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Determinants of systemic banking crises in the Countries of Central and Eastern Europe

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Abstract
There are significant discrepancies in the literature due to differences in methodology for identifying determinants of financial crises. This has led to an increase in uncertainty concerning, on the one hand, the choice of the model and, on the other hand, the choice of indicators. The purpose of this paper is to identify, from a wide range of financial, macroeconomic, external and institutional indicators, proposed by the recent literature, the determinants of systemic banking crises in countries of Central and Eastern Europe mainly taking into account model uncertainty using Bayesian model averaging (BMA).The empirical results indicate that banking crises in countries of Central and Eastern Europe took place during phases of economic growth, characterized by excessive growth of the domestic credit (GDP percent), a high growth liquidity reserve to total bank assets ratio, a large flow of foreign direct investments, a private sector credit boom and an increase in the real interest rates.
JEL codes: G01, C11
Keywords: systemic banking crises, Bayesian model averaging.

1. Introduction:

Systemic banking crises are more and more frequent during the post-Bretton Woods era. To this date, there is no consensual definition of banking crisis. However, a systemic banking crisis is usually spotted when the collapse of one or more banks in a given country extends to all the banking system of this country.

Several countries in Central and Eastern Europe have experienced severe banking crises during the 1990s, caused mainly by the policies of financial liberalization and economic restructuring established during this period, making those economies highly vulnerable to shocks.

According to Mannasoo and Mayes (2005), the 1990s crisis that hit the countries of Central and Eastern Europe was largely predictable. Indeed, the state-owned banks dominated, for over a decade, by allocation of loans under a risk-based approach. Many of these banks were initially insolvent according to the criteria of the market and therefore needed to be recapitalised. Thus, capital account liberalization and the opening of the economy to market forces precipitated the failure of the latter. This has resulted in the initiation of systemic banking crises in several of these countries and a sharp contraction in economic activity. For example, according to Laeven and Valencia (2012), the proportion of non-performing loans was estimated at more than 70 percent of total Bulgarian bank assets during the 1996 crisis.

Similarly, the integration of some of these countries into the European Union has led to a strong interconnection of financial markets in these countries with those of Western Europe, which has exacerbated the vulnerability of these markets to external shocks. Walko (2008) claims that the 2008 crisis, which took place in the advanced economies of Western Europe, has led to a significant increase in real interest rates and risk premiums and strong currency devaluation in most countries of Central and Eastern Europe like Hungary, Romania and Latvia...

According to Dietz and Protsky (2009), this highly significant currency depreciation resulted in a sharp contraction of credit, deterioration in the quality of bank's assets portfolio and erosion of bank capital. Indeed, the proportion of non-performing loans is estimated at the end of 2008 to over 15% (Laeven and Valencia (2012)). This led to a sudden disruption in capital flows. This has led to the outbreak of a systemic banking crisis in autumn 2008 in Latvia.

There is an abundant empirical literature on banking crises. Most of these studies generally use two econometric approaches[1], namely the non-parametric signals approach and limited dependent variable Logit / Probit models. From the late eighties ten new empirical methodologies described as "revolutionary" have been used to identify the determinants of banking crises, such as the neural networks[2], the regime switching Markov models[3] and recursive binary trees[4].

In addition, the indicators used in the literature differ from one study to another. In fact, According to Bell (2000), the choice of independent variables may be influenced by several factors, including the nature of economies (developed, emerging, transition ...) and their stage of financial development (the structure of banking systems, the characteristics of the means of payment, the size and nature of interbank relationships ...).

Given the scarcity of a single theoretical framework linking all potential determinants with the occurrence of the banking crises, the issue of uncertainty on the model, the choice of independent variables and the estimates obtained should be taken into consideration.

This paper examines the systemic banking crisis, explicitly taking into account the uncertainty of the model using Bayesian statistical techniques, particularly the Bayesian model averaging (BMA) that provides a methodology[5] for calculating the average values of the parameters of all alternative models, using the posterior probabilities of each model as respective weights to assess the relative importance of different variables.

Although the only previous work that addressed model uncertainty in the field of analysis of financial crises are those of Cuaresma and Slacik (2009) and Babecký et al. (2012), to our knowledge, this is the first attempt using this technique in identifying the determinants of systemic banking crises.

[1] Gaytan and Johnson (2002) and Demirgüc and Detragiache (2005)
[2] Maillet, Olteanu and Rynkiewicz (2004)
[3] Ho (2004) and Brunetti, Mariano, Scotti and Tan (2007)
[4] Duttagupta and Cashin (2008)
[5] see Raftery (1995), Sala-i-Martin and al.(2004), Fernández and al. (2001) and Crespo-Cuaresma and Doppelhofer (2007)

The contribution of this study is to revisit binary variables models in the context of systemic banking crises by explicitly taking into account uncertainty of the model to answer the following research question: What are the determinants of systemic banking crises in countries of Central and Eastern Europe?

The paper is structured as follows. In *section 2*, we provide a brief theoretical *background* of the determinants of systemic banking crises. Then, section 3 presents a description of the methodology which will be used including the construction of the dependent variable of banking crisis, econometric model to be applied, the database and its properties. Section 4 provides the empirical result. Section 5 concludes.

2. Theoretical background

2.1. Definition of banking crises:

What is a banking crisis? When it occurs? And how long it lasts? There is no consensual answer to these questions. The literature offers many, and sometimes contrasting, definitions that vary substantially to one study to another. This can be explained by the constant change of the financial and banking environment, due to deregulation, *interconnections* in *financial markets*, disintermediation and increased proliferation of ever more complex and innovative financial instruments, making the empirical evaluation of a crisis or financial distress more difficult.

The main classifications[6] of banking crises that have been used largely in many empirical analyses are: Caprio and Klingebiel (2003), Demirguç-Kunt and Detragiache (1998, 2005), Caprio et al. (2005) and Laeven and Valencia (2008, 2012).

Table 1 resumes the characteristics of the main classifications of banking crises. We note that these classifications vary significantly in terms of samples sizes, coverage periods and the definition of banking crises.

A common methodological used by these classifications to identify episodes of banking crises, more specifically "crisis" beginning/ending dates, and whether the crisis was "systemic" or not, rely on information collected from the central banks and/or bank regulators.

Table 1. Characteristics of each the main classifications of banking crises:

	Caprio and Klingebiel (2003)	Demirguç-Kunt and Dandragiache (1998, 2005)	Caprio and al. (2005)	Laeven and Valencia (2008,2012)
Coverage period	1970-2002	1980-2002	1970-2005	1970-2011
sample size	93	94	126	+100
Number of crisis episodes	168	77	121	134
Average length of *banking crises*	4	4	5	3

Source: Author's calculation

2.2. Determinants of systemic banking crises:

[6] These five lists are all updates, modifications and / or extensions of the list of Caprio and Kinglebiel (1996, 1999). The list of Caprio and Kinglebiel (1996a, 1999) cover more than 90 countries and 100 episodes of banking crises over the period 1970-1998. These define a banking crises as Caprio and Klingebiel (2003) (see Appendix I. Table 4 for the definition of banking crises according to each study)

The variables used to study the determinants of banking crises differ from one study to another. According to Frankel and Saravalos (2010), there is an extensive literature on early warning indicators of financial crises. However, these studies face many difficulties. First, the definition of a financial crises crisis and the extent of its impact vary considerably from one country to another (emerging markets, transition economies and developed countries) and from one period to another. Then, the results of these studies cannot be generalized, and the lessons drawn from one crisis are perhaps not relevant to others.

The magnitude of the systemic banking crises and their impact on both financial and real system led to the development of a large empirical literature which aims to identify the main determinants of these crises.

Most of the existing studies highlight the key role of financial, macroeconomic, external and institutional indicators in the emergence of systemic banking crises in the last 20 years (See, for exemple, Demirguc-Kunt and Detragiache, 1998a, 2005; Lambregts Ottens , 2006....).

Many theorists[7] validate empirically the robustness of the following macroeconomic variables: the real GDP growth rate, inflation, real exchange rates, the growth of international reserves and the short-term real interest rate as the key determinants of banking crises. According to Davis and Dilruba (2008), these variables are able to capture adverse macroeconomic shocks, which may weaken the banking sector by increasing, for example, the share of non-performing loans.

Moreover, the empirical literature confirms the relevance of financial indicators in the emergence of banking problems. Among the indicators of financial fragility, theorists consider different measures reflecting the ability of banks to avoid crises such as liquidity risk measured by the bank reserves to total bank assets ratio. According to Kaminsky and Reinhart (1998), high levels of this ratio reflect the inability of banks to deal with a potential banking crisis. In addition, numerous studies[8] highlight the existence of a significant positive correlation between banking sector problems and excessive credit expansion measured by change in private sector credit growth and domestic credit as percentage of GDP. According to these studies, the pre-crisis periods are often characterized by rapid real growth of domestic credit to GDP and a sharp increase in private sector credit and, therefore, an increase in credit risk.

The theoretical and empirical literature has established the relevance of external indicators, such as: deterioration of terms of trade, increase of current account deficits, declining exports and rising imports, increase of M2 to reserves ratio and the massive flows of foreign capital, to increase distress in *banking industry*[9]. Even if foreign direct investment (FDI) has contributed significantly to stimulate economic growth in countries of Central and Eastern Europe, however, according to Dietz et al. (2008), a sharp inflow of foreign capital may contribute to the weakening of the financial system and trigger a crisis by encouraging excess in liquidity and increase in bank loans. Also, Sopanha (2006) claims that deterioration of the current account due to an increase in imports of goods and services causes a boom in consumption rather than investment. This may increase external debt and *leads* to a persistent *bleeding of foreign*

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[7] See, for exemple, Galbis (1993), Velasco (1987), Obstfeld and Rogoff (1995), Kaminsky and Reinhart (1996), Ergungor and Thompson (2005)…

[8] See Pill and Pradhan (1995), Eichengreen and Arteta, Lambregts and Ottens (2006), and Buyukkarabacak Valev (2010), Saravalos and Frankel (2010) and Babecký et al. (2012) ...

[9] See, for exemple, Kaminsky and Reinhart (1998), Kaminsky (2000), Demirguc-Kunt and Detragiache (1998a, 2005) Lestano et al. (2004), and Lambregts Ottens (2006) and Falcetti and Tudela (2008) ... among others, empirically validate the relevance of some indictors as: deterioration of trade terms, the widening of current account deficits, the decline in exports in increasing the likelihood of financial crises.

exchange *reserves*, making an economy more vulnerable to shocks, and therefore to financial crises.

Finally, the rising problems of the banking sector may be due to insufficiency of prudential regulation [10] and the absence of deposit-insurance system. In order to test the hypothesis, which states that a lack of prudential regulation promotes the emergence of systemic banking crisis, several theorists use GDP per capita as a measure of structural economic development. This variable is generally positively correlated with the effectiveness of the prudential supervision of the banking system (See, for exemple, Demirguc-Kunt and Detragiache 1998a, 2005 ; Davis and Dilruba, 2008). Moreover, the theory is controversial as to the relationship between deposit-insurance[11] system and banking crises. On the one hand, some theorists suggest that the establishment of a deposit insurance system reduces the likelihood of occurrence of self-fulfilling banking crises. On the other hand, others argue that the presence of a deposit-insurance system increases the probability of occurrence of banking crises. Thus, the expected sign of this indicator is ambiguous, because even if an explicit deposit-insurance reduces the incidence of bank panic, it is, however, likely to increase the risk due to moral hazard.

3. Methodology:

3.1. The banking crisis variable:

The identification of the determinants of banking crisis requires a prior construction of the binary variable of banking crisis. To this end, we have identified and dated episodes of difficulties in the banking sector during the period 1994-2011, mainly by referring to the classification of Laeven and Valencia (2008, 2012). Indeed, according to the brief comparison between the different classifications (Table 1), it is better to adopt the list of Laeven and Valencia. This list incorporates, on the one hand, a larger number of countries, including countries of Central and Eastern Europe and, on the other hand, information relating to the global banking crisis of 2008. Table 3 in Appendix I presents our sample of countries with the dates of banking crises identified by the studies of Laeven and Valencia.

Thus, let Y_{it} the dummy variable of banking crisis that takes a unit value when a banking crisis is identified in country i at time t and zero otherwise.

$$Y_{it} = \begin{cases} = 1 & if\ crise \\ = 0 & otherwise \end{cases} \tag{1}$$

The dependent variable takes the unit value in the first year of the crisis and zero otherwise. Indeed, insofar as the episodes of banking crises occur over a long period (on average four years), Demirguc-Kunt and Detragiache (1998a) have suggested to retain only the first year of the banking crisis.

3.2. Econometric specification:

Over the past four decades, a large literature has established a set of early warning signals of financial and / or economic crises. The characteristic of this literature is, on the one hand, the diversity of theories and empirical approaches and, on the other hand, the variety of criteria used to assess the adequacy of early warning signals, through time, countries and types of crises.

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[10] Demirguc-Kunt and Detragiache (1998a, 2005), Demirguc-Kunt et al. (2005,2008 b) and Menkhoff Suwanaporn (2007) and Laeven and Levine (2008, 2010 and 2012) ...

[11] This is a binary variable of deposit-insurance that takes unit value for country / years in which a regime of an explicit deposit insurance is in place and zero otherwise.

A vast literature uses Bayesian model averaging (BMA), most specifically, in economics to identify in particular the determinants of economic growth[12]. These models take into account the issue of uncertainty in both the model and the choice of independent variables.

The only previous studies that addressed model uncertainties in the field of early warning indicators are those of Cuaresma and Slacik (2009) and Babecký and al. (2012). Cuaresma and Slacik (2009) use the BMA approach to identify early warning indicators of currency crises in emerging markets (Asia, Latin America and Eastern Europe) over the period from January 1994 to March 2007. To highlight the contribution of the Bayesian approach compared to traditional models as logit models, they have adopted the same approach and the same sample of countries and variables as Bussière (2007). According to the results of this study, the results of the BMA approach are consistent with the findings of Bussière (2007). In addition, changes in real exchange rates and financial variables are able to explain the increase in the probability of currency crises. Similarly, Babecký and al. (2012) using the BMA approach to identify early warning indicators of financial crises in developed economies in Europe (40 countries) over the period 1970-2011. According to them, the BMA model provides a systematic method to deal with the model uncertainty by taking into account different model combinations and weighting them according to their model fit. In addition, the BMA approach allows estimating the coefficients of each variable as a weighted average of all models included in the model space. Thus, the weights correspond to the posterior probability of inclusion in each model of the model space. Babecký and al. results' indicate that banking crises (systemic and non-systemic) and currency crises tend to be preceded by booms in economic activity, in particular: private sector credit growth, increase in foreign direct investment flows, rising monetary market rates and increase in world GDP and inflation.

We use BMA to identify the determinants of banking crises from a list of 19 potential indicators. We consider the following linear regression model:

$$y = \alpha_\gamma + X_\gamma \beta_\gamma + \varepsilon \qquad \text{and} \qquad \varepsilon \sim N(0, I\sigma^2) \tag{2}$$

Where

y : is a binary variable indicating the starting date of the crisis

α_γ : is a constant

β_γ : is a vector of coefficients

ε : a white noise error term

X_γ : denotes the subset of relevant independent variables

The K number of potential independent variables gives 2^K potential models. The index γ is used to refer to a specific model among the 2^K models. An average is then calculated from information from the model using the posterior probabilities of the model implemented by Bayes' theorem:

$$p\left(M_\gamma \middle| y, X\right) \propto p\left(y \middle| M_\gamma, X\right) p\ (M_\gamma) \tag{3}$$

Where $p\left(M_\gamma \middle| y, X\right)$ is the posterior probability of the model that is proportional to the marginal likelihood of the model $p\left(M_\gamma \middle| y, X\right)$ times the model priori probability $p\ (M_\gamma)$.

[12] Fernandez and al. (2001), Sala-i-Martin et al. (2004), Feldkircher and Zeugner, (2009) and Moral-Benito (2011)

The relevance of an exogenous variable in explaining the endogenous variable is given by the posterior inclusion probability (PIP). The PIP designates the likelihood that a given variable is included in the regression. It is calculated as follows:

$$PIP = p(\beta_\gamma \neq 0|y) = \sum_{\beta_\gamma \neq 0} p(M_\gamma|y) \tag{4}$$

The variables with a high PIP (0.5 or greater) is considered as robust determinants of the dependent variable.

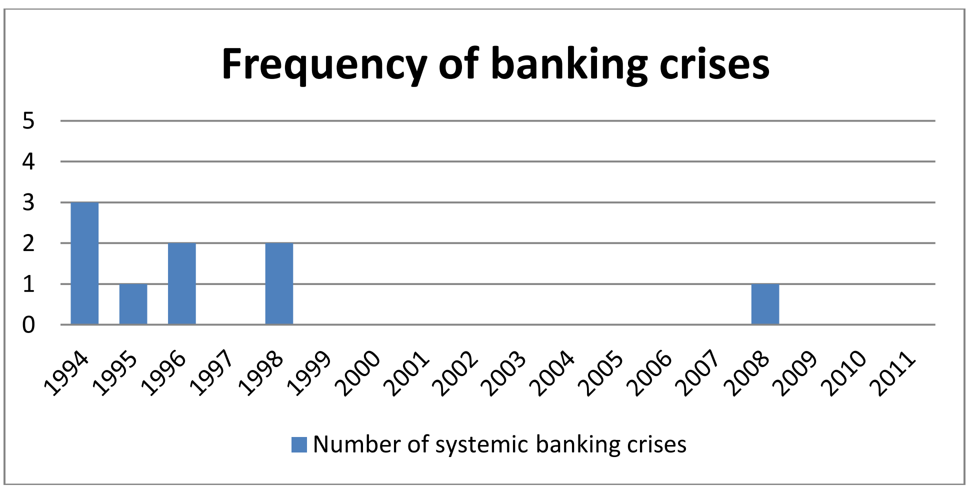
In general, it is not possible to review all models if the number of potential independent variables is large. Therefore, we use the Markov Chain Monte Carlo Model Comparison (MC3) method, introduced by Madigan and York (1995). The MC3 algorithm takes into account the models, whose prior probabilities are high and are therefore able to give a correct estimate of the posterior probability[13].

3.3. Data and properties:

Our sample consists of eight emerging economies of Central and Eastern Europe, namely Estonia, Lithuania, Latvia, Poland, Slovakia, Hungary, Bulgaria and Croatia (Table 3, Appendix).

We use panel data with annual frequency for the period 1994-2011. According to this criterion, 144 annual observations are identified, including 20 episodes of banking crisis (Table 5, Appendix). Figure 1 provides some stylized facts on banking crises in our sample. We found that the frequency of banking crises was high in the early 1990s and gradually declined towards the end of the decade. Among the eight countries in the sample, five had at least one banking crisis during the observation period, which lasted an average 2 years (Table 5, Appendix), also in some countries, the duration of the crisis was over 5 years (e.g. Slovakia and Latvia). Only one country has experienced a recurrence of banking crises during the sampling period of 18 years, namely Latvia has experienced two systemic banking crises.

Figure 1. Frequency of banking crises over the period 1994-2001:



Note: Only the first year of crisis have been taken into account.
Source: Authors' calculations

[13] We use the BMS library developed by R Zeugner and available on http://bms.zeugner.eu/

Our choice of independent variables takes into account, on the one hand, the empirical and theoretical literature[14] on the main determinants of banking crises and, on the other hand, the availability of data. We classified our independent variables into four distinct categories: macroeconomic, external, financial and institutional variables. Our data are mainly extracted from World Development Indicators of the World Bank and International Financial Statistics of the International Monetary Fund (IMF). Table 2 in Appendix summarizes the independent variables, the data source and the expected theoretical sign between the dependent variable and each independent variable.

Analysis of descriptive statistics (Table 6, Appendix) shows that the number of observations of the independent variables varies from one variable to another due to data unavailability. Furthermore, we found that some variables have very large fluctuations compared to others during the studied period.

The study of the average change of the independent variables during quiet periods and crisis periods (Table 7, Appendix) shows that crises period are often characterized by a decline in domestic and private credit growth as percentage of GDP. This may be explained by the establishing of credit rationing policies during periods of banking crises. We also note that the periods of crisis in the countries in our sample are characterized by a decline in foreign direct investment, a substantial increase in inflation and a significant decline in the growth of international reserves.

Given the large number of potential independent variables and to overcome the problems of collinearity, we conducted a selection process of variables to exclude variables whose correlation with another independent variable is greater than or equal to 0.5. To this end, we performed the Pearson correlation test to test the null hypothesis of no correlation ($\rho = 0$) where ρ is the correlation coefficient. This test is intended to exclude from the econometric regression, variables capturing the same information and have, on the one hand, very large and statistically significant correlation coefficients, and on the other hand, are more involved in collinearity problems (table 8, Appendix). Thus, given that there is a strong significant correlation between inflation and real interest rate (-0.99), GDP per capita (gdppercap) and the money multiplier (moneymult) (0.7903), real GDP growth and industrial production index (0.7713), real GDP growth and GDP per capita (gdppercap) (0.895), imports (import) and exports (export) (0.9236) and these latter two with current (currentaccount) account, it was preferable to retain only the following variables: real interest rate (rir), M2 to international reserves (M2RV), the money multiplier (moneymult), real GDP growth (gdpgrowth), current account (currentaccount) and to exclude the other variables in our regressions.

4. Empirical Results:

The main purpose of this study is to identify the determinants of banking crises in the countries of Central and Eastern Europe, explicitly taking into account the uncertainty of the model by using Bayesian statistical techniques.

The estimation results of the Bayesian model averaging (BMA) are illustrated in Figures 2 and 3. Posterior Inclusion probabilities (PIP) and expected posterior mean of the parameter as well as the posterior variances of the parameters are given in Tables 9 and 10, Appendix.

The results of the first regression (Appendix, Table 9), illustrated in Figure 2 below, indicate that banking crises in the countries of Central and Eastern Europe took place during phases of economic growth characterized by excessive domestic credit growth (GDP percent), strong

[14] Cf, see Section 2

growth in bank reserve liquidity to total bank assets ratio, an inflow of foreign direct investment and growth in M2 to international reserves ratio. This is in disagreement with the results of Reinhart and Rogoff (2008) and Duttagupta and Cashin (2008) who argue that banking crises emerge during periods of slow economic growth.

Among the financial variables selected in this study, only the variables domestic credit as percentage of gdp (domesticcredit) and liquidity reserves to total bank assets ratio (bankliquidratio) have a PIP more than 0.5, respectively equal to 0.99002107 and 0.99978609 with positive coefficients. These results are consistent with the theoretical and empirical literature on the determinants of banking crises, including the work of Alessi and Detken (2011), Kaminsky and Reinhart (1999), Borio and Lowe (2002), Demirgüç-Kunt and Detragiache (1998, 2005) who attribute a decisive role to excessive credit growth in the emergence of banking crises.

According to Demirgüç-Kunt and Detragiache (1998, 2005), the excessive growth of domestic credit leads to a greater risk-taking by banks and therefore an increase in the bank reserves liquidity to total bank assets ratio. This generally reflects deterioration in loan quality and higher proportion of non-performing loans, which greatly increases the likelihood of a systemic banking crisis.

Moreover the money multiplier (moneymult) and the *private sector credit growth* (creditgrowth) are positively correlated with the dependent variable of banking crises (bankcrise), since these two variables have positive coefficients in most regressions of the model space given by BMA. However, unlike previous studies[15] these two indicators do not seem to play an important role in the emergence of systemic banking crises in the countries of Central and Eastern Europe, as they have a PIP less than 0.5.

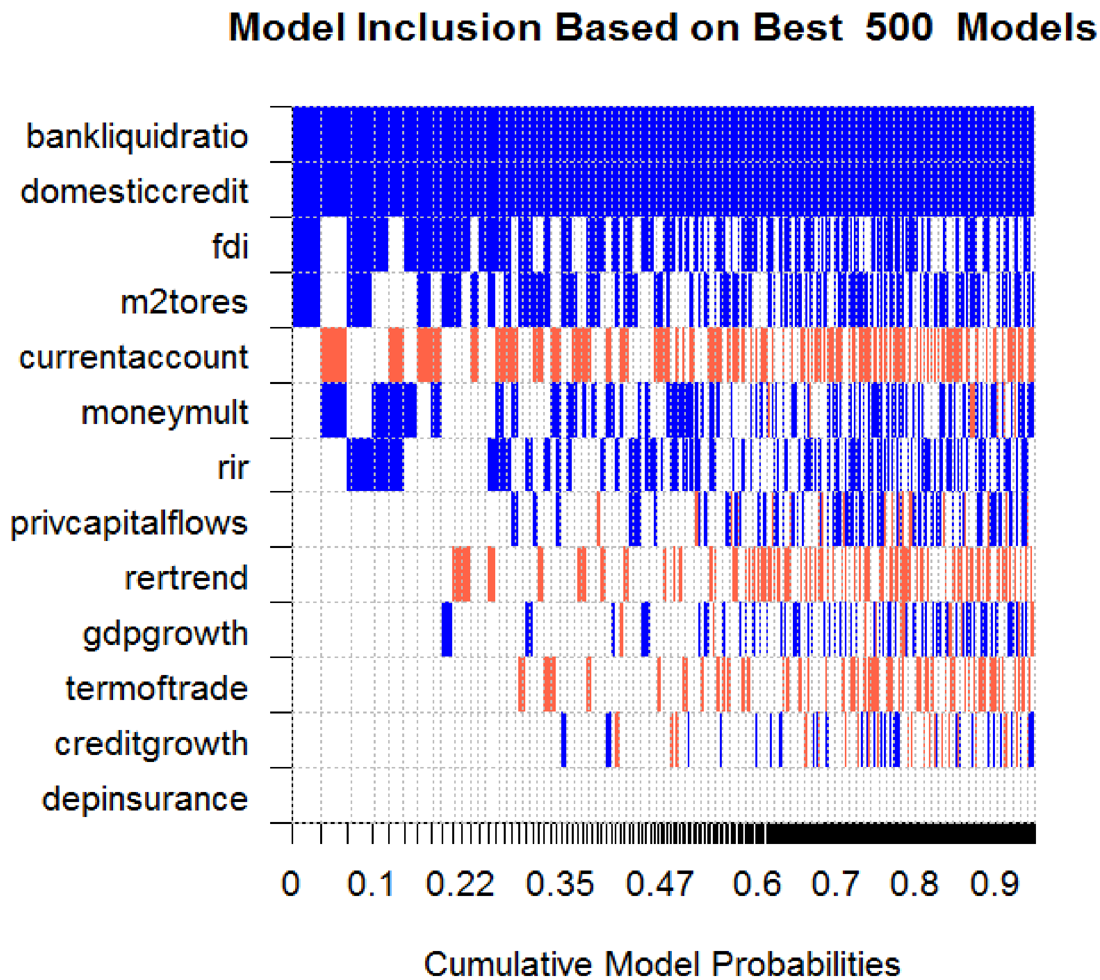
In addition, neither the macroeconomic nor the institutional variables selected in this study appear to be robust determinants of systemic banking crises in the countries of Central and Eastern Europe,

According to the results of the BMA model, real GDP growth (gdpgrowth) is not a strong determinant of banking crisis (PIP = 0.21860807). Similarly, this variable has a positive coefficient in almost all regression the model space given by BMA. This result is consistent with the work of Laeven and Valencia (2012) who argue that no significant output losses have been recorded in the case of systemic banking crises which took place in a period of transition to a market economy, especially in the countries of our sample.

Similarly, the institutional variable of deposit-insurance (depinsurance), although it has a positive coefficient, reflects an excessive risk-taking by banks and therefore an increase in the problem of moral hazard. However, it is not significant (PIP = 0.00997499) and does not seem to increase the likelihood of a banking crisis.

[15] Kaminsky and Reinhart (1999), Demirgüç-Kunt and Detragiache (1998, 2005), Haggen and Ho (2007), Eichengreen and Arteta, Lambregts and Ottens (2006), and Buyukkarabacak Valev (2010), Saravalos and Frankel (2010).

Figure 2. Estimation results of the first BMA regression:



Note: Rows = potential determinants of systemic banking crises, Columns = best models according to marginal likelihood, Full cell = variable included in model, blue = positive sign, red = negative sign.

Finally, according to the results of our study, external variables, in particular foreign direct investment (fdi) (PIP = 0.61597049) and M2 to international reserves ratio (m2tores) (0.50672939) are significant and positively correlate with the likelihood of the emergence of systemic banking crises. These results are consistent with the results of Babecký et al. (2012) and Kaminsky and Reinhart (1998), who found that the M2 ratio compared to reserves which are a measure of vulnerability of the banking system to currency crisis undergoes a strong increase of 70% during the period preceding the financial crisis compared to its average during the quiet period, suggesting that the banks' exposure to currency crises plays a key role in the emergence of banking crises.

According to the second model given in Table 10, Appendix and illustrated in Figure 3 below, we found that when we introduce the variable private credit growth with one period lag, our results vary significantly. Indeed, the significance of the financial variable domestic credit as percentage of GDP (domesticcredit) increases (PIP = 1). Thus, the rapid expansion of domestic credit promotes the emergence of problems in the banking system. Banks with a view of maximizing their profitability minimize credits allocation conditions, granting risky loans to customers who are not necessarily very creditworthy. In case of rising interest rates, many customers are not able to honour their commitments. This leads to increased non-performing loans and therefore to the deterioration of the banks' balances sheets (Davis and Dilruba, 2008 ; Klomp, 2010).

Moreover, some financial variables such as the lagged private credit growth (lagcreditgrowth) and the money multiplier (moneymult) enter the list of significant variables with a PIP respectively equal to 0.85305414 and 0.5046864, and with positive coefficients as well. These findings are consistent with the work of Demirgüç-Kunt and Detragiache (1998a, 2005), Reinhart and Rogoff (2011) who have shown that excessive private credit growth leads to the insolvency of the private sector and therefore the emergence of banking crises. Indeed, high credit growth, lagged by one period, indicates that a country where the banking sector is highly exposed to private sector borrowers is more vulnerable, perhaps because of a mismanaged financial liberalization policy.

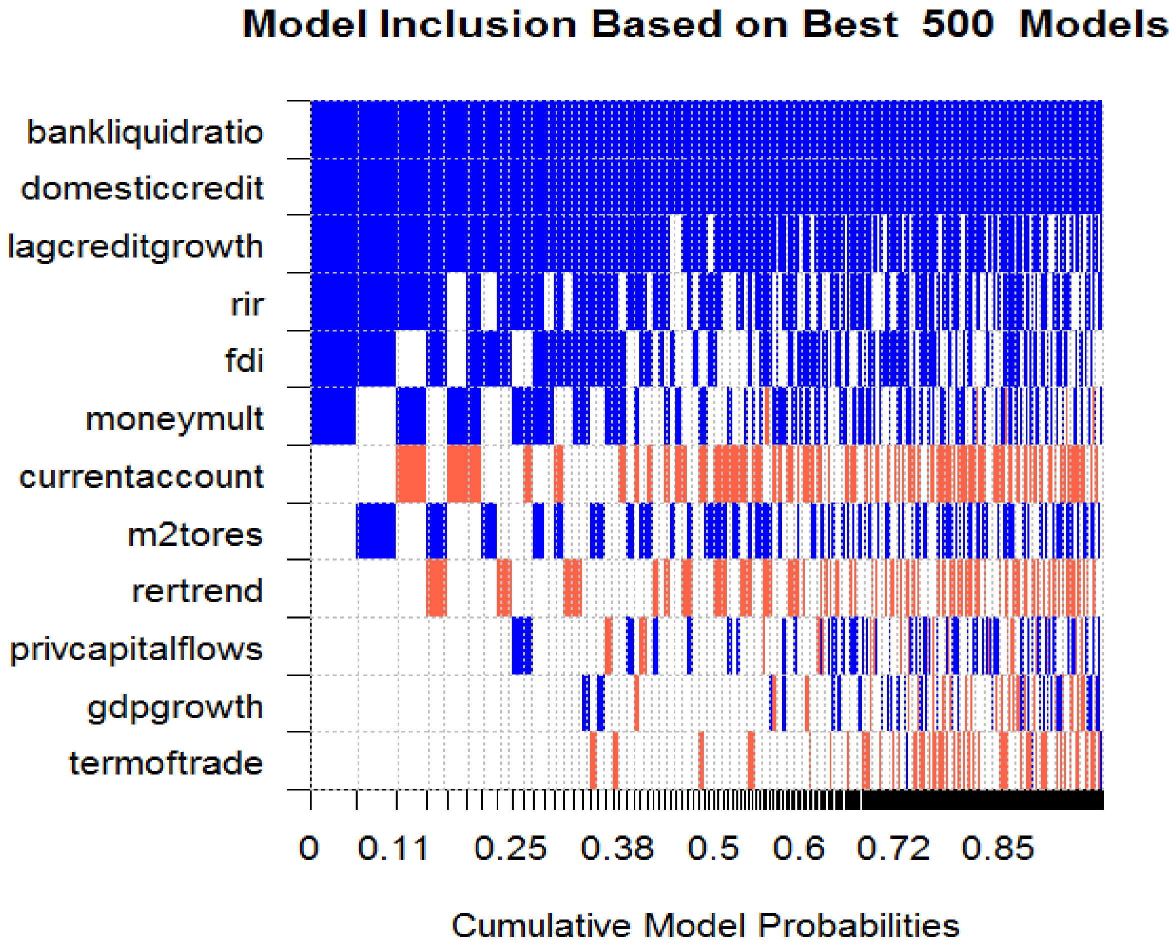
However, the variable money supply as defined by M2 to international reserves (m2tores) seems to have lost its significance, with a PIP less than 0.5 (PIP = 0.41709303).

The macroeconomic variable, the real interest rate (rir), has also entered the list of significant variables with a positive coefficient and a PIP of 0.67340779. This is consistent with the theoretical and empirical literature that argues that exposure to real interest rate is also a source of bank fragility. This is consistent with the assumption that greater and more volatile real interest rates during the years 1980 and 1990 have contributed to the increase in the likelihood of emergence of banking crises (Demirgüç-Kunt and Detragiache, 2005).

However, macroeconomic variables such as the deviation of the exchange rate (rertrend) from its trend, the current account deficit (currentaccount), the terms of trade (termoftrade) and real GDP growth (gdpgrowth) and the institutional variable deposit-insurance (depinsurance) do not appear to be determinants of banking crises in both regressions given that these variables hold PIP less than 0.5. This is partly in contradiction with the previous literature which argues that low GDP growth and a sharp increase in the ratio M2 to international reserves are associated with a high probability of a systemic banking crisis.

In summary, the results of our two econometric specifications show that banking crises in the countries of Central and Eastern Europe took place during phases of economic growth, characterized by excessive domestic credit growth (as percentage of GDP), strong growth in liquidity reserve to total bank assets ratio, an inflow of foreign direct investment, a private credit boom and rising real interest rates.

Figure 3. Estimation results of the second BMA regression:



Note: Rows = potential determinants of systemic banking crises, Columns = best models according to marginal likelihood, Full cell = variable included in model, blue = positive sign, red = negative sign.

5. Conclusion:

This paper provides a new perspective on financial crises, identifying factors causing banking crises in the countries of Central and Eastern Europe. This is done by explicitly considering model uncertainty using Bayesian statistical techniques, particularly the use of Bayesian model averaging (BMA).

The BMA model has the advantage of taking into account the uncertainty of the model, by considering the various combinations of the models and weighting them according to their adjustments in the model. The BMA approach also allows for estimating the coefficients of each variable as a weighted average of all models included in the model space.

Although this model has recently been used in the analysis of currency crises and twin crises, to our knowledge, this is the first study that uses this technique in identifying the determinants of systemic banking crises. The use of this approach was motivated by the ability of the BMA to provide a systematic method to analyze, on the one hand, the uncertainty of the model and to check on the other hand, the robustness of the results of a given specification compared to the overall specifications of the model space (Babcky et al. (2012)).

To identify the factors behind banking distress, we selected several categories of indicators, i.e. macroeconomic indicators, external indicators, financial indicators and institutional indicators. The results of our two specifications indicate that banking crises in the emerging countries of Central and Eastern Europe took place during phases of economic growth, characterized by an excessive growth of domestic credit as percentage of GDP, a strong growth liquidity reserves to total bank assets ratio, an inflow of foreign direct investment, a private credit boom and rising real interest rates, which is consistent with the work of Babecký et al. (2012). Moreover, regardless of the real interest rate, neither macroeconomic indicators nor institutional indicators seem to have a significant role in the emergence of banking crises in our sample.

Certainly the use of ordinary least squares (OLS), when the dependent variable is a binary variable, has some limitations. However, as has been stated by Babecký et al. (2012), « *alternative estimation methods such as logit or probit models have their own limitations when the distributional assumptions do not hold, for example in the presence of heteroscedasticity* » (P.28), which is the case of this study despite a relatively homogeneous panel.

This study is not exhaustive. A possible extension of this research is the development of an early warning system of a banking crisis to determine the predictive performance of BMA in detecting the emergence of systemic banking crises. Indeed, given the vulnerability of the banking sector to shocks and given the changing nature of banking risks, the use of early warning systems (EWS) for the prevention of crises is necessary.

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Appendix

Table 2. Sources and data descriptions:

		Indicators	Descriptions	Sources	Expected signs
Dependent Variable					
1		bankcrise	Binary variable constructed from the study of Laven and Valencia (2008, 2012)		
Independents Variables					
2	**Institutional variables**	depinsurance	Binary variable constructed from the work of Demirguc-Kunt and al. (2005) and updated by the FDIC (2011)		+/-
3		gdppercap	GDP divided by the number of the country habitants	WDI	-
4	**Financial variables**	bankliquidratio	Bank liquidity reserves to bank assets ratio	IFS	+
5		domesticcredit	Domestic credit as a percentage of GDP	IFS	+
6		creditgrowth	Private sector credit growth	IFS	+
7		moneymult	Money multiplier = M2 to the Base Currency	IFS	+
8	**Macroeconomic variables**	rertrend	Deviation of the exchange rate to the trend: $DEV_{Exchange\ rate} = \frac{Exchange\ rate - TREND}{TREND} \times 100$ The Hodric Prescott filter is used for the calculation of the trend.	IFS	+
9		resgrowth	Exchange reserves of the central bank (U.S.)	IFS	-
10		Rir	Real interest rate	IFS	+
11		inflation	Rate of change in consumer prices	IFS	+
12		indproduction	Index of industrial production	IFS	-
13		gdpgrowth	Gross Domestic Product	IFS	-
14	**External variables**	m2tores	M2 to reserves ratio	IFS	+
15		currentaccount	Current deficit as a percentage of GDP	WDI	-
16		export	Exports growth rate as a percentage of GDP	WDI	-
17		fdi	Foreign direct investment as a percentage of GDP	WDI	+
18		privcapitalflows	Foreign private capital flows as a percentage of GDP	WDI	+
19		import	Imports Growth rate as a percentage of GDP	WDI	+
20		termoftrade	Change in the terms of trade	WDI	-

Table 3. List of countries with the respective dates of banking crises:

Country	Dates of banking crises
Lithuania	1995-1996
Hungary	1991-1995
Slovak Republic	1998-2002
Bulgaria	1996-1997
Croatia	1998-1999
Estonia	1992-1994
Poland	1993-1994
Latvia	1995-1996 2008-2011

Table 4. Definitions of banking crises:

	Sources	Definitions
1	Caprio and Klingebiel (2003)	A systemic banking crisis occurs when most or all of bank's capital was exhausted. Caprio and Klingebiel use expert judgments when countries do not have reliable data which reflect the size of their losses.
2	Demirguç-Kunt and Detragiache (1998, 2005)	A banking crisis is considered to be systemic if the following four conditions are met: "(1) The ratio of non-performing assets to total assets in the banking system exceeded 10%; (2) The cost of the rescue operation was at least 2% of GDP; (3) Banking sector problems resulted in a large scale nationalization of banks; (4) Extensive bank runs took place or emergency measures such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees were enacted by the government in response to the crisis" (1998, p. 16)
3	Caprio and al. (2005)	Caprio and al. use the same definition as Caprio and Klingebiel (2003) (see above)
4	Laeven and Valencia (2008, 2012)	"A banking crisis is considered to be systemic if the following two conditions have to hold: (1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations); and (2) Significant banking policy intervention measures in response to significant losses in the banking system.' The first year that both criteria are met is considered to be the starting year of the banking crisis, and policy interventions in the banking sector are considered significant if at least three out of the following six measures were used: (1) extensive liquidity support; (2) bank restructuring costs; (3) significant bank nationalizations; (4) significant guarantees put in place; (5) significant asset purchases; and (6) deposit freezes and bank holidays." (2012, P.4)

Table 5. Number of observations, frequency of banking crises and tranquil periods by country:

Country	Observation	Banking crisis	
		Crise period	Quiet period
Lithuania	18	2	16
Hungary	18	2	16
Slovak Rep	18	5	13
Bulgaria	18	2	16
Croatia	18	2	16
Estonia	18	1	17
Poland	18	1	17
Latvia	18	5	13
Total	144	20	124

Table 6. Descriptive statistics:

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable					
bankcrise	144	0.15	0.3580674	0	1
Independents Variables					
depinsurance	144	0.8111111	0.3925122	0	1
rertrend	144	-3.332862	37.67908	-330.8186	116.6504
resgrowth	144	25.61012	54.41892	-96.12292	336.656
bankliquidratio	144	12.0207	9.945682	1.16005	57.47282
domesticcredit	144	35.77245	25.39245	0.0497851	107.9847
creditgrowth	139	8.709881	46.68976	-328.7469	251.0125
m2tores	144	329.3328	166.6727	1.949022	648.1811
moneymult	144	-15.1464	94.49238	-1011.544	11.67696
rir	144	27.50011	109.2988	-1.129477	1058.373
inflation	144	4.565641	7.973221	-23.99344	23.49617
indproduction	135	-3.841471	6.67065	-27.15748	18.03534
currentaccount	138	51.84786	16.51496	21.61797	92.26584
export	144	5.260788	6.709501	-16.06889	51.89585
fdi	144	3.263013	5.682061	-22.93405	12.23323
gdpgrowth	141	3564.939	2260.119	-17.54528	8693.835
gdppercap	144	54.98995	18.29894	19.65187	88.52395
import	140	-3.05E+13	3.96E+14	-5.15E+15	3393.29
termoftrade	136	-41.58052	1225.315	-14924.43	4897.671
privcapitalflows	144	4.371382	4.501045	-9.177752	28.65236

Note : Mean, Std. Dev, Max and Min, respectively denote the average, standard deviation, maximum and minimum.

Table 7. Average change of the independent variables during quiet periods and periods of banking crises:

	Average change	
Independents Variables	**Bankcrise = 0**	**Bankcrise =1**
rertrend	-0.369034	-5.826457
resgrowth	27.69801	-3.620316
bankliquidratio	14.1967	7.556674
domesticcredit	38.0744	29.72127
creditgrowth	9.195771	14.60751
m2tores	8.942251	4.686564
moneymult	1161523	376241
rir	332.8388	280.5407
inflation	-15.55578	-9.483379
indproduction	27.32896	29.89632
currentaccount	4.736146	1.389984
export	-3.878969	-3.272194
fdi	52.49098	42.08411
gdpgrowth	6.441779	1.513017
gdppercap	3.542525	-0.9296719
import	3655.477	2190.407
termoftrade	55.58535	45.95082
privcapitalflows	0.0000854	-0.0005747

Table 8. ***Pairwise correlation Matrixes :***

	rertrend	**resgrowth**	**bankliquidratio**	**domesticcredit**	**creditgrowth**	**m2tores**	**moneymult**	**rir**
rertrend	1							
resgrowth	-0.0509	1						
bankliquidratio	0.0818	-0.0316	1					
domesticcredit	0.0915	-0.1862*	-0.1621*	1				
creditgrowth	0.2408*	-0.0786	0.0183	-0.0067	1			
m2tores	0.0443	-0.0801	0.0597	0.0485	0.0186	1		
moneymult	0.0473	-0.0581	0.0537	0.1825*	-0.1066	0.3142*	1	
Rir	0.0846	**-0.5045***	-0.0463	0.1963*	0.2798*	0.0559	0.0906	1
inflation	-0.1071	**0.5882***	0.0379	-0.2373*	-0.2555*	-0.0557	-0.0989	**-0.9892***
indproduction	0.0779	0.1167	-0.1361	-0.1301	0.2797*	0.1024	0.1326	0.0758
currentaccount	0.0116	0.2126*	0.1582*	-0.1674*	-0.0999	-0.104	-0.0188	-0.1231
export	-0.0328	-0.1158	0.1221	0.3189*	-0.0775	0.3254*	0.2791*	0.032
Fdi	0.0485	-0.0369	-0.1123	0.1512*	0.0609	0.2150*	0.1012	0.0626
gdpgrowth	0.1497*	-0.0282	-0.2086*	-0.0225	0.2112*	-0.0211	-0.0034	0.3164*
gdppercap	-0.0805	-0.1826*	0.0614	0.4386*	-0.1209	0.2086*	**0.7903***	0.1657*
import	-0.0409	-0.1697*	0.037	0.3228*	-0.0191	0.2499*	0.1812*	0.0696
termoftrade	0.0021	-0.008	-0.0537	-0.0715	-0.0142	0.0248	0.0159	-0.011
privcapitalflows	0.0083	-0.0562	-0.0066	-0.1520*	0.0674	0.124	0.0465	0.0523

* Significant at the level of 5%.

Table 8. *Pairwise correlation Matrixes (continuation) :*

	inflation	indproductio n	currentaccoun t	export	Fdi	gdpgrowt h	gdpperca p	import	termoftrad e	privcapitalflow s
inflation	1									
indproduction	-0.2861*	1								
currentaccount	0.1431	-0.0897	1							
export	-0.0856	0.2259*	**- 0.5740***	1						
Fdi	-0.0917	0.0992	-0.4205*	0.2824*	1					
gdpgrowth	-0.3985*	**0.7713***	-0.2303*	0.1234	0.1372	1				
gdppercap	-0.2023*	0.126	-0.1784*	0.4223*	0.1373	**0.895***	1			
import	-0.1261	0.2195*	**-0.5058***	**0.9236***	0.3565*	0.1848*	0.3762*	1		
termoftrade	0.0168	-0.0011	0.0301	0.0415	-0.0188	-0.0244	-0.0955	0.0224	1	
Privcapitalflow s	-0.0858	0.2195*	-0.4640*	0.1510*	0.3279*	0.2298*	0.0451	0.2963*	-0.0241	1

* Significant at the level of 5%

Table 9. Estimation results of the first BMA regression:

	PIP	Post Mean	Post SD	Cond.Pos.Sign
bankliquidratio	0.99978609	2.12E-01	0.037420973	1
domesticcredit	0.99002107	1.21E-01	0.022063301	1
fdi	0.61597049	1.55E-01	0.152266485	0.9999991
m2tores	0.50672939	2.97E-03	0.003775085	0.99592176
currentaccount	-0.48041506	7.47E-02	0.097991618	0.00052185
moneymult	0.42975949	6.04E-03	0.009880723	0.95395563
rir	0.40634001	1.56E-03	0.002475272	0.99273266
privcapitalflows	0.27863059	3.58E-02	0.107153709	0.81511808
rertrend	-0.27037846	1.53E-01	0.387127753	0.00532836
gdpgrowth	0.21860807	1.35E-02	0.05370902	0.8601079
termoftrade	-0.20374628	1.46E-04	0.000522551	0.0104077
creditgrowth	0.16876995	8.62E-05	0.002568444	0.59029893
depinsurance	0.00997499	7.09E-02	0.721375565	1

Note: PIP, Post Mean, Cond.Pos.Sign denote subsequently inclusion probability, a posteriori average, a posteriori variance and conditional sign-post.

Table 10. Estimation results of the second BMA regression:

	PIP	Post Mean	Post SD	Cond.Pos.Sign
domesticcredit	1	1.13E+00	1 0.0173466068	1
bankliquidratio	0.99953949	2.02E+00	1 0.0355180522	1
lagcreditgrowth	0.85305414	1.41E+00	2 0.0081119015	1
rir	0.67340779	3.15E+00	3 0.0028184195	1
fdi	0.60944479	1.34E+00	1 0.1333585079	0.99999994
moneymult	0.5046864	7.48E+00	3 0.0096227351	0.976142
currentaccount	0.46087612	-6.22E+00	2 0.0860241326	0.00006875
m2tores	0.41709303	2.16E+00	3 0.0032765934	0.99940273
rertrend	0.31015094	-2.01E+00	1 0.4134183136	0
privcapitalflows	0.26723063	2.96E+00	2 0.0923901215	0.75446901
gdpgrowth	0.17023912	3.00E+00	3 0.0398587756	0.64409761
termoftrade	0.16409621	-6.98E+00	5 0.0003977805	0.02742701
creditgrowth	0.00028718	4.20E+00	6 0.0002794649	0.99767292
depinsurance	0	0.00E+00	0 0.0000000000	NA

Note: PIP, Post Mean, Cond.Pos.Sign denote subsequently inclusion probability, a posteriori average, a posteriori variance and conditional sign-post.