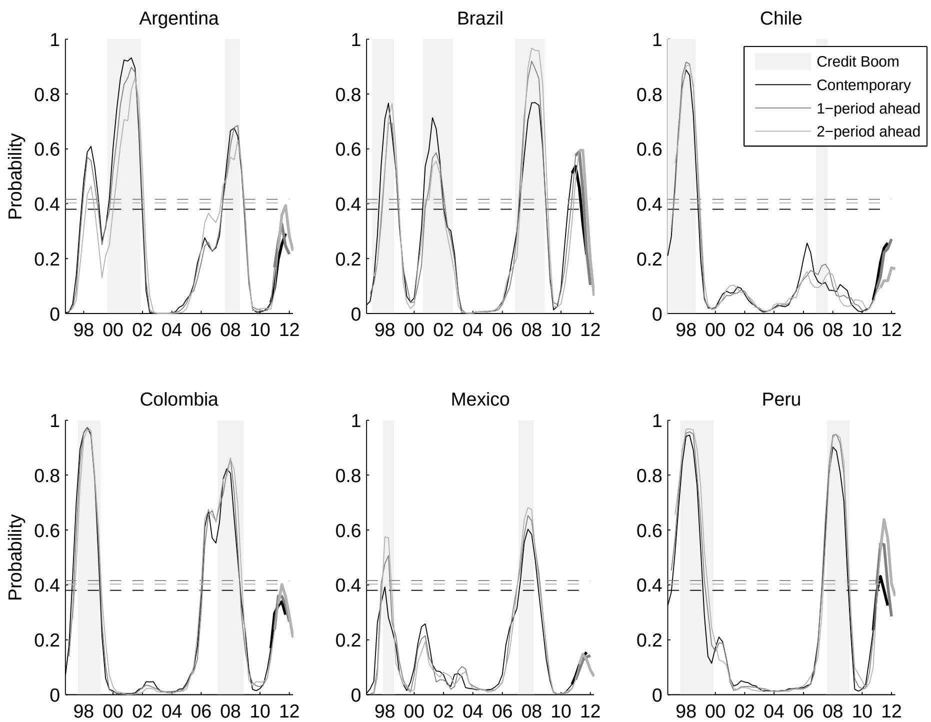
Figure 5. Probability of Credit Boom at time $t + h$, $h = 1, 2$: Logit Model with Panel Data



To asses the usefulness of our method as an early warning indicator of credit boom, we compute the BMA probabilities for $h = 1, 2$ and $\alpha_i = \alpha$. Figure 5 shows the estimated BMA probabilities for $h = 1$ (thin black line) and $h = 2$ (thin gray line). The predictions (thick lines) for $h = 1, 2$ are also drawn. The threshold for $h = 1$ (black dashed line) and $h = 2$ (gray dashed line) are estimated in 37.3% and 35.9%, respectively. Under this setting, the probabilities of detecting a credit boom at time $t+1$ and $t+2$ are 80% and 79.8%, while the probabilities of not having false alarms are 90.6% and 90.4%, respectively. Consequently, our method can be used to anticipate credit booms at least six months in advance. The performance of this methodology, as early warning indicator, depends on each country and the horizon h. For example, the predicted probabilities accurately anticipate all booms in Argentina, Colombia, Peru and the second booms in Brazil and Mexico. However, our method fails to anticipate Mexico's first boom and Chile's second one. The remaining booms are anticipated but their time warning is very small.

To see if the growth rate is a sufficient indicator of current or future credit booms, we repeat the econometric exercise but this time we include the credit growth rate within the explanatory variables. Figure 6 shows the estimated (thin line) and predicted (thick line) probabilities. The results are presented for $h = 0$ (black line), $h = 1$ (dark gray line) and $h = 2$ (light gray line). As can be seen in Figure 6, the fit is enhanced when the credit growth rate is included. We estimate a threshold of 38% (dashed line) that implies a probability of detecting a credit boom of 80.3% and a probability of not having false alarms of 92%. These values are higher than those found using only the set of macroeconomic aggregates. Moreover, the estimated boom probabilities when $h = 1, 2$ exhibit a better anticipation of the lending boom events. Unlike the results presented for the model without credit growth rate, this new exercise weakly detects the Mexico's first credit boom. Furthermore, the estimated probabilities for the second booms of Argentina,

Figure 6. Probability of Credit Boom: Logit Model with Panel Data (Including Credit Growth Rate)



Colombia and Mexico are higher.

Panel B in Table 2 reports the PIP and the main statistics of this BMA estimation for $h = 0$. These results show that macroeconomic aggregates are still relevant in the estimation. In fact, variables with the highest PIP are asset prices (L2), private consumption (L0, L3), credit growth rate (L3), RER (L3) and current account (L3, L0). These covariates and their sign agree with those of the previous econometric exercise. Nevertheless, capital flows are not as relevant as before.

Appendix B reproduces the econometric exercise for the logistic regression model with fixed effects. The results in the Appendix B are very similar to those reported here. Perhaps, the most interesting results are that the estimated and predicted probabilities for Argentina, Colombia and Mexico are, in general, lower in the model with fixed effects. On the contrary, the same probabilities for Brazil are higher. This result suggests that the characteristics of the Brazilian economy lead to a credit boom probability that is on average higher than in the rest of the region. This increase in the average probability is captured by the other countries when the model without fixed effects is considered.

5 Conclusions

In this paper, we present a novel methodology to identify and predict credit boom episodes based on macroeconomic aggregates. We show that this econometric method works as an early warning tool on the building up of lending booms, and hence, it can be used for policymakers.

Our findings show that macroeconomic variables provide valuable information to determine the existence of credit booms and to give early warning signals on the construction of new ones. Moreover, our results suggest that the determinant factors of these boom episodes across countries are similar, and therefore, our estimates can be used to predict booms of countries that are not considered in our sample. Even if the credit growth rate is included as explanatory variable, the macroeconomic variables remain relevant to estimate and predict lending boom episodes.

The results show that the estimated probabilities of credit boom achieve a very good fit of episodes previously determined by Mendoza and Terrones (2008)'s methodology. Nevertheless, if the credit growth rate is added to the set of covariates, the fit is enhanced.

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A Data Description: Macroeconomic Aggregates

Variable	Definition	Source
Credit	Claims on private sector from other depository corporations and other financial corporations, denoted in per-capita terms by the population in age to work *	International Monetary Found (IMF) (22d and 42d)
GDP	Gross domestic product *	IMF(99bvp)
Private Consumption	Households consumption expenditures *	IMF(96f)
Investment	Gross fixed capital formation *	IMF(93e)
Public Expenditures	Government consumption expenditures *	IMF(91f)
Imports	Imports (f.o.b) *	IMF(70d)
Exports	Exports (f.o.b) *	IMF(71vd)
Foreign Exchange rate	Exchange rate, national currency to SDRs **	IMF(aa)
Terms of trade	Terms of trade	Central Bank Websites
Asset Prices	Share prices index **	IMF(62.ep)
Current account	Net current account as percentage of GDP	Central Banks Websites
Capital inflows	Net capital and financial account as percentage of GDP	Central Banks Websites

* The variable is seasonally adjusted and expressed in real terms. ** The variable is defined in real terms.

We express the nominal variables in real terms through the CPI.

B Empirical Analysis: Logit Model with Panel Data and Fixed Effects

In a second set of exercises, we compute the BMA probabilities stated in equation (3) for a model with fixed effects. Figure 7 shows the results: the estimated (thin line) and predicted (thick line) probabilities for $h = 0$ (black line), $h = 1$ (dark gray line) and $h = 2$ (light gray line). The set of data does not include the credit growth rate. Similar to the results reported in Figure 3, these new estimated probabilities show an outstanding identification of the lending boom episodes. In the setting of BMA probabilities for $h = 0$, the estimated threshold is 39%, the probability of detecting a credit boom is 79% and the probability of not having false alarms is 92%. All lending boom periods are identified, except for the first episode in Mexico and the second one in Chile.

In general, the BMA probabilities for $h = 1, 2$ anticipate the boom episodes. In particular, this early warning indicator works well with the first booms of Brazil, Colombia, Peru and Argentina. However, the results show that the model has some difficulties anticipating the first boom in Chile in 1997.

With respect to the PIP indicator, Panel A in Table 3 show that the covariates with the highest values are private consumption (L0, L1), asset prices (L1), RER (L3, L2), investment (L3) and public spending (L0). However, macroeconomic aggregates such as the capital flows and the current account are no longer within the most important variables of the indicator. These results suggest that their contribution within the estimation is now captured by the fixed effect of each country.

In a final econometric exercise, we compute again the BMA probabilities assuming a model with fixed effects and including the credit growth rate in the set of covariates. Figure 8 shows the estimated and predicted probabilities for $h = 0$ (black line), $h = 1$ (dark gray line) and $h = 2$ (light gray line). Similar to previous figures, the thin line represents the estimated values while the thick line is used for the predicted probabilities. In general, our findings are maintained. Nonetheless, Figure 6 shows that the fit of the episodes of boom improves when the credit growth rate is included. The estimated threshold is 46.2%, and hence, the probability of detecting a credit boom is 79% while the probability of not having false

Figure 7. Probability of Credit Boom: Logit Model with Fixed Effects and Panel Data

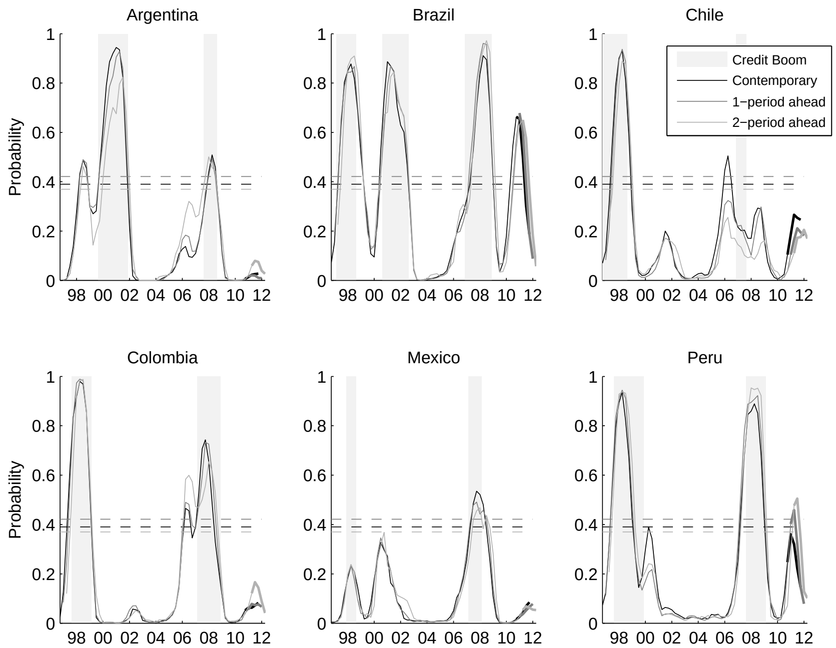


Table 3. Logit Model with Panel Data and Fixed Effects: Bayesian Analysis

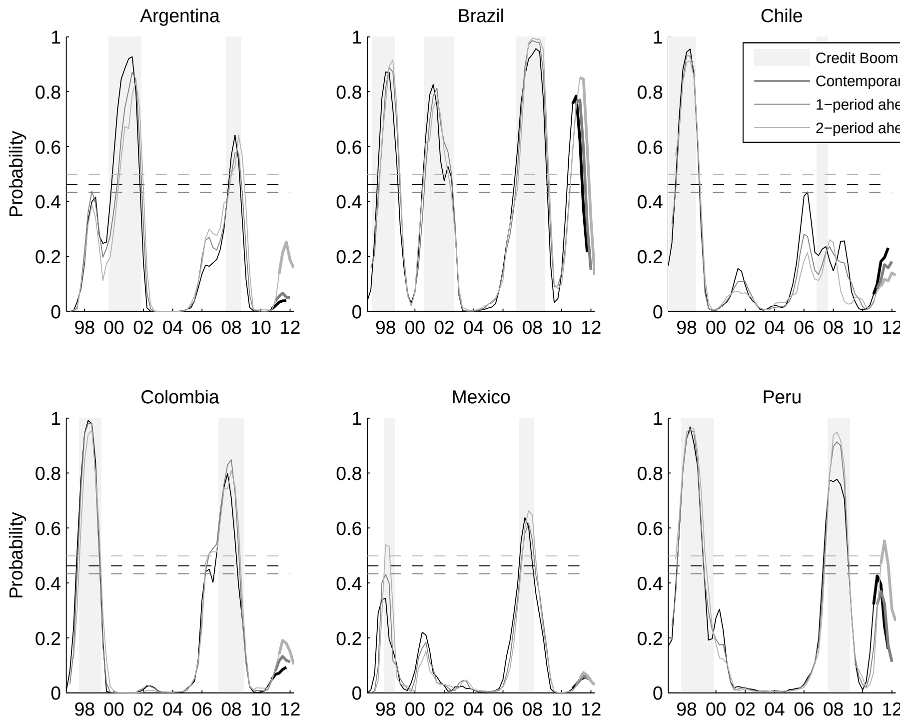
(A) Without the Credit Growth Rate

Variable	PIP	Sign Certainty
Priv. Consumption, L0	1,00	1,00
Asset Prices, L1	0,99	1,00
Investment, L3	0,98	1,00
RER, L3	0,94	0,01
RER, L2	0,94	0,02
Public spending, L0	0,75	0,96
Priv. Consumption, L1	0,74	0,99
Current Account, L2	0,67	0,09
Public spending, L1	0,59	0,95
Current Account, L1	0,57	0,28
Current Account, L3	0,57	0,09
GDP, L0	0,56	0,68
Current Account, L0	0,56	0,32
Capital Flows, L1	0,54	0,85
Capital Flows, L3	0,53	0,94

(B) With the Credit Growth Rate

Variable	PIP	Sign Certainty
Asset Prices, L1	1,00	1,00
Investment, L2	1,00	0,95
Credit Growth, L3	1,00	1,00
Priv. Consumption, L0	1,00	1,00
RER, L3	0,99	0,00
Investment, L3	0,96	0,98
Credit Growth, L2	0,94	0,99
Public spending, L3	0,90	0,95
RER, L2	0,90	0,02
Public spending, L1	0,81	0,97
Public spending, L0	0,81	0,97
Credit Growth, L1	0,79	0,95
Current Account, L0	0,78	0,13
Current Account, L1	0,73	0,16
Current Account, L2	0,63	0,05

Figure 8. Probability of Credit Boom: Logit Model with Fixed Effects and Panel Data (Including the Credit Growth Rate)



alarms is 96.5%. The estimated probabilities for $h = 1, 2$, exhibit a better anticipation of the lending boom events. Unlike the results of the model without credit growth rate, the estimated probabilities for the second booms of Colombia and Mexico are higher.

The main statistics of the estimation for $h = 0$ are reported in Panel B in Table 3. The results show that macroeconomic aggregates are relevant in the estimation, even if the credit growth rate is added to the covariates. The variables with the highest PIP are asset prices (L1), investment (L2), credit growth rate (L3), private consumption (L0) and RER (L3). These covariates and their sign agree with previous results. The effect of covariates such as the capital flows and the current account is again captured by the fixed effect of each country.