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Credit Funding and Banking Fragility: An Empirical Analysis for Emerging Economies*

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Abstract

This paper proposes an empirical model to identify and forecast banking fragility episodes using information on the credit funding sources. We predict the probability of occurrence of such episodes 0, 3 and 6 months ahead employing a Bayesian Model Averaging of logistic regressions. The exercises use monthly balance sheet data since the middle of the nineties for the banking system of nine emerging economies: Brazil, Colombia, Croatia, Czech Republic, Mexico, Peru, Poland, Taiwan and Turkey. Our findings suggest that the increasing use of wholesale funds to support credit expansion provides warning signals of banking frailness. The in-sample and out-of-sample predictions indicate that the proposed technique is a suitable tool for forecasting short-term financial fragility events. Therefore, monitoring these funds through our tool could become useful in prudential practice.

Keywords: credit cycle, financial stability, wholesale funds, balance sheet, logistic model regression, Bayesian model averaging.

JEL Codes: C11, C52, C53, G01, G21

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1 Introduction

Since the global financial crisis in 2007, academics and policymakers have renewed their interest in the identification and prediction of episodes of banking stress and financial crises. On the causes and triggers of such episodes, literature has re-emphasized on the two traditional sources of risk and vulnerability: the rapid growth of lending to firms conducting to credit booms and sharp variations on asset prices (e.g. Jordà et al. (2011), Roy & Kemme (2012), Kauko (2014) and Davis et al. (2016)) and the drying up of market liquidity turning into systemic insolvency (e.g. Caggiano et al. (2014) and Jutasompakorn et al. (2014)). Nevertheless, there is a burgeoning empirical literature that associates the credit cycle, the liquidity shocks and the financial stability to the funding sources of the banking system, distinguishing between retail deposits and wholesale funding (e.g. Adrian & Shin (2010), Huang & Ratnovski (2009, 2011), Amidu (2013), and Jung & Kim (2015)).

The approach to the structure of credit funding has some underlying issues. First, retail deposits are liabilities of a bank with non-bank domestic creditors (i.e. households) while wholesale funds are resources coming generally from market institutions[1]. Second, retail deposits grow in line with long-term real activity, while wholesale resources grow with the credit cycle and exhibit a higher volatility. Third, banks make use of wholesale funding to complement the limited supply of deposits, and hence, satisfy the demand for lending in periods of rapid credit growth, fund long-term assets and exploit the investment opportunities in the market. Fourth, an excessive leverage based on short-term wholesale funds may trigger the risk of liquidity and raise the vulnerability of financial institutions as a result of adverse shocks and the sudden withdraw of this type of resources (e.g. Demirgüç-Kunt & Huizinga (2010), Shin & Shin (2011), López-Espinosa et al. (2012), Damar et al. (2013) and Jung & Kim (2015)). And, fifth, changes in the dynamics of wholesale funds could provide signals about periods of banking distress, exposure to systemic risk and situations of vulnerability which would, eventually, lead to a financial crisis (Adrian & Shin (2010), Huang & Ratnovski (2009, 2011) and Hahm et al. (2013)).

Motivated by the findings and suggestions displayed in previous literature, our aim in this paper is twofold. Firstly, we establish an empirical relationship between episodes of banking fragility and the evolution of funding sources of credit (i.e. retail deposits and wholesale funding). Secondly, we use this link to exploit the signals provided by wholesale funds to design an early warning indicator of future periods of fragility. To the best of our knowledge, this is the first time that this empirical relationship has been tested on several emerging economies to build a monitoring tool for financial stability, which is the main contribution in this paper.

In particular, our exercises predict the probability of occurrence of an episode of banking fragility as a function of the credit funding sources, and compute a threshold over which this probability provides signals of alert. These fragility episodes are understood as time spans of extreme risk and over-exposure of banks to adverse shocks. The probability is computed through the average of a large set of logistic regression predictions using Bayesian Model Averaging (BMA). This technique takes into account the uncertainty not only on the parameter estimation but also on the model selection (i.e. the set of variables to be included in the regression). We perform predictive inference for 0-, 3- and 6-month time horizons.

Regarding the dataset, exercises are carried out on a sample of nine emerging economies from

[1] Shin & Shin (2011) and Hahm et al. (2013) associate wholesale funds with non-core liabilities such as repos, call loans, certificate of deposits (firms), short-term foreign bank debt and long-term bank debt securities. Retail deposits are linked to core liabilities such as cash, demand deposits, time deposits, certificate of deposits (households), trust accounts and other deposits.

different regions of the world: Brazil, Colombia, Croatia, Czech Republic, Mexico, Peru, Poland, Taiwan and Turkey. The information comes mainly from the monthly balance sheet of the consolidated banking sector. The sample period is not homogeneous between countries, but for most of them, it is available between the second-half of the nineties and June 2013. We perform two sets of exersices. The first one considers the full period, while the second one divides the sample into two parts to run in-sample and out-of-sample exercises, and evaluate their performance.

The results show that the increasing use of wholesale funds, particularly to support credit expansion, entails potential elements of risk and, hence, episodes of banking fragility. Within them, foreign credit and interbank operations are relevant factors to identify and predict most of such episodes. The in-sample and out-of-sample forecasts indicate that the proposed technique generates an effective instrument for predicting fragility events in the short-term. Hence, monitoring credit funding sources with our warning indicator could become valuable to predict events of financial stress and evaluate macroprudential scenarios.

The remainder of this paper is organized as follows. In Section 2, we present a brief literature review on the credit funding structure based on wholesale funds. Section 3 introduces the empirical methodology. Section 4 provides details on data and the construction of a dummy of historical episodes of banking fragility. In Section 5, we carry out the exercises, describe the results and evaluate the performance of the in-sample and out-of-sample forecastings. Finally, Section 6 offers some brief conclusions.

2 Literature

Literature on credit funding structure has been displaying a rapid expansion into several lines of research. However, the majority of papers have concentrated in studying the relationship between retail deposits and wholesale funding, and the dangers for financial stability of an excessive leverage on this latter type of resources (e.g. Huang & Ratnovski (2011)). Accordingly, the increasing use of short-term wholesale funding is a trigger of systemic risk and vulnerability of financial institutions. Works by Huang & Ratnovski (2009) on Canadian and OECD banks during the recent financial turmoil, Shin & Shin (2011) for the Korean banking system and López-Espinosa et al. (2012) on a set of large international banks between 2001 and 2009, show that a credit funding strategy based on wholesale funds leads to an increased risk of liquidity and a decline in economic stability.

Previous evidence is also supported by Shin (2009), Huang & Ratnovski (2011) and Georgescu (2015), who argue that this funding strategy may lead to sudden withdraws from the banking system as a result of noisy negative news in the market. In particular, Shin (2009) points out that illiquidity shocks during the global financial crisis led to the silent run of wholesale funds from UK banks, and later, the disappearance of some of them. In turn, Adrian & Shin (2010) and Hahm et al. (2013) state that changes in the evolution of wholesale funding provide forward signals of risk and vulnerability to diverse shocks. For instance, Adrian & Shin (2010) point out that variations in repos are useful to forecast changes in the financial market risk. Hahm et al. (2013) find empirical evidence on the role of non-core liabilities to signal vulnerability in an international sample of banks for emerging and developing economies between 2000 and 2010. Moreover, Lozano & Guarin (2014) use the dynamics of deposits and wholesale funds to estimate periods of financial fragility for the Colombian banking system between 1996 and 2012.

Another branch of literature has focused on the link between wholesale funding, leverage and asset prices. These relationships are studied by Adrian & Shin (2010) for the US market, Dewally & Shao (2013) for the Canadian banking sector and Damar et al. (2013) for 49 countries of both advanced and emerging economies. These papers found that this relationship is procyclical and the degree of procyclicality depends on the availability of short-term resources. Furthermore they also concluded that the global financial crisis produced an abrupt drop of liquidity that impacted the leverage and the maturity gap between assets and liabilities.

Unlike previous references, other papers have examined the relationship between the funding structure and the supply of credit. For instance, Allen & Paligorova (2015) study this link for Canadian banks, while Leony & Romeu (2011) and Jung & Kim (2015) focus on the Korean banking system. They state that during the recent financial crisis private banks reduced the lending to firms because of the disruptive effects of an excessive reliance on short-term wholesale funding and a high vulnerability to liquidity shocks. Nevertheless, Leony & Romeu (2011) point out that, for the Korean economy, public banks were able to provide financial stability to the system by expanding lending. Similar results are found by Haan de & Van den End (2013), who show that the largest Dutch banks between 2004 and 2010 responded to negative liquidity shocks by selling investments in securities. In a similar line, Agur (2013) analizes how the funding structure affects credit allocation to firms and amplifies the capital requirements.

An important question that has finally emerged from literature on credit funding is how the deposit market competition and, particularly, the substitution between retail deposits and wholesale funds affects the risk and profits of the banks. This subject has been studied by Demirgüç-Kunt & Huizinga (2010) and Amidu (2013) for an international sample of banks between 2000 and 2008, and by Craig & Dinger (2013) for the US banking sector between 1997 and 2006. These papers evidenced that a strategy based on wholesale funding increases the risk and lowers the rate of returns. Besides, the studies by Dinger & Craig (2014) and Ritz & Walther (2015) argue that the uncertainty on funding conditions and demand for loans entails a more intense competition for funding resources and reductions in profitability.

3 Empirical Model

We employ a Bayesian average of logistic regression models to predict the probability of occurrence of a banking fragility episode using information on credit funding sources. The BMA methodology allows us to deal simultaneously with uncertainty coming from both parameter estimates and model variables selection. Furthermore, this technique takes into account model uncertainty by going through all possible models that can arise from the combination of a given set of variables. Recent BMA applications on the construction of early warning indicators are Babecký et al. (2013, 2014), Guarin et al. (2014) and Lozano & Guarin (2014).

3.1 BMA Logistic Regression

Suppose a direct forecasting model such that

$$\tilde{y}_{t+h} = \theta' X_t + \epsilon_{t+h} \tag{1}$$

for the time index $t = 1, \ldots, T - h$ and forecasting horizon $h \geq 0$. The variable $\tilde{y}_{t+h}$ denotes the fragility of the banking system at time $t + h$, θ is the parameter vector, X_t stands for the set of explanatory variables available at time t and ϵ_{t+h} is the error term.

We stress that $\tilde{y}_{t+h}$ is unobservable and, therefore, we use a dummy y_{t+h} as proxy of occurrence of banking fragility, such that

$$y_{t+h} = \begin{cases} 1 & \text{if } \tilde{y}_{t+h} > c \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

where c is a critical level above which there is a fragility episode (i.e. an excesive level of financial vulnerability or high banking exposition to diverse shocks). This dummy is computed from financial risk indicators.

We assume that ϵ follows a logistic distribution. Consequently, we use the logistic regression model to perform both in-sample and out-of-sample predictive inference. More precisely, we compute the posterior predictive probability $P\left(\widehat{y}_{t+h} = 1 \mid D\right)$ of occurrence of banking fragility episodes at time $t+h$ given the data set D. Hence, the variable $\widehat{y}_{t+h}$ stands for the prediction or alternative realization of y_{t+h} generated by the model.

The BMA technique is used to estimate the probability $P\left(\widehat{y}_{t+h} = 1 \mid D\right)$ given a data set $D = \{y_{h+1:T}, X_{1:T-h}\}$. In particular, we assume there is a set of models $M_1, \ldots, M_K$ where $K = 2^N$ and N is the total number of variables in X other than the constant[2]. The k-th model M_k is defined by a subset of covariates of X. Instead of using a single model, BMA constructs $P^{BMA}\left(\widehat{y}_{t+h} = 1 \mid D\right)$ as a weighted average of all possible models, hence, avoiding the mistake of ignoring model uncertainty.

The BMA probability of occurrence of a banking fragility episode at time $t+h$ is defined as

$$P^{BMA}\left(\widehat{y}_{t+h} = 1 \mid D\right) = \sum_{k=1}^{K} P\left(\widehat{y}_{t+h} = 1 \mid M_k, D\right) P\left(M_k \mid D\right), \tag{3}$$

which is a weighted average of the posterior predictive probability conditioned on the model M_k and on the data D, where the weights are given by the posterior model probability $P\left(M_k \mid D\right)$.

The probability $P\left(\widehat{y}_{t+h} = 1 \mid M_k, D\right)$ in Eq. (3) can be written as

$$P\left(\widehat{y}_{t+h} = 1 \mid M_k, D\right) = \int_{\Theta_k} P\left(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t\right) P\left(\theta_k \mid M_k, D\right) d\theta_k \tag{4}$$

where Θ_k denotes the parameter space for model M_k, $P\left(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t\right)$ corresponds to the predictive likelihood that $\widehat{y}_{t+h} = 1$, conditioned on θ_k, M_k and evaluated on the set of explanatory variables X_t, while $P\left(\theta_k \mid M_k, D\right)$ stands for the posterior distribution of the parameter vector θ_k given the k-th model.

Replacing Eq. (4) in (3), the BMA predictive probability can be rewriten as

$$P^{BMA}\left(\widehat{y}_{t+h} = 1 \mid D\right) = \sum_{k=1}^{K} \int_{\Theta_k} P\left(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t\right) P(\theta_k, M_k \mid D) d\theta_k \tag{5}$$

where $P\left(\theta_k, M_k \mid D\right) = P\left(\theta_k \mid M_k, D\right) P\left(M_k \mid D\right)$. Eq. (5) is a weighted average of predictive probabilities whose weights are given by $p(\theta_k, M_k \mid D)$, the joint posterior probability of θ_k and M_k. For more technical details on this set up refer to Appendix A.

The BMA estimation is performed through the well-known Metropolis-Hastings (MH) sampling algorithm along with the Reversible Jump Markov Chain Monte Carlo (RJMCMC) extension introduced by Green (1995). The MH algorithm is a computational tool based on acceptance/rejection decision rules that performs the approximation of complex multi-dimensional distributions, where analytical formulae or other numerical techniques are not applicable. In addition, the RJMCMC

[2]We force the model to always have a constant term. The first column of X is a vector of ones.

algorithm allows the construction of these complex distributions on spaces of varying dimension (see Hoeting et al. (1999), Raftery et al. (1997), Raftery et al. (2005), Brooks et al. (2003), Green (2003) and Green & Hastie (2009) and the references therein for details of these two techniques).

In order to carry out the estimations, the MH and the RJMCMC algorithms generate draws of both the parameter vector θ_k and model M_k that simulate the joint posterior distribution $P(\theta_k, M_k \mid D)$. The simulated values of θ_k and M_k along with observations of the set of variables X_t are used to compute the predictive probability $P\left(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t\right)$ for each draw. The full set of these probabilities are used to compute a weighted average, where the relative weight is given by $P(\theta_k, M_k \mid D)$.

We remark that Eq. (5) provides direct predictions of the BMA probability $P^{BMA}\left(\widehat{y}_{t+h} = 1 \mid D\right)$ for the in-sample period $h+1 : T$ given the observed dataset $D = \{y_{h+1:T}, X_{1:T-h}\}$. Nevertheless, to perform out-of-sample predictions for the time span $T+1 : T^*$ with $T^* \geq T+1$, we need to add new information $X^* = X_{T-h+1:T^*-h}$ to our current set of explanatory variables. Thus, to compute out-of-sample predictive inference, Eq. (5) can be rewritten as

$$P^{BMA}\left(\widehat{y}_{t+h} = 1 \mid X_t^*, D\right) = \sum_{k=1}^{K} \int_{\Theta_k} P\left(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t^*\right) P(\theta_k, M_k \mid D) d\theta_k \tag{6}$$

for $t = T-h+1 : T^*-h$ and $h \geq 0$. Note that the predictive probability $P\left(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t^*\right)$ is now evaluated on X_t^* instead of X_t while the parameter vector θ_k and model M_k are the same recovered from the in-sample estimation with a joint posterior distribution $P(\theta_k, M_k \mid D)$ and dataset $D = \{y_{h+1:T}, X_{1:T-h}\}$.

3.2 Cut-off Probability

We also compute a cut-off probability $\tau \in [0,1]$ above which the probability $p^{BMA}\left(\widehat{y}_{t+h} = 1 \mid D\right)$ for $t = 1, \ldots, T-h$ and $h \geq 0$ provides a signal of banking fragility[3]. The value τ is computed as the solution to the minimization problem

$$\underset{\tau \epsilon [0,1]}{Min}\, \phi(\tau) \text{ subject to } \gamma(\tau) \leq \overline{\gamma} \tag{7}$$

where $\phi(\tau)$ and $\gamma(\tau)$ are the probabilities of false alarms (*i.e. Type II Error*) and undetected episodes of fragility (*i.e. Type I Error*), respectively. The parameter $\overline{\gamma}$ corresponds to the maximum value of γ admitted by the policymaker.

The values of $\phi(\tau)$ and $\gamma(\tau)$ are defined as

$$\phi(\tau) = \frac{\sum_{t=1}^{T} \mathbf{1}_{\{(\bar{y}_{t+h}(\tau)=1) \wedge (y_{t+h}=0)\}}}{T_\phi} \quad \text{and} \quad \gamma(\tau) = \frac{\sum_{t=1}^{T} \mathbf{1}_{\{(\bar{y}_{t+h}(\tau)=0) \wedge (y_{t+h}=1)\}}}{T_\gamma}, \tag{8}$$

where $\mathbf{1}_{\{\cdot\}}$ is a dummy equal to 1 if condition $\{\cdot\}$ is satisfied, and 0 otherwise, while T_γ and T_ϕ are the true number of months in the sample with and without episodes of fragility, respectively.

[3] Following Davis & Karim (2008) and Babecký et al. (2014), we set a cut-off probability that takes into account the preferences of the policymaker. In particular, we consider the minimization of a loss function that gives more relevance to missed crises than false alarms.

Table 1. Wholesale Funding Sources

Brazil	***Colombia***	***Croatia***
Money market instruments	Bonds	Bonds and money market instruments
Liabilities to other financial institutions	Liabilities to other local financial institutions	Foreign liabilities
Long-term foreign liabilities	Foreign liabilities	Other liabilities
	Interbank funds and repos	
Czech Republic	***Mexico***	***Peru***
Non-marketable debt securities	Local funding	Interbank funds
Other debt securities	Foreign funding	Other liabilities
Other liabilities	Other liabilities	Liabilities to financial institutions and international organizations
Poland	***Taiwan***	***Turkey***
Overnight and repos	Foreign liabilities	Local credit
Foreign liabilities	Liabilities to financial institutions	Foreign credit
Other liabilities	Other liabilities	Other liabilities

The variable $\bar{y}_{t+h}(\tau)$ is defined as

$$\bar{y}_{t+h}(\tau) = \begin{cases} 1 & \text{if } p^{BMA}\left(\widehat{y}_{t+h} = 1 \mid D\right) \geq \tau \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

and correspond to a dummy of the estimated periods of fragility. The number of these episodes depends on the cut-off probability. If τ goes down, there will be more warnings and the probability of false alarms could increase. On the contrary, if τ goes up, there will be fewer warnings and the probability of having undetected frailness periods would be greater.

4 Data

Our sample considers nine emerging economies: Brazil, Colombia, Croatia, Czech Republic, Mexico, Peru, Poland, Taiwan and Turkey. For each country, the dataset includes the balance sheet of the banking system, the gross domestic product (GDP) and other indicators of economic activity. The balance sheet is denominated in local currency and is reported in a non-standardized format. All data are available at monthly frequency, except for the GDP, which is a quarterly time series. The sample period is not homogenous between countries, but for the majority of them, data are available since the second-half of the nineties until June 2013. For each country, data were downloaded from the websites of its central bank, its financial industry regulatory authority and its national institute of statistics. Appendix B reports the variables of our dataset, the available sample period and their sources.

4.1 Set of Explanatory Variables

Our set of explanatory variables includes three types of credit funding sources. The first two are retail deposits and wholesale funds, which are constructed from the liabilities of the balance sheet. The classification of these variables considers the characterization of funding sources done by Shin & Shin (2011) and Hahm et al. (2013). In particular, our definition for retail deposits collects most concepts for demand deposits, saving deposits, term deposits (households) and small remaining deposits. In the case of wholesale fundings, several items from the available disaggregation of the balance sheet are considered. For example, foreign credits, interbank operations (e.g. repos), bond issuance, local credit from other institutions and money market instruments. Table 1 reports the items included as wholesale funds for each country. All variables are defined as percentages of total liabilities.

Table 2. Financial Risk Indicators

Financial Risk Indicator	*Brazil*	*Colombia*	*Croatia*	*Czech Republic*	*Mexico*	*Peru*	*Poland*	*Taiwan*	*Turkey*
Credit									
Overdue- to gross-loans ratio		✓			✓	✓	✓	✓	✓
Unproductive- to gross-loans ratio		✓							
Liquidity									
Deposits to gross-loans ratio	✓	✓	✓	✓	✓	✓		✓	✓
Non-covered liabilities ratio		✓							
Liquidity index			✓						
Profitability									
Returns-on-assets ratio		✓			✓	✓			
Returns-on-equity ratio		✓			✓	✓			
Solvency									
Equity to assets ratio		✓		✓					
Leverage									
Debt to equity ratio	✓	✓	✓	✓		✓	✓		✓

We include, as third credit funding source, the resources coming from the liquidation of portfolio investments held by banks. Lozano & Guarin (2014) provide evidence on the importance of these resources to fund the expansion of lending for Colombia. The proxy for this funding source is the ratio between total portfolio investments and total credit. The set of explanatory variables also includes the monthly growth rate of economic activity as control[4].

4.2 Banking Fragility Episodes

Our fragility dummy y_{t+h} in Eq. (2) aims to capture episodes of extreme exposure to risk and financial vulnerability to adverse shocks. The construction of this dummy considers 5 types of risk through 8 standard indicators[5]. Table 2 summarizes the available risk indicators taken from the balance sheet for the banking system of each country. It also considers that the cyclical component of each risk indicator is computed using the Christiano & Fitzgerald (2001) filter[6]. So, phases of cycle high enough are associated to time spans of extreme fragility to adverse shocks. For each indicator, we define a dummy variable equal to 1 for periods where the cycle is above a specific threshold and 0 otherwise. Individual risk dummies are added to obtain a dummy y_{t+h} for each country. Each threshold is defined as the value corresponding to the $90th$ percentile of the empirical distribution of cyclical values of the risk indicator.

Figure 1 shows the resulting episodes of banking frailness defined by y_{t+h} (grey areas), and compares them with periods of credit boom (blue solid line). The red dashed line identifies the starting date of the sample for each country. The time spans of lending boom are computed using the methodology by Mendoza & Terrones (2008). This method identifies periods when the cyclical component of credit is above a determined threshold[7]. This latter is defined in our exercise as being the $90th$ percentile of the empirical distribution of the credit cycle data.

As it can be seen, most of the fragility episodes based on risks are close or overlap those periods reported by the recent literature on events of financial stress and banking crises (e.g. Laeven & Valencia (2012), Cumperayot & Kouwenberg (2013) and Reinhart & Rogoff (2014)). The results capture two generalized periods of fragility through countries. The first one is associated with the

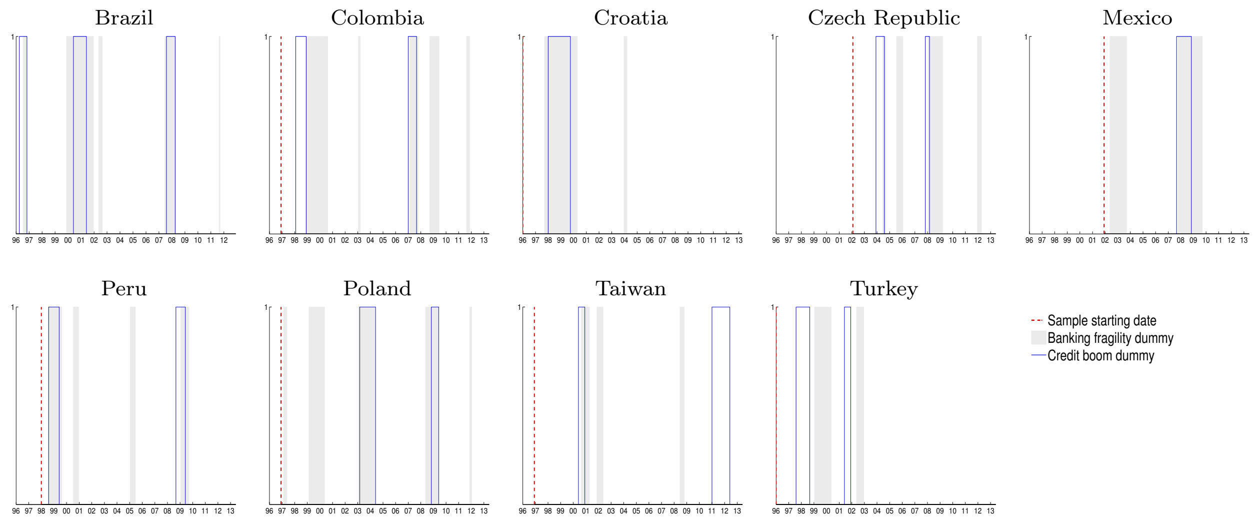
[4]The monthly economic activity index is constructed based on Litterman (1983). This methodology employs quarterly time series of GDP, and several variables that provide some evidence on the monthly dynamics of the real activity. Those variables are reported in Appendix B.

[5]When necessary, these indicators have been adjusted to show a higher risk by a higher positive value of the index.

[6]We run the filter with frequencies that allow us to capture cycles of short- and medium-term and avoid noise signals (e.g. frequencies associated with time spans between 3 and 84 months).

[7]Our proxy for credit is defined as the total lending to $M2$ ratio.

Figure 1. Episodes of Banking Fragility and Credit Booms



crises faced by some emerging economies at the end of the 90's and beginning of the next decade, while the second one is linked to the global financial crisis in 2008. Except by Croatia and Turkey in the second period, all countries show time spans with some evidence of extreme risk.

Episodes differ between countries (e.g. starting dates, ending dates and their extensions) reflecting the distinct characteristics of each of these periods (e.g. level of risk and speed of recovery). For instance, although Mexico and Brazil show episodes of vulnerability during the recent global financial crisis, these events are different in terms of their duration and severity. For Mexico this period is relatively long (i.e. around 2 years) and severe because of the proximity with the US market while for Brazil the time span is relatively short as a result of a quick recovery due, possibly, to a banking system strong enough. In the case of Croatia and Turkey, their risk indicators considered in our sample were not largely impacted by the last crisis. Some other short-term episodes were also identified between 2003 and 2004 (e.g. Colombia, Croatia, Mexico and Poland), at the end of 2005 (e.g. Czech Republic and Peru), in 2007 (e.g. Colombia) and at the end of 2011 (e.g. Brazil, Colombia, Czech Republic and Poland). Some of these events could be associated with the increasing capital inflow into these countries, the fast credit growth, the spillover effects of the US quantitive easing policy and the debt crisis in Greece.

Figure 1 also illustrates the stylized fact that credit booms precede or overlap episodes of banking fragility. This finding provides mild support to the ideas by Shin & Shin (2011), which state that events of rapid credit growth usually provide signals on financial vulnerability. It is particularly clear for the end of the nineties and the global crisis of 2008, even though there are other particular events of lending booms that are not associated to episodes of banking fragility (Czech Republic in 2004 and Taiwan at the end of 2011). Likewise, there are several periods of banking fragility where there are no signals of credit boom episodes (e.g. Colombia and Czech Republic at the end of 2011, Mexico in 2003, Peru in 2005 and Poland in 2000).

5 Results

5.1 Description of the Exercises

For each country, we carry out two sets of exercises differentiated by the sample period. The first one considers all available information (Section 5.2), while the second one divides the sample into two parts to perform in-sample and out-of-sample assessments (Section 5.3).

The first set carries out the BMA estimation of the probability $P^{BMA}(\hat{y}_{t+h} = 1 \mid D)$ in Eq. (5). The set X_t considers all of the credit funding sources, the economic activity index and up to six (6) lags of each of these variables. Once we have estimated the predictive probabilities, we compute the cut-off probability τ defined in Eq. (7) and set the estimated periods of banking fragility as those time spans where $P^{BMA}(\hat{y}_{t+h} = 1 \mid D) \geq \tau$.

All regression exercises consider predictions for $h = 0$-, 3- and 6-month time horizons. The results for $h = 0$ provide an alternative tool for the identification of current events of frailness and could capture events that are not recognized by traditional risk indicators. Furthermore, our tool generates a unique warning signal instead of many measures of risk with several qualitative implications. For $h = 3$ and 6, our exercises produce a warning signal to anticipate possible episodes of extreme risk. In fact, with our BMA estimates of parameters and models, we can use the information set until the final date in our sample, June 2013, to make predictions of banking fragility for September and December of 2013.

The second set of exercises carries out in-sample and out-of-sample predictions to provide evidence of the accuracy of our warning indicator. The sample is divided into two periods; the first is used to perform in-sample predictions, while the second is employed to run out-of-sample forecastings. The cut-off date is set depending on the data length for each country. This specific date aims to capture enough information of financial risk to make plausible estimations and robust forecastings. Hence, we set January 2006 as the cut-off month for Brazil, Croatia, Peru, Poland, Taiwan and Turkey. In the case of Mexico, Colombia and Czech Republic, this date is set to January of 2007, 2008 and 2009, respectively.

We use the first part of the data to perform the in-sample estimation of the BMA probability in Eq. (5), the cut-off probability τ and the estimated fragility events. Afterward, we use the in-sample estimates of θ_k and M_k and out-of-sample data to compute the probability $P^{BMA}(\hat{y}_{t+h} = 1|X^*, D)$ in Eq. (A.5). This predictions are compared with the in-sample cut-off probability to estimate the frailness events for the second part of the data.

Both sets of exercises are performed with the MH and RJMCMC algorithms using Markov chains with $1,000,000$ draws. We consider a uniform model prior which gives each model the same prior probability. In order to avoid overfitting and guided by the literature discussed in Section 2, we assumed that the estimated coefficients of wholesale funds have a positive impact on the BMA probability while for retail funds, investment/credit ratio and economic activity, the expected impact is negative[8]. Therefore, we use a Log-Normal prior distribution such that for positive expected coefficients $\theta \geq 0$, $\theta \sim \mathcal{LN}\left(\mu, \sigma^2\right)$ and for negative expected coefficients $\theta < 0$, $-\theta \sim \mathcal{LN}\left(\mu, \sigma^2\right)$, where $\mu = 0$ and $\sigma^2 = 10$ (we use a large variance to reflect the uncertainty about the parameter set). The cut-off probability τ is computed by solving the minimization problem (7) with a maximum type I error $\overline{\gamma} = 15\%$. We set this $\overline{\gamma}$ to have on average 4 undetected months of banking fragility

[8]The expected negative sign for retail deposits is related to its definition in the BMA regressions. When the wholesale funds (as percentage of total liabilities) increases in credit boom phases, the retail deposits could decrease (as percentage of total liabilities).

for our country sample. Nevertheless, this value $\overline{\gamma}$ can be changed according to the policymaker preferences. All computations are performed in Matlab.

5.2 Direct Predictions: h-steps ahead

Figure 2 plots the predicted BMA probability for $h = 0$ (blue line) and $h = 6$ (dash-dot black line) months ahead and the associated cut-off probability using a thicker same-style line. Our estimated fragility episodes correspond to those time spans where the predicted probability is higher than the cut-off probability. These episodes, estimated from funding credit sources, are compared with the corresponding historical periods based on risks (gray areas). Appendix D shows the same figure for $h = 3$-month horizon.

Results show that our warning tool identifies and also anticipates most periods of fragility. Nevertheless, the identification is more accurate for shorter horizons. There are at least two identified common episodes of extreme risk across countries: the crisis faced by some economies at the end of the 90's, or at the beginning of the new century (e.g. Brazil, Colombia, Croatia, Peru, Poland, Taiwan and Turkey), and the global financial crisis starting in 2008 (e.g. Brazil, Colombia, Czech Republic, Mexico, Peru, Poland and Taiwan).

The exercises also provide signals of other banking frailness episodes around 2003 and 2004 for Colombia, Croatia, Mexico, Poland and Turkey; and between the end of 2011 and 2012 for Colombia, Peru and Poland. Some of the episodes are characterized by short durations. Interestingly, our technique identifies an episode between the end of 2009 and the beginning of 2010 for Croatia and Turkey despite there were no signals of extreme risk. Nonetheless, this period could be associated to the Greek crisis.

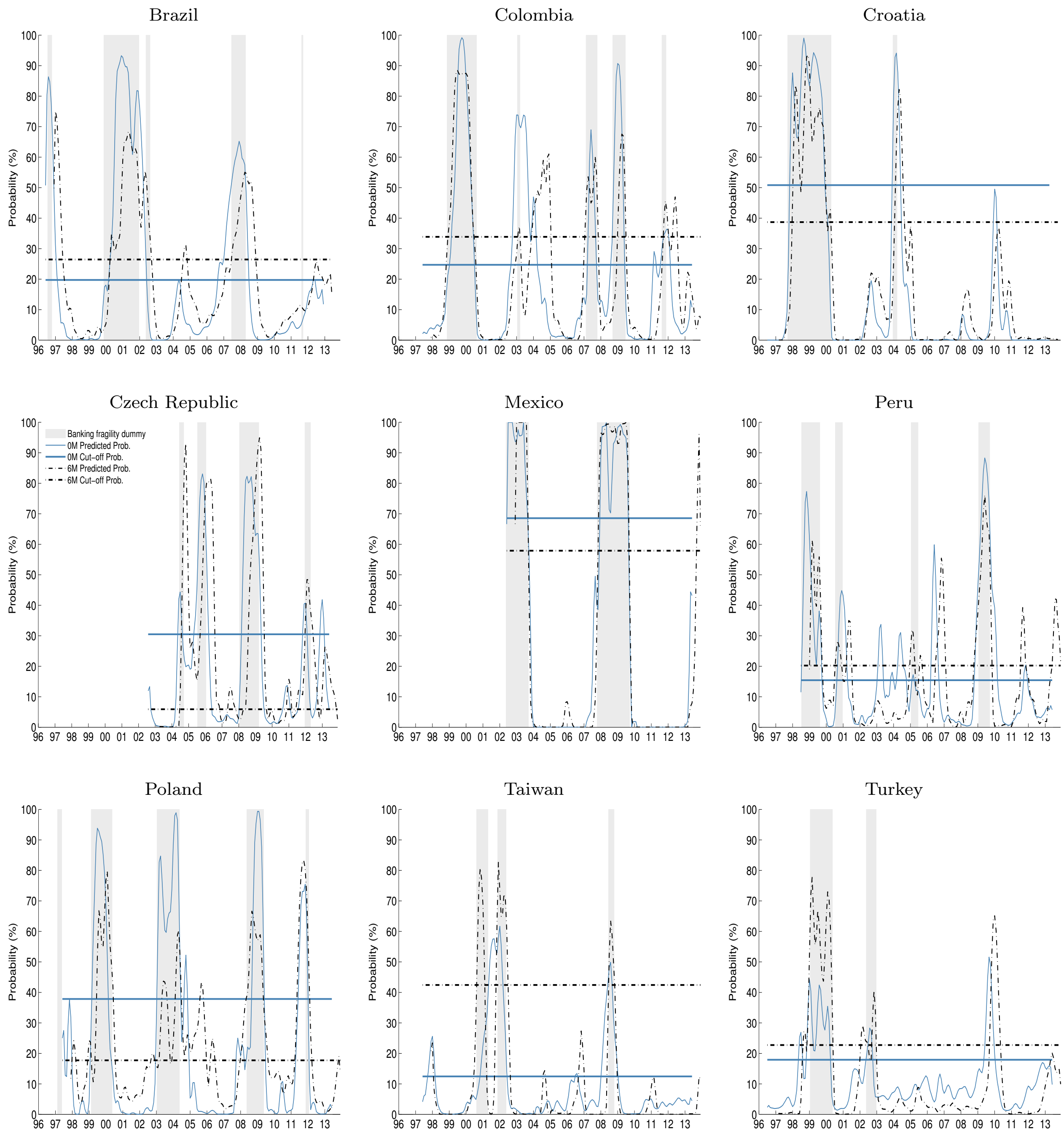
Table 3 shows the performance of the BMA warning instrument using an approach based on signaling analysis (see Babecký et al. (2014) and Christensen & Li (2014)). Under this approach, the null hypothesis is the occurrence of a banking fragility episode at month $t + h$, while the alternative hypothesis is the lack of the same event. For each time horizon h, we report the cut-off probability τ, the probability of missed fragility events (*i.e. Type I Error,* $\gamma(\tau)$), the probability of false alarms of fragility (*i.e. Type II Error,* $\phi(\tau)$), the probability of fragility events correctly called (*i.e. complement of Type I Error*), the probability of no false alarms (*i.e. complement of Type II Error*), the probability of fragility events given no alarm, the probability of no fragility events given no alarm and the noise-to-signal (NtS) ratio[9].

Results in Table 3 illustrate the good performance of our warning tool to identify (i.e. $h = 0$-month) and predict (i.e. $h = 3$-, 6-month) events of banking frailness for each country. As it is evidenced, the probability of missed events of fragility is lower than 15% (i.e. the probability of fragility events correctly called is bigger than 85%). This maximum value of Type I Error entails to having a probability of false alarms (i.e. *Type II Error*) in all time horizons less than 10% for Croatia, Mexico and Turkey and 20% for Brazil and Colombia (i.e. in all of these cases, the probability of no false alarms is larger than 80%).

The same indicator (*Type II Error*) for Peru, Taiwan, Czech Republic and Poland is also lower than 20% for most time horizons. However, in the cases of Czech Republic and Poland for $h = 6$ months, these probabilities achieved values of 53% and 35%, respectively. These particular figures could be interpreted as noisy results linked to both a low cut-off probability for these two countries

[9]NtS refers to the ratio between the probability of false alarms and the probability of fragility events correctly called.

Figure 2. Predicted Probability of Banking Fragility



and a small number of episodes[10]. At the end of each time horizon, Table 3 also shows that the NtS ratio is less than 20% for majority of countries.

[10]In fact, if we allow a larger type I error of 25%, the type II error for Czech Republic and Poland falls to 32% and 12%, respectively.

Table 3. Predictive Probability of Banking Fragility: Performance Evaluation

	Brazil	*Colombia*	*Croatia*	*Czech Republic*	*Mexico*	*Peru*	*Poland*	*Taiwan*	*Turkey*
T (months)	199	193	202	131	133	180	193	193	204
Events of fragility (months)	42	43	34	27	39	31	45	18	23
Prediction: 0 months ahead									
Cut-off probability	19.7	24.7	50.8	30.5	68.6	15.4	37.8	12.5	17.9
Missed fragility events - EI	11,9	14,0	14,7	14,8	5,1	12,9	13,3	11,1	13,0
False alarms - EII	17,8	15,3	1,8	11,5	0,0	24,2	6,8	13,1	7,7
Fragility events correctly called	88,1	86,0	85,3	85,2	94,9	87,1	86,7	88,9	87,0
No false alarms	82,2	84,7	98,2	88,5	100,0	75,8	93,2	86,9	92,3
Fragility events given no alarm	3,7	4,5	2,9	4,2	2,1	3,4	4,2	1,3	1,8
No fragility events given no alarm	96,3	95,5	97,1	95,8	97,9	96,6	95,8	98,7	98,2
NtS (ratio %)	20,2	17,8	2,1	13,5	0,0	27,7	7,8	14,8	8,9
Prediction: 3 months ahead									
Cut-off probability	25.1	45.0	60.5	29.4	76.6	17.3	25.4	10.7	21.4
Missed fragility events - EI	14.6	14.0	11.8	14.8	8.3	13.8	11.1	11.1	13.0
False alarms - EII	11.6	2.7	1.2	7.9	0.0	23.6	15.2	27.3	5.6
Fragility events correctly called	85.4	86.0	88.2	85.2	91.7	86.2	88.9	88.9	87.0
No false alarms	88.4	97.3	98.8	92.1	100.0	76.4	84.8	72.7	94.4
Fragility events given no alarm	4.2	4.0	2.4	4.1	3.1	3.4	3.9	1.6	1.8
No fragility events given no alarm	95.8	96.0	97.6	95.9	96.9	96.6	96.1	98.4	98.2
NtS (ratio %)	13.6	3.2	1.4	9.3	0.0	27.4	17.1	30.7	6.5
Prediction: 6 months ahead									
Cut-off probability	26.4	33.9	38.7	5.9	57.9	20.2	17.7	42.4	22.7
Missed fragility events - EI	12.8	14.0	14.7	14.8	3.0	11.5	13.3	11.1	13.0
False alarms - EII	14.3	14.6	3.1	53.1	0.0	17.6	35.2	1.2	9.1
Fragility events correctly called	87.2	86.0	85.3	85.2	97.0	88.5	86.7	88.9	87.0
No false alarms	85.7	85.4	96.9	46.9	100.0	82.4	64.8	98.8	90.9
Fragility events given no alarm	3.6	4.7	3.1	8.0	1.1	2.4	6.1	1.2	1.9
No fragility events given no alarm	96.4	95.3	96.9	92.0	98.9	97.6	93.9	98.8	98.1
NtS (ratio %)	16.4	16.9	3.6	62.3	0.0	19.9	40.6	1.3	10.5

All values are defined as probabilities (%) unless otherwise stated in parentheses. EI and EII stand for type I error and type II error.

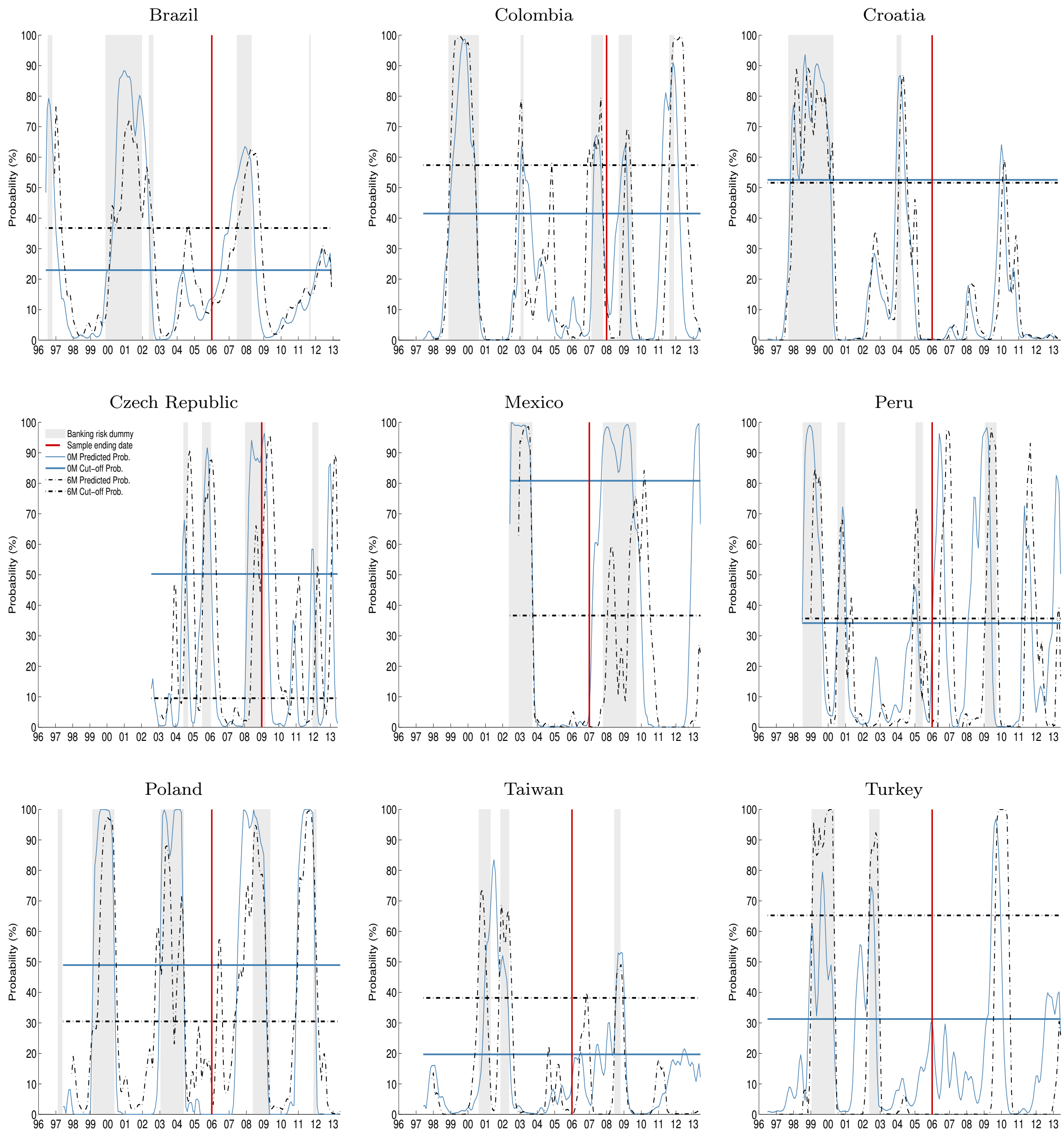
Direct predictions are based on parameters estimated by the BMA logistic regression, whose statistics are shown in Annex C. We report the highest posterior inclusion probability (i.e. PIP[11]), the posterior mean and standard deviation. The current value and the i lags of the regressors $(\cdot)$ are denoted by L_i. The relevant variables in the BMA prediction exercise, lags and PIPs depend on the time horizon and the characteristics of each country. To exemplify this point, for $h = 0$, we find that the most important are: Money market (L2) for Brazil, Foreign funds (L2) for Colombia, Money and bonds (L6) for Croatia, Non market securities (L0) for Czech Republic, Local funds (L1) for Mexico, Interbank resources (L1) for Peru, Foreign funds (L1) for Poland, Liabilities to financial institutions (L6) for Taiwan and Local funds (L2) for Turkey.

5.3 Predictive ability: In-Sample and Out-of-Sample Performance

Figure 3 plots both in-sample and out-of-sample BMA predicted probabilities for $h = 0$ (blue line) and $h = 6$ (dash-dot black line) months ahead. As in the previous section, the cut-off probability is plotted using a similar style with a thicker line. A vertical red line divides the total data into two: in-sample (left-side) and out-of-sample (right-side) periods. Once again, our estimated fragility episodes are compared with the historical periods of extreme risk (gray areas). Table 4 reports the performance of our in-sample and out-of-sample exercises. Furthermore, Appendix E shows the same figure for $h = 3$-month horizon.

[11] The probability that a given variable is included in the BMA regression

Figure 3. Predictive Ability: In-Sample and Out-of-Sample Performance



The results across countries confirm anew the suitable performance of our alert instrument. In general, fragility episodes identified with the full sample are again captured through both in-sample and out-of-sample forecasts, for all time horizons. In particular, we were able to recover the fragility episodes associated to the crisis at the end of the 90's, the recent global financial crisis, and some

Table 4. Predictive Ability: In-Sample and Out-of-Sample Performance

	Brazil	*Colombia*	*Croatia*	*Czech Republic*	*Mexico*	*Peru*	*Poland*	*Taiwan*	*Turkey*
In-Sample									
T (months)	116	128	115	54	56	174	187	187	198
Events of fragility (months)	31	31	34	9	16	26	45	18	23
Prediction: 0 months ahead									
Cut-off probability	22.9	41.5	52.6	50.2	80.8	20.2	17.7	42.4	22.7
Missed fragility events - EI	12.9	12.9	8.8	11.1	12.5	11.5	13.3	11.1	13.0
False alarms - EII	14.1	6.2	4.9	2.2	0.0	17.6	35.2	1.2	9.1
Fragility events correctly called	87.1	87.1	91.2	88.9	87.5	88.5	86.7	88.9	87.0
No false alarms	85.9	93.8	95.1	97.8	100.0	82.4	64.8	98.8	90.9
Fragility events given no alarm	5.2	4.2	3.8	2.2	4.8	2.4	6.1	1.2	1.9
No fragility events given no alarm	94.8	95.8	96.3	97.8	95.2	97.6	93.9	98.8	98.1
NtS (ratio %)	16.2	7.1	5.4	2.5	0.0	19.9	40.6	1.3	10.5
Prediction: 3 months ahead									
Cut-off probability	30.2	53.0	59.2	47.7	52.9	54.1	49.6	13.2	46.6
Missed fragility events - EI	13.3	12.9	8.8	0.0	0.0	14.3	12.9	14.3	4.3
False alarms - EII	15.7	0.0	2.6	4.8	0.0	3.0	1.4	27.6	0.0
Fragility events correctly called	86.7	87.1	91.2	100.0	100.0	85.7	87.1	85.7	95.7
No false alarms	84.3	100.0	97.4	95.2	100.0	97.0	98.6	72.4	100.0
Fragility events given no alarm	5.4	4.1	3.8	0.0	0.0	4.4	5.5	3.1	1.1
No fragility events given no alarm	94.6	95.9	96.2	100.0	100.0	95.6	94.5	96.9	98.9
NtS (ratio %)	18.1	0.0	2.8	4.8	0.0	3.5	1.6	32.2	0.0
Prediction: 6 months ahead									
Cut-off probability	36.8	57.4	51.6	9.5	36.6	35.7	30.5	38.2	65.2
Missed fragility events - EI	14.3	12.9	11.8	0.0	0.0	11.1	12.9	14.3	4.3
False alarms - EII	13.4	5.5	5.3	51.3	0.0	7.5	10.4	4.8	0.0
Fragility events correctly called	85.7	87.1	88.2	100.0	100.0	88.9	87.1	85.7	95.7
No false alarms	86.6	94.5	94.7	48.7	100.0	92.5	89.6	95.2	100.0
Fragility events given no alarm	5.3	4.4	5.3	0.0	0.0	3.1	6.3	2.4	1.1
No fragility events given no alarm	94.7	95.6	94.7	100.0	100.0	96.9	93.8	97.6	98.9
NtS (ratio %)	15.7	6.3	6.0	51.3	0.0	8.4	12.0	5.6	0.0
Out-of-Sample									
T (months)	83	65	87	77	77	89	89	89	89
Events of fragility (months)	11	12	0	18	23	8	14	4	0
Prediction: 0 months ahead									
Missed fragility events - EI	9.1	25.0	-	27.8	13.0	37.5	28.6	0.0	-
False alarms - EII	33.3	18.9	3.4	11.9	9.3	42.0	30.7	18.8	24.7
Fragility events correctly called	90.9	75.0	-	72.2	87.0	62.5	71.4	100.0	-
No false alarms	66.7	81.1	96.6	88.1	90.7	58.0	69.3	81.2	75.3
Fragility events given no alarm	2.0	6.5	-	8.8	5.8	6.0	7.1	0.0	-
No fragility events given no alarm	98.0	93.5	-	91.2	94.2	94.0	92.9	100.0	-
NtS (ratio %)	26.9	14.8	-	8.0	5.3	29.6	14.5	14.7	-
Prediction: 3 months ahead									
Missed fragility events - EI	9.1	50.0	-	27.8	0.0	12.5	35.7	0.0	-
False alarms - EII	25.0	17.0	2.3	15.3	22.2	28.4	33.3	25.9	13.5
Fragility events correctly called	90.9	50.0	-	72.2	100.0	87.5	64.3	100.0	-
No false alarms	75.0	83.0	97.7	84.7	77.8	71.6	66.7	74.1	86.5
Fragility events given no alarm	1.8	12.0	-	9.1	0.0	1.7	9.1	0.0	-
No fragility events given no alarm	98.2	88.0	-	90.9	100.0	98.3	90.9	100.0	-
NtS (ratio %)	23.0	8.4	-	10.4	11.1	18.3	19.3	28.6	-
Prediction: 6 months ahead									
Missed fragility events - EI	9.1	41.7	-	22.2	47.8	0.0	14.3	25.0	-
False alarms - EII	8.3	17.0	3.4	59.3	18.5	24.7	41.3	3.5	11.2
Fragility events correctly called	90.9	58.3	-	77.8	52.2	100.0	85.7	75.0	-
No false alarms	91.7	83.0	96.6	40.7	81.5	75.3	58.7	96.5	88.8
Fragility events given no alarm	1.5	10.2	-	14.3	20.0	0.0	4.3	1.2	-
No fragility events given no alarm	98.5	89.8	-	85.7	80.0	100.0	95.7	98.8	-
NtS (ratio %)	12.2	13.4	-	60.7	7.6	17.5	29.8	5.2	-

All values are defined as probabilities (%) unless otherwise stated in parentheses. EI and EII stand for type I error and type II error.

particular events of risk around 2003 and 2004, and between the end of 2011 and the beginning of 2012. The out-of-sample forecasts also provide signals of fragility at the end of 2009 and the beginning of 2010 for Croatia and Turkey, possibly associated with the Greek crisis as we already mentioned.

Performance results show that, in general, new in-sample estimates provide more accurate signals of frailness events in terms of Type I and II errors, and higher cut-off probabilities than those reported for the full sample. The events of fragility correctly called as well as the months of no false alarms have higher probabilities. Moreover the NtS ratio is usually smaller, providing evidence of higher precision in the identification ($h = 0$ months ahead) and anticipation ($h = 3$ and 6 months ahead) of these events.

From another perspective, results of out-of-sample forecasts provide early warnings of the fragility episodes reported by the historical dummy. These findings are of special interest for policy decision making, particularly, for 3- and 6-month horizons. Note that the probabilities of type I error are a little higher than those found for the in-sample period. Nonetheless, these statistics are outstanding if we consider two facts. Firstly, the small number of frailness events registered for the second part of the sample. Secondly, the indicator is always providing signals of fragility although the warning could be lagged respect to the starting point of such events. The lags are 1 or 2 months in most cases. We can also see that the BMA probability in out-of-sample forecasts is noisier than in the in-sample prediction and, therefore, the probability of false alarms is higher.

Summarizing, both in-sample and out-of-sample forecasts for 0-, 3- and 6-month time horizons provide evidence of the accuracy and usefulness of this warning tool for monitoring and tracking of financial vulnerabilities from information coming from the wholesale funds.

6 Conclusions

In this paper we develop an empirical model to identify and predict banking fragility episodes using information of the credit funding sources. Our empirical strategy encompassed, firstly, the definition of a frailness measure from standard financial risks and, subsequently, the generation of an early warning instrument. The latter is based on the BMA predictive probability of occurrence of such episodes. The funding sources of loans are disaggregated into retail deposits and wholesale funds. We consider a sample of nine emerging economies from different regions of the world: Brazil, Colombia, Croatia, Czech Republic, Mexico, Peru, Poland, Taiwan and Turkey. For each country, the dataset includes the monthly balance sheet of the consolidated banking system denominated in local currency and reported in a non-standardized format.

In general, results exhibit an adequate fit between the predicted probability and the historical episodes of vulnerability based on risks. Our warning indicator is able to capture two common events across countries which are widely recognized: the banking frailness at the end of the 90's or at the beginning of the new decade, specially for some emerging economies (Brazil, Colombia, Croatia, Peru, Poland and Turkey), and the global financial crisis around 2008 (with clear effects on Brazil, Colombia, Czech Republic, Mexico, Peru, Poland, Taiwan and Turkey). Interestingly, the exercises also provide signals of other fragility episodes which are not necessarily associated with signals of extreme financial risks.

From these results, it can be concluded that the increasing use of wholesale funds(e.g. foreign credit, interbank operations), particularly to support credit expansion, entails potential elements of risk and, hence, episodes of financial fragility. The in-sample and out-of-sample results support the conclusions and indicate that the proposed technique is a suitable tool for predicting such episodes in the short-term. The signaling analysis reinforces our findings. Since changes in the funding sources used for lending could be a potential source of banking instability, monitoring them could become useful in prudential practice. This suggestion could be important for policymakers and relevant for policy discussions on regulation of financial institutions.

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A BMA Logistic Regression Details

The posterior density of θ_k given the k-th model in Eq.(5) is stated as

$$P(\theta_k \mid M_k, D) = \frac{P(y_{t+h} \mid \theta_k, M_k, X_t)\, P(\theta_k \mid M_k, X_t)}{P(y_{t+h} \mid M_k, X_t)} \tag{A.1}$$

where $P(y_{t+h} \mid \theta_k, M_k, X_t)$ is the marginal likelihood distribution of y_{t+h} given θ_k, M_k and X_t, while $P(\theta_k \mid M_k, X_t)$ is the prior distribution of the parameter vector θ_k under model M_k. The predictive probability in Eq.(5) and the likelihood function in Eq. (A.1) and Eq. (A.5) are computed assuming a cumulative logistic distribution such that $P(\widehat{y}_{t+h} = 1 \mid \theta_k, M_k, X_t) = F(\theta_k, M_k, X_t)$ and

$$P(y_{t+h} \mid \theta_k, M_k, X_t) = \prod_{t=1}^{T} F(\theta_k, M_k, X_t)^{y_{t+h}} \left(1 - F(\theta_k, M_k, X_t)\right)^{(1-y_{t+h})} \tag{A.2}$$

where

$$F(\theta_k, M_k, X_t) = \frac{\exp^{\theta'_k X_t}}{1 + \exp^{\theta'_k X_t}} \tag{A.3}$$

In turn, the posterior model probability is defined as

$$P(M_k \mid D) = \frac{P(y_{t+h} \mid M_k, X_t)\, P(M_k)}{\sum_{k=1}^{K} P(y_{t+h} \mid M_k, X_t)\, P(M_k)} \tag{A.4}$$

where $P(M_k)$ is the prior model probability and

$$P(y_{t+h} \mid M_k, X_t) = \int_{\Theta_k} P(y_{t+h} \mid \theta_k, M_k, X_t)\, P(\theta_k \mid M_k, X_t)\, d\theta_k, \tag{A.5}$$

is the marginal likelihood for model M_k, which corresponds to the value of the likelihood function after integrating out the random parameter vector θ_k. Eq. (A.5) is approximated by the Laplace method such that

$$P(y_{t+h} \mid M_k, X_t) \approx (2\pi)^{\frac{R_k}{2}} \mid \psi \mid^{\frac{1}{2}} P\left(y_{t+h} \mid \theta_k^{+}, M_k, X_t\right) P\left(\theta_k^{+} \mid M_k, X_t\right) \tag{A.6}$$

where R_k is the dimension of θ_k, θ_k^{+} is the posterior mode of θ_k, and ψ is minus the inverse Hessian of $h(\theta_k) = log\left(P(y_{t+h} \mid \theta_k, M_k, X_t)\, P(\theta_k \mid M_k, X_t)\right)$ evaluated at $\theta_k = \theta_k^{+}$.

B Dataset

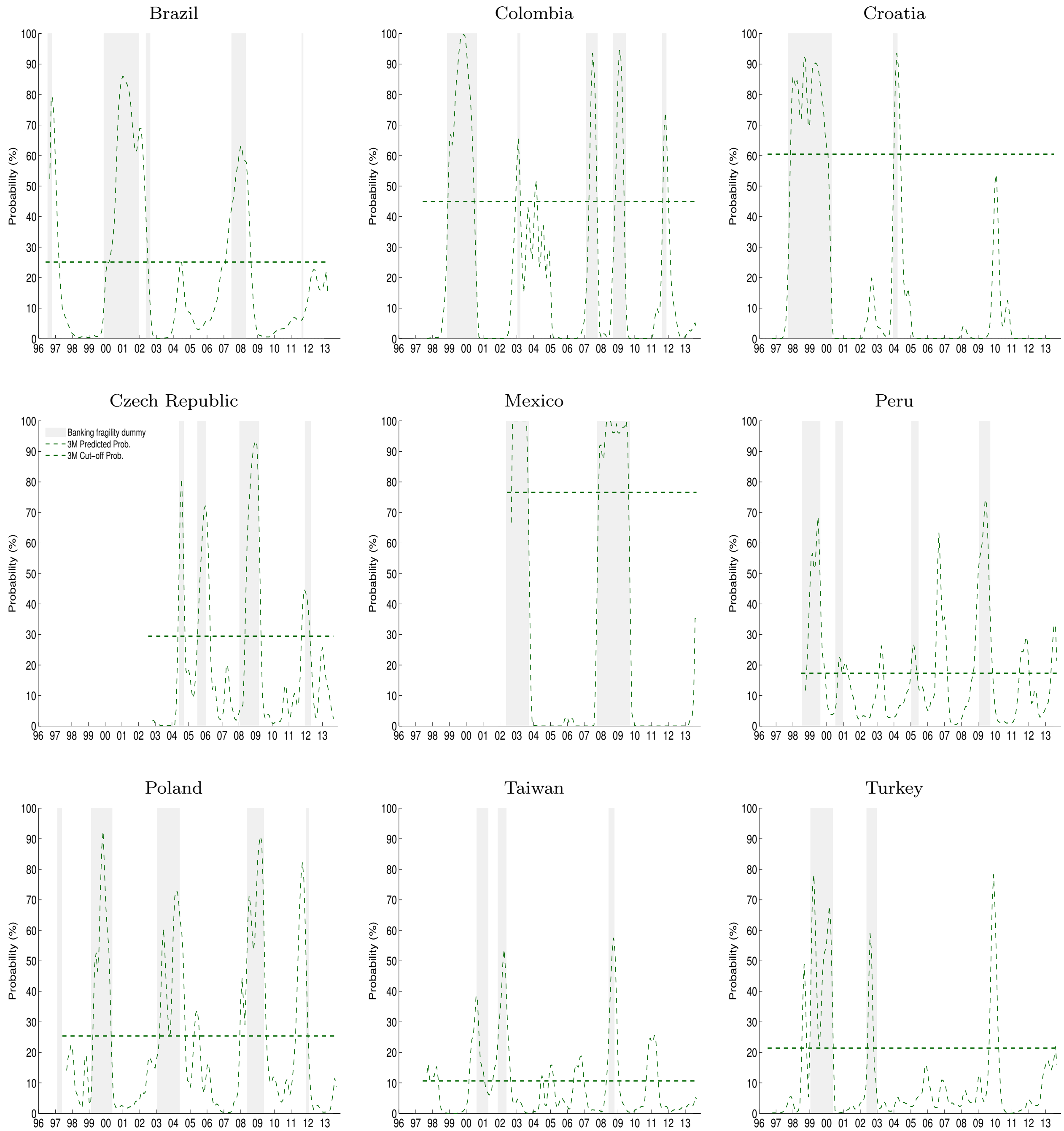
Country and available data	Source	Country and available data	Source
Brazil (December 1995 **- June** 2013**)**		**Peru (January** 1998 **- June** 2013**)**	
Balance sheet	Central Bank	Balance sheet	Central Bank
GDP	Central Bank	GDP	Central Bank
Economic Activity Indicators	Central Bank	*Economic Activity Indicators*	
Manufacturing employment	OECD	Peruvian monthly GDP	INEI
Consumer confidence indicator	OECD		
Composite leading indicator	OECD		
Colombia (December 1996 **- June** 2013**)**		**Poland (December** 1996 **- June** 2013**)**	
Balance sheet	Financial Superintendece	Balance sheet	Central Bank
GDP	DANE	GDP	Central Bank
Economic Activity Indicators		*Economic Activity Indicators*	
Consumer confidence indicator	Fedesarrollo	Manufacturing future prod. tendency	OECD
Consumer expectations indicator	Fedesarrollo	Construction employment	OECD
Economic conditions indicator	Fedesarrollo	Composite leading indicator	OECD
Economic activity index	Banco de la República	Retail trade confidence indicator	OECD
Industrial production index	DANE		
Croatia (June 1994 - **June** 2013**)**		**Taiwan (December** 1996 **- June** 2013**)**	
Balance sheet	National Bank	Balance sheet	Central Bank
GDP	IMF	GDP	Central Bank
Economic Activity Indicators		*Economic Activity Indicators*	
Croatian industrial production index	IMF	Composite leading indicator	Bloomberg
Value of exports	IMF	Coincident leading indicator	Bloomberg
Czech Republic **(January** 2002 **- June** 2013**)**		**Turkey (December** 1996 **- June** 2013**)**	
Balance sheet	National Bank	Balance sheet	Electronic data system
GDP	National Bank	GDP	OECD
Economic Activity Indicators		*Economic Activity Indicators*	
Consumer confidence indicator	Bloomberg	Manufacturing future prod. tendency	OECD
Economic sentiment indicator	Bloomberg	Manufacturing order inflows tendency	OECD
		Composite leading indicator	OECD
Mexico **(December** 2001 **- June** 2013**)**			
Balance sheet	Central Bank		
GDP	St. Louis Fed		
Economic Activity Indicators			
Business confidence indicator	OECD		
Manufacturing production	OECD		
Composite leading indicator	OECD		

C Logistic Regressions Results

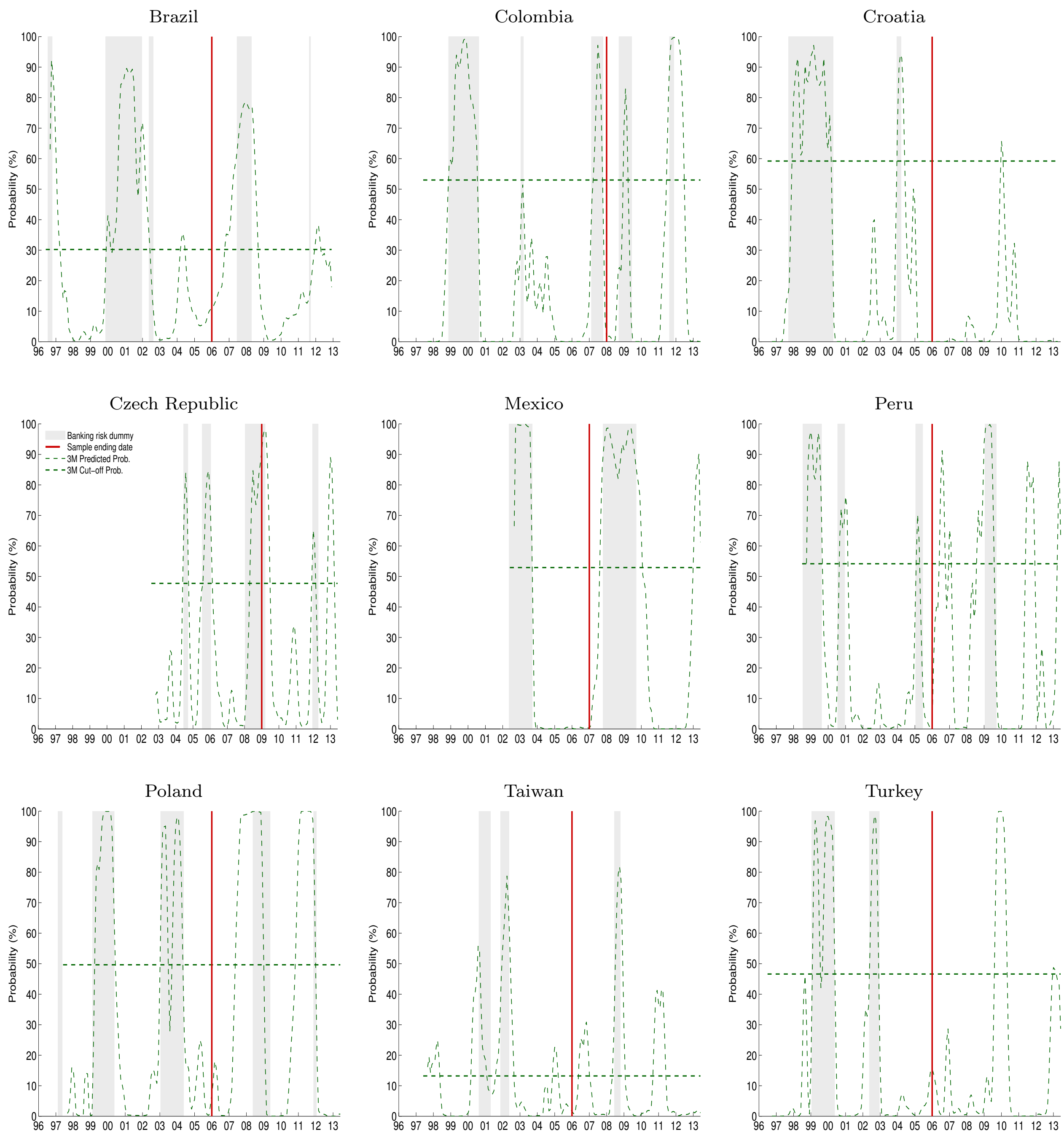
Variable	Lag	PIP	Mean	S.D.	Variable	Lag	PIP	Mean	S.D.	Variable	Lag	PIP	Mean	S.D.
					0-Month horizon									
Brazil					**Colombia**					**Croatia**				
Retail depostis	L2	0.97	-0.94	0.32	Foreign	L2	1.00	1.87	0.96	Economic Act.	L4	1.00	-0.91	0.40
Money Market	L2	0.84	0.29	0.26	Economic Act.	L3	1.00	-0.97	0.41	Money and Bonds	L6	1.00	2.69	0.28
Money Market	L3	0.68	0.16	0.22	Securities	L4	1.00	-0.48	0.05	Inv. Redemption	L5	0.93	-1.29	0.58
Money Market	L4	0.38	0.05	0.11	Interbank	L6	1.00	0.20	0.25	Inv. Redemption	L3	0.91	-0.74	0.67
Retail depostis	L1	0.26	-0.06	0.20	Economic Act.	L6	1.00	-0.06	0.17	Economic Act.	L5	0.90	-0.19	0.38
Czech Republic					**Mexico**					**Peru**				
Non market sec.	L0	1.00	0.18	0.49	Retail depostis	L1	1.00	-0.01	0.06	Economic Act.	L0	1.00	-0.51	0.10
Inv. Redemption	L0	1.00	-0.99	0.20	Local fund.	L1	1.00	0.07	0.18	Interbank	L1	0.80	1.93	1.48
Securities	L1	1.00	0.62	1.01	Economic Act.	L2	1.00	-1.32	0.13	Interbank	L3	0.72	1.48	1.41
Retail depostis	L2	1.00	-1.01	0.49	Retail depostis	L3	1.00	-0.02	0.09	Interbank	L2	0.65	0.92	1.41
Non market sec.	L2	1.00	0.97	1.26	Inv. Redemption	L3	1.00	-0.99	0.18	Interbank	L5	0.38	0.52	0.97
Poland					**Taiwan**					**Turkey**				
Other No Core	L0	1.00	2.53	0.85	Liabilities to FI	L6	0.75	3.22	2.05	Economic Act.	L6	1.00	-0.17	0.07
Foreign	L1	0.93	1.65	0.81	Inv. Redemption	L3	0.74	-0.35	0.24	Local Credit	L6	0.88	1.40	0.81
Economic Act.	L5	0.93	-1.14	0.60	Other No Core	L6	0.65	0.80	0.74	Retail depostis	L3	0.59	-0.17	0.28
Foreign	L4	0.55	0.81	0.86	Retail depostis	L5	0.55	-0.16	0.45	Retail depostis	L4	0.58	-0.17	0.26
Over and Repos	L4	0.54	0.66	0.82	Foreign	L4	0.35	0.17	0.62	Other No Core	L0	0.44	0.02	0.08
					3-Month horizon									
Brazil					**Colombia**					**Croatia**				
Money Market	L0	0.64	0.31	0.31	Foreign	L0	1.00	3.61	1.06	Investment	L0	0.83	-0.82	0.53
Retail depostis	L0	0.55	-0.66	0.62	Economic Act.	L0	1.00	-1.17	0.41	Economic Act.	L1	0.64	-0.74	0.62
Retail depostis	L2	0.41	-0.30	0.38	Securities	L3	1.00	-0.70	0.30	Money and Bonds	L3	0.54	3.04	2.99
Money Market	L1	0.20	0.06	0.17	Interbank	L4	1.00	1.03	0.40	Inv. Redemption	L2	0.50	-0.80	0.84
Inv. Redemption	L2	0.14	0.00	0.01	Economic Act.	L5	1.00	-0.85	0.57	Economic Act.	L2	0.49	-0.50	0.66
Czech Republic					**Mexico**					**Peru**				
Non market sec.	L0	1.00	5.82	1.44	Investment	L2	1.00	-0.48	0.72	Core	L6	1.00	-0.66	0.29
Securities	L2	0.94	4.27	2.12	Economic Act.	L2	1.00	-0.06	0.18	Interbank	L0	1.00	1.29	1.17
Investment	L1	0.82	-0.64	0.55	Inv. Redemption	L3	1.00	-0.76	0.74	Inter.Org	L3	0.90	-0.89	1.00
Securities	L4	0.79	0.08	0.30	Other wholesale	L5	1.00	0.44	0.80	Retail depostis	L1	0.68	-0.30	0.34
Inv. Redemption	L5	0.52	-0.06	0.15	Retail depostis	L6	1.00	-4.83	0.24	Interbank	L3	0.62	0.09	0.29
Poland					**Taiwan**					**Turkey**				
Foreign	L1	1.00	1.95	0.34	Retail depostis	L6	0.94	-1.75	0.59	Retail depostis	L0	1.00	-0.81	0.27
Economic Act.	L6	0.92	-0.41	0.24	Liabilities to FI	L6	0.91	3.38	1.20	Local Credit	L2	1.00	0.07	0.22
Over and Repos	L3	0.89	0.48	0.47	Economic Act.	L4	0.89	0.00	0.01	Local Credit	L5	1.00	2.84	0.14
Economic Act.	L1	0.83	-0.19	0.19	Foreign	L2	0.87	0.05	0.17	Economic Act.	L6	1.00	-0.30	0.07
Over and Repos	L4	0.63	0.29	0.41	Foreign	L1	0.79	0.05	0.17	Other wholesale	L2	1.00	0.02	0.08
					6-Month horizon									
Brazil					**Colombia**					**Croatia**				
Retail depostis	L1	1.00	-0.70	0.16	Economic Act.	L0	1.00	-0.92	0.18	Inv. Redemption	L0	0.98	-1.33	0.43
Money Market	L0	0.53	0.20	0.23	Foreign	L1	1.00	1.01	0.53	Economic Act.	L1	0.57	-0.30	0.29
Foreign	L6	0.22	0.05	0.14	Securities	L1	1.00	-0.25	0.15	Money and Bonds	L1	0.44	0.96	1.58
Foreign	L5	0.21	0.06	0.16	Interbank	L2	1.00	1.08	0.30	Economic Act.	L0	0.42	-0.31	0.38
Money Market	L4	0.16	0.00	0.02	Bonds	L3	1.00	1.82	0.77	Money and Bonds	L2	0.36	0.61	1.20
Czech Republic					**Mexico**					**Peru**				
Non market sec.	L0	1.00	6.52	1.33	Retail depostis	L0	1.00	-0.15	0.37	Retail depostis	L1	1.00	-1.19	0.28
Securities	L1	1.00	4.37	1.88	Other wholesale	L0	1.00	0.05	0.16	Inter.Org	L0	1.00	-2.31	1.21
Non market sec.	L1	0.92	0.08	0.27	Inv. Redemption	L0	1.00	-1.90	0.78	Inv. Redemption	L3	1.00	-0.09	0.09
Inv. Redemption	L3	0.57	-0.04	0.14	Other wholesale	L1	1.00	0.05	0.16	Interbank	L6	0.99	1.75	0.95
Investment	L1	0.53	-0.53	0.52	Retail depostis	L2	1.00	-2.63	1.96	Inv. Redemption	L2	0.95	-0.06	0.08
Poland					**Taiwan**					**Turkey**				
Foreign	L1	0.96	1.41	0.42	Retail depostis	L4	1.00	-4.60	2.33	Local Credit	L2	1.00	3.98	1.51
Over and Repos	L0	0.60	0.46	0.47	Retail depostis	L6	0.99	-3.15	1.13	Local Credit	L6	1.00	2.21	1.46
Over and Repos	L1	0.58	0.48	0.52	Liabilities to FI	L2	0.99	9.39	3.64	Inv. Redemption	L6	0.72	-0.03	0.03
Economic Act.	L0	0.55	-0.25	0.26	Liabilities to FI	L0	0.94	5.31	2.99	Other wholesale	L2	0.68	0.19	0.62
Economic Act.	L1	0.49	-0.15	0.21	Foreign	L6	0.86	3.43	3.53	Other wholesale	L4	0.62	0.08	0.29

Models always include the constant term as regressor. Nevertheless it is not presented.

D Estimated Banking Fragility Probability for $h = 3$-Month



E Predictive Ability: In-Sample and Out-of-Sample Performance for $h = 3$-Month

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