Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER THESIS

Systemic Risks Assessment and Systemic Events Prediction: Early Warning System Design for the Czech Republic

Author: Bc. Diana Žigraiová

Supervisor: PhDr. Ing. Petr Jakubík Ph.D.

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Declaration of Authorship

The author hereby declares that she compiled this thesis independently, using only the listed resources and literature and that this thesis has not been used to obtain a different or the same degree.

Prague, May 17, 2013

Signature

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Abstract

This thesis develops an early warning system framework for assessing systemic risks and for predicting systemic events, i.e. periods of extreme financial instability with potential real costs, over the short horizon of six quarters and the long horizon of twelve quarters on the panel of 14 countries both advanced and developing. Firstly, Financial Stress Index is built aggregating indicators from equity, foreign exchange, security and money markets in order to identify starting dates of systemic financial crises for each country in the panel. Secondly, the selection of early warning indicators for assessment and prediction of systemic risks is undertaken in a two-step approach; relevant prediction horizons for each indicator are found by means of a univariate logit model followed by the application of Bayesian model averaging method to identify the most useful indicators. Next, logit models containing useful indicators only are estimated on the panel while their in-sample and out-of-sample performance is assessed by a variety of measures. Finally, having applied the constructed EWS for both horizons to the Czech Republic it was found that even though models for both horizons perform very well in-sample, i.e. both predict 100% of crises, only the long model attains the maximum utility of 0,5 as well as maximizes area under Receiver Operating Characteristics curve which measures the quality of the forecast.

JEL Classfication	C33, E44, F47, G01
Keywords	Systemic risk, Financial stress, Financial crisis, Early warning indicators, Bayesian model averaging, Early warning system

Author's e-mail	diana.zigraiova@yahoo.com
Supervisor's e-mail	PetrJakubik@seznam.cz

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Abstrakt

Táto práca vytvára systém včasného varovania na hodnotenie systémového rizika a predpoveď systémových udalostí, t.j. období extrémnej finančnej nestability spojených s možnými reálnymi nákladmi, pre krátky horizont šiestich kvartálov a dlhý horizont dvanástich kvartálov na panele štrnástich krajín obsahujúcom vyspelé aj rozvojové ekonomiky. Najprv je zostavený indikátor finančného stresu pomocou agregácie indikátorov z trhov cenných papierov, peňažného, akciového a devízového trhu s cieľom určiť počiatok systémových finančných kríz pre jednotlivé krajiny v panele. Zaďalšie, výber indikátorov včasného varovania na hodnotenie a predpoveď systémového rizika prebieha v dvoch krokoch; príslušné horizonty predpovede pre každý indikátor sú určené pomocou jednopremenného logit modelu, za čím nasleduje nájdenie najužitočnejších indikátorov použitím metódy Bayesian model averaging. Potom sa logit modely zahrňujúce len užitočné indikátory aplikujú na panel krajín a ich výkon v rámci vzorky a mimo nej je hodnotený prostredníctvom viacerých štatistík. V závere po aplikovaní zostaveného modelu pre oba horizonty na Českú republiku bolo zistené, že zatiaľ čo oba modely majú veľmi dobrý výkon v rámci vzorky, t.j. oba predpovedajú 100% kríz, iba dlhý model dosahuje maximálny úžitok 0,5 a tiež maximalizuje plochu pod Receiver Operating Characteristics krivkou poukazujúcou na kvalitu predpovede.

Klasifikácia	C33, E44, F47, G01
Kľúčové slová	Systémové riziko, finančný stres, finančná kríza, indikátory včasného varovania, Bayesian model averaging, systém včasného varovania

E-mail autora	diana.zigraiova@yahoo.com
E-mail vedúceho práce	PetrJakubik@seznam.cz

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Master Thesis Proposal

Institute of Economic Studies
Faculty of Social Sciences
Charles University in Prague

Author:	**Bc. Diana Žigraiová**	Supervisor:	PhDr. Ing. Petr Jakubík Ph.D.
E-mail:	diana.zigraiova@yahoo.com	E-mail:	PetrJakubik@seznam.cz
Phone:	737420946	Phone:	777066091
Specialization:	*Finance, Financial Markets and Banking*	Defense Planned:	June 2013

Proposed Topic:

Systemic Risks Assessment and Systemic Events Prediction: Early Warning System Design for the Czech Republic

Topic Characteristics:

The aim of this thesis topic is to construct a framework that would allow for systemic risks assessment and for out-of-sample prediction of systemic events, i.e.: periods of high financial stress that often bear a negative effect on the real economy, on a country level and subsequently apply it to the Czech Republic. Firstly, the methodology will be built up and tested for the panel of countries followed by the application to the case of the Czech Republic. In order to ensure robustness of the model a panel of 15 countries that experienced in their existence a crisis and belonging in different world regions-Europe/Asia/Latin America will be used. Both developing and mature countries (Argentina, Brazil, Mexico, Thailand, South Korea, Japan, US, Russia, Turkey, UK, Hungary, Poland, Euro area, Switzerland, Sweden) are to be employed to evaluate the model's ability to identify historical periods of elevated financial stress as well as its out-of-sample performance using high stress levels associated with the global recent crisis. Indicators for systemic stress have to be developed in the model for each country which would comprise of several market segments within a country (equity, bond, exchange rate, money market) as large shocks are accompanied by co-movements among different variables. As financial instability resulting from high stress episodes can negatively impact real economy to the point of harming economic growth and welfare, it is necessary to study the link between the systemic stress indicators and real economy variables which reflect the accumulating vulnerabilities in both a country's as well as global economy. Individual standalone indicators will be selected in each category by their usefulness/utility obtained from the utility function which reflects policymakers' preference towards either Type I or II statistical errors (either failure to detect crisis or false signaling). Afterwards several models including most useful standalone indicators and country-specific systemic stress indices will be tested with respect to the usefulness measure and percentage of crises predicted such as pooled, fixed effects model, only regional countries included models (Asia, Latin America, Europe), developing only and mature only countries models. Next, for all models their out-of-sample prediction performance will be observed over horizons of different length (4, 6, 8 quarters) to test which models and over which horizon are capable of anticipating the global recent crisis. Finally, the individual models constructed for different country groups will be applied to all available data for the Czech Republic with the objective of identification of historical periods of increased financial stress similarly as out-of-sample detection performance for the recent crisis with truncated data. Furthermore, this model can be used for future predictions when containing all the data till present. The thesis could contribute to the research on crises detection mechanisms, especially for the countries that have not been often in the midst of such efforts as is the case of the Czech Republic.

Hypotheses:

1. The model for the systemic risks assessment and crises prediction suitable for the Czech Republic can be found among the studied alternatives (pooled, fixed effects, for mature/developing countries, geographical country groups).
2. Construction of the indicator of systemic stress: equally weighted vs. varying subindex weights can be developed.
3. Identification of major systemic events in the data sample and issuing of an early warning signal for the recent crisis can be successful by the selected appropriate model for the Czech Republic.

Methodology:

Publicly accessible databases will be used for data needed for calculations of standalone indicators and indices of systemic stress in the course of the work, e.g.: EIU Country Data, OECD iLibrary, World Bank data resources, Eurostat. All models will be constructed using logistic regression approach with country-specific indicators of systemic stress as endogenous variables and a set of macro-financial variables for each country at time t as explanatory ones. The dependent variable is the probability that a systemic event happens for a given country meaning that the indicator of systemic stress equals 1 after having hit/surpassed a chosen threshold level. The indicator of systemic stress could be calculated by either weighting all its subindices for individual market segments equally (arithmetic average) or by varying the weights of market segment subindices with respect to the risk they carry to the overall system (analogy for the portfolio approach). For the latter a VAR model is used. Finally, the weights will be estimated by impulse response functions.

Outline:

1. Introduction to the Topic and Literature Overview
2. Construction of Indicator of Systemic Stress Measure (Comparison of the equally weighted measure and the variable weights measure)
3. Selection and Calculation of Variables for Macro-financial Vulnerabilities
4. Empirical Analysis (Optimal Threshold Calculations for Vulnerability Indicators and Usefulness Levels)
5. Logit Model (Evaluation of Different Alternatives)
6. Out-of-Sample Performance of the Models

7. Application of the Methodology to the Czech Republic and Evaluation
8. Conclusion

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Acronyms

EWS	Early Warning System
ERM	Exchange rate mechanism
FSI	Financial Stress Index
CFSI	Cleveland Financial Stress Index
ECB	European Central Bank
GIFT	Global Index of Financial Turbulence
STLFSI	St. Louis Fed's Financial Stress Index
GARCH	Generalized autoregressive conditional heteroscedasticity
GDP	Gross Domestic Product
IMF	International Monetary Fund
NCB	National Central Bank
OECD	Organization for Economic Cooperation and Development
BIS	Bank for International Settlements
WB	World Bank
EIU	Economist Intelligence Unit
CPI	Consumer Price Index
BMA	Bayesian Model Averaging
PIP	Posterior inclusion probability
MCMC	Markov Chain Monte Carlo
LR	Likelihood Ratio
OLS	Ordinary Least Squares
U	Utility
PCP	Percentage correctly predicted
ROC	Receiver Operating Characteristics
NtS	Noise to Signal
ADF	Augmented Dickey-Fuller
3M T-bill	3 month Treasury bill
M2	Monetary aggregate M2
UK	United Kingdom
USA	United States of America
Q	quarter of a year

1 Introduction

In the wake of recent global crisis research in the area of financial stability has demonstrated its importance and as such has attracted renewed attention. Hence, early warning literature with its main focus on monitoring and measuring systemic risks and predicting systemic events seeks to enable identification of periods of elevated financial stress, that could potentially inflict real costs on the economy, by means of an early warning system (EWS). This thesis contributes to the early warning literature by developing an EWS framework for two horizons, the short of six quarters and the long of twelve quarters, preceding a materialization of a systemic event on the panel of 14 countries (both advanced and developing economies). The constructed EWS for both horizon lengths is then applied to the Czech Republic where its suitability is assessed via its in-sample performance.

The first step udertaken in this thesis in building an EWS is the construction of an aggregate measure of financial stress within the financial system, i.e. Financial stress index (FSI), for each country in the panel. This approach to systemic risk measurement allows for a more objective identification of systemic event starting dates as opposed to crises identification exploiting qualitative information such as Laeven and Valencia (2008).

Secondly, identification of useful leading indicators of crisis occurrence from the accumulated set of 40 potential indicators is dealt with in two steps. Firstly, the assumption of the common fixed horizon at which all indicators issue early warning signals is eased and for each indicator this horizon is estimated separately by a univariate logit model. In the second step, selection of only the most useful indicators is executed systematicaly and concisely via Bayesian model averaging (BMA), a relatively new technique in early warning literature as employed in Babecky, Havranek et al. (2011, 2012), that distinguishes the most useful indicators from among all possible combinations of indicators entered into BMA. Additionally, this thesis offers assessment of usefulness of potential leading indicators by means of signalling analysis, i.e. a framework accounting for preferences between issuing false alarms and missing systemic events.

Next, the discrete choice model (logit model) contaning only the most useful indicators is estimated for both horizons while its in-sample and out-of-sample performance over the pre-crisis period of the global recent crisis and over the last two years (2011Q1-2013Q1) is evaluated by a set of performance measures, i.e. utility measure (U) from signalling analysis, percentage of observations correctly predicted (PCP), percentage of crises predicted, Noise to Signal ratio (NtS) and size of area under Receiver Operating Characteristics (ROC) curve.

Finally, the EWS for both horizons constructed on the panel of countries is applied to the Czech Republic using Bayesian estimation of logit model due to perfect prediction problem. The model in-sample performance for the Czech Republic is assessed by the same set of performance measures that were employed for model verification on the panel of countries.

All in all, this thesis is organized as follows. Chapter 2 presents an overview of early warning literature, EWS and financial stress measures. Chapter 3 states methodology and develops the Financial stress index (FSI) while chapter 4 presents the resulting FSIs for the panel of countries. In chapter 5 systemic events are identified from the calculated FSIs. Chapter 6 deals with the identification of leading indicators for systemic events detection. Chapter 7 introduces, estimates and evaluates performance of systemic events probability prediction framework, i.e. logit model, for both horizons, short of 6 quarters and long of 12 quarters. Chapter 8 focuses on the application of the developed EWS for both horizons to the Czech Republic, its estimation and in-sample performance evaluation. Finally, chapter 9 concludes.

2 Early Warning System for Crises Prediction: A Literature Overview

Early warning systems (EWS) can be characterized as functional, data-driven approaches which draw attention to variables associated with past crises with the main objective of alerting policy-makers of the potential for future crises (Gramlich, Miller et al., 2010). Essentially EWSs are based on the two basic assumptions:

1. The existence of causality between crises and crisis-driving factors.
2. Possibility of crisis-driving factors identification ex ante.

In the financial context, EWSs can be used for risk prediction of both a single financial institution risk from microeconomic point of view as well as the risk of an entire financial system, i.e. macroeconomic risk. Of the aforementioned risks the latter is the point of interest of this thesis. Before the concepts and development of EWSs over the years are presented, it would be prudent to provide the general definition of systemic risk as „the possibility that an event will trigger a negative feedback loop that significantly affects financial markets' ability to allocate capital and serve intermediary functions, which, in turn, will create spillover effects on the real economy that have no clear self-healing mechanism“ (Hendricks, Kambhu, and Mosser (2007, p. 65)). And as such the functioning of the financial system is impaired to the extent that economic growth and welfare suffer materially (Peltonen and Lo Duca, 2011).

The earliest literature on macroeconomic risk focused on currency crises. In the paper by Krugman (1979) he concluded that under a fixed-rate exchange system, credit expansion exceeding money demand growth diminishes foreign reserves and eventually leads to a speculative attack on the currency. An influential contribution to this branch of literature were a series of papers by Eichengreen, Rose and Wyplosz (1994, 1995, 1996) which center on countries that pegged their exchange rates (fixed-rate exchange system) and come to the finding that the behaviour of key macroeconomic variables for European exchange rate mechanism (ERM) countries vary across periods, but that these differences do not appear in countries outside of the ERM. These results make them conclude there are no clear early warning signals of speculative attacks as opposed to conclusions of many of the subsequent papers in the literature. One of such papers by Frankel and Rose (1996) shifts the focus of this literature towards modeling currency crashes for developing countries using probit analysis. In their study they use solely large exchange rate movements for their currency crisis definition unlike Eichengreen et al. (1994, 1995, 1996). The ultimate finding of Frankel and Rose (1996) is that an early warning of a currency crisis can be provided by their model as low levels of foreign direct investment and international reserves, high domestic credit growth, high foreign interest rates, and the overvaluation of the real exchange rate increase the probability of a currency crash.

In the wake of the Mexican crisis, Kaminsky and Reinhart (1999) develop an EWS model to consider currency and banking crises and analyse the links between the two. In a series of subsequent papers, Kaminsky, Lizondo and Reinhart (1998) and Goldstein, Kaminsky and Reinhart (2000) build upon this research using the signal extraction method which allows for assessment of macroeconomic and financial variables' behaviour around the time of the crisis. They found that the majority of crises have numerous weak economic fundamentals at their core which led them to the conclusion that banking and currency crises in emerging markets do arrive with certain early warnings. However, the model's predictive power is greater for currency crises than for banking crises. Based on this body of research with the inclusion of some recent papers, e.g. Reinhart and Rogoff (2009), a common conclusion can be derived that banking crises occur when rapid credit expansion fuels sustained asset-price growth that substantially deviates from trend (Borio and Lowe, 2002).

In general, financial stress can apply to various institutions or segments of the economy, such as financial companies, securities, banking system, market segments such as foreign exchange markets. In light of this fact, there have been some attempts at categorizing financial crises into types and measuring them individually. Ishihara (2005), for example, defined six types of financial crises (banking liquidity, banking solvency, balance of payments, currency, external debt, growth rate, and financial crisis) as well as proposed their measures. As excessively narrow crisis definition may lead to inconsistent policies, as well as crises being progressively multidimensional, a broader concept for financial crises assessment should be beneficial. In this regard, De Bandt and Hartmann (2000) offer a systemic crisis definition as an "event that affects a considerable number of financial institutions or markets in a strong sense". The more recent research characterizes systemic crises by means of transition structures where "systemic risk is the movement from one stable (positive) equilibrium to another stable (negative) equilibrium" (Hendricks, Kambhu, and Mosser (2007)). Following this line of reasoning there has been a shift from classical bank-based crises to more recent market-based ones.

2.1 Financial Stress Indicators: An Overview

Despite the fact that root causes of financial crises throughout history are often diverse along with their propagating channels and market segments that are consequently affected, it is still interesting to compare these events in terms of systemic stress levels reached. For this reason a general objective of constructing a financial stress index (FSI) is to measure, in an analytical way, the level of instability (frictions, stresses) within a financial system and to present the findings in a single statistic.

Formerly, the literature on financial crises has substantially depended on historical narratives of crisis episodes, that is mostly for banking crises connected with bank capital erosion and disruption of lending; cases which typically demanded public intervention (Caprio and Klingebiel, 2006). Other such documented episodes further banking crises cases with those of currency crises which exhibit reserves depletion and/or major changes in exchange rate mechanism (e.g. Kaminsky and Reinhart, 1999). Despite the fact that these historical crises narratives provide a wide database of crisis episodes, there has been an outbreak of a more analytically based research that aspires to quantify financial stress within the economy by means of a single comprehensive statistic, FSI. The underlying reason for this branch of research is the existence of several drawbacks linked to the above-mentioned historical approches to crises identification. Firstly, these crisis episodes are known ex post to have large output effects and often required large public intervention while high stress episodes of little macroeconomic impact were often disregarded. Secondly, episodes identified by historical approaches usually spread over considerable time periods and thus incorporate stresses of varying magnitudes making it challenging to identify stress peak dates. Lastly, as databases tend to focus on banking and currency crises, security market stress or liquidity squeezes are easily overlooked, e.g. Long-Term Capital Management collapse of 1998. To avoid these problems, extreme values of a composite indicator - FSI are used for financial stress identification.

The purpose of the following literature review is to highlight varying methodologies for FSI calculation and raw measures aggregation into the composite stress measure.

For Canada Illing and Liu (2006) constructed a financial stress index by attempting various aggregation techniques for individual stress measures. Their final FSI, based on its performance in capturing stress events in Canada, was composed of 11 variables whose weights were determined as size of the market into which each variable belonged relative to the total credit measure in the economy. The Cleveland Financial Stress Index (CFSI) constructed by Oet et al. (2011) also uses credit-weighting technique as they deemed it the most preferable.

Other approach for variables aggregation into FSI is a variance-equal weighting, i.e. arithmetic average of individual stress measures. Good examples of this aggregation method are papers by Cardarelli, Elekdag and Lall (2011), Yiu, Ho and Jin (2010), The ECB (2009a) or Peltonen and Lo Duca (2011). The FSI by Cardarelli, Elekdag and Lall (2011) is built for 17 advanced economies and while they grouped individual stress measures into three subindices, for securities, banking and foreign exchange markets, this was not of importance for FSI calculation as simple average was ultimately used. Yiu, Ho and Jin (2010) computed their FSI for Hong Kong using 6 raw measures. The FSI by ECB (2009a) called the Global Index of Financial Turbulence (GIFT) was built for 29 countries employing indicators from equity, fixed-income and exchange rate markets and again using arithmetic average for their aggregation. Peltonen and Lo Duca (2011) created a parsimonious FSI for 28 countries altogether which comprised five raw stress measures.

Another method of FSI computation and aggregation is a principal components approach (Hakkio and Keeton, 2009). The underlying reasoning being that financial stress is the most important factor for observed correlation between individual indicators and that it can be identified by the first pricipal component of the correlation matrix calculated for standardized indicators. The calculation of weights for each raw measure entering their FSI is based on the respective measure's contribution to the first principal component. Kliesen and Smith (2010) adopted the same approach for calculation of St. Louis Fed's Financial Stress Index (STLFSI).

Last but not least, The FSI for Greece constructed by Louzis and Vouldis (2011) aggregated five subindices into the composite measure by estimating their cross correlation by a multivariate GARCH model, in other words, by application of portfolio-theoretic principles. The use of portfolio approach to indicators aggregation in financial crisis literature, more specifically in composite indicators calculation, was pioneered in the paper by Hollo, Kremer, Lo Duca (2010) and applied also in its subsequent version of 2012.

3 Developing a Measure of Financial Stress

To ensure robustness of the Early Warning System model this thesis has for its objective to construct; a measure of financial stress within the economy, i.e. FSI, shall be developed in this chapter for the panel of 15 countries and one region (Euro area). The panel includes mature economies as well as developing ones from different geographical regions. In order to facilitate comparisons of FSI and its underlying components with macroeconomic variables which will be used later in the EWS model itself, FSI is constructed on a quarterly basis.

The FSI was calculated with the following characteristics in mind:

- *Systemic nature of the index:* the index should incorporate indicators from main segments of domestic financial market as impact of a negative shock on the economy is typically observable in several of its segments. The more systemic a shock, the larger the co-movement among variables pertaining to different market segments. Aggregation of these market-specific indicators within the FSI allows to adequately track the crisis evolution.
- *Cross-country character of the model:* as EWS will be built on a panel of countries and only subsequently applied to the

Czech Republic, a uniform set of indicators will be used for FSI calculation. In case it can not be done so due to data unavailability for some countries within the panel, a substitute indicator is used. This alternative FSI is also computed for every other country in the sample as a robustness check in order to verify that it captures high stress periods appropriately.

- *Parsimony of the FSI composition:* the choice to use a minimum set of indicators for FSI construction can be justified by firstly, restricted availability of data across time and countries and secondly, by the fact that once indicators for vital parts of the economy are included in the index adding more components does not significantly change the shape of the composite stress measure (Hollo, Kremer and Lo Duca, 2010). Moreover, inclusion of too many indicators „could potentially contaminate the FSI with noisy indicators" (Cardarelli, Elekdag and Lall, 2011).

3.1 FSI Composition

Keeping the previously mentioned features of the FSI developed in this thesis in mind, the FSI as a country-specific composite financial stress index, was calculated by aggregating the following 5 components:

1. *Negative quarterly returns of the main equity index,* calculated from equity returns which were multiplied by -1 so that negative returns increase financial stress while positive returns were set to 0.
2. *Realised volatility of the main equity index,* calculated by determining standard deviation of the main equity index values over the last 12 months leading to each observation date.
3. *Realised volatility of the nominal effective exchange rate,* resulting from computing standard deviation of nominal effective exchange rate values over the last 12 months leading to each observation date.

4. *The TED spread,* measured as the difference between 3-month interbank rate and 3-month Treasury bill rate. This component represents the credit risk associated with interbank lending. The higher the TED spread the more the default risk on interbank loans is perceived.
5. *Realised volatility of the yield on 3-month Treasury bills,* calculated as standard deviation of 3-month Treasury bill yields over the last 12 months preceding each observation date.

For some countries an alternative set of indicators was developed due to data unavailability. These indicators are aggregated into a so-called „Alternative FSI“ which differs from the originally constructed FSI in 2 components, namely the last 2 components (4 and 5) are substituted by the following indicators:

1. *Inverted interest rate spread*, calculated as the difference between interest rate paid by banks on demand, savings or time deposits minus interest rate charged by banks on loans. In general, the measure is used as a proxy for profitability in a banking sector.
2. *Realised volatility of the yield on long-term government bonds*, calculated as standard deviation of long-term government bond yields over the last 12 months preceding each observation date.

The following table 3.1 offers overview of the above-mentioned components that are aggregated into both composite systemic stress indices, FSI and Alternative FSI, as well as their sources.

Component	Subcomponent	Description	Source
Main equity index		negative returns	author based on Eurostat, EIU CountryData, Reuters
Main equity index		realised volatility	author based on Eurostat, EIU CountryData, Reuters
Nominal effective exchange rate		realised volatility	author based on BIS
TED spread	3M interbank rate	%	NCB, OECD, IMF, Reuters
	3M T-bill rate	%	NCB, IMF, Reuters
3M T-bill rate		realised volatility	author based on NCB, IMF, Reuters
Inverted interest rate spread	Deposit rate	%	NCB, IMF
	Lending rate	%	NCB, IMF
Long-term government bond rate		realised volatility	author based on NCB, IMF, Reuters

Table 3.1: FSI and Alternative FSI components
source: author based on listed sources

Moreover, the composition of this FSI accounts for the four fundamental characteristics of the financial stress widely documented in the literature (e.g. Hakkio and Keeton, 2009, Fostel and Geneakoplos 2008):

- *Significant shifts in asset prices* (here captured through main equity index returns)
- *A sudden increase in risk or uncertainty* (here captured through realised volatility of the main equity index, treasury bills rate realised volatility, alternatively through realised volatility of yield on government bonds and realised volatility of nominal effective exchange rate)
- *Abrupt changes in liquidity* (here expressed by TED spread)
- *State of the banking system* (here its health is approximated by interest rate spread as a proxy for profitability)

As stated earlier, the developed FSI can be deemed systemic as it incorporates financial stress indicators from key market segments:

- *Equity market* (negative returns of the main equity index, realised volatility of the main equity index)
- *Foreign exchange market* (realised volatility of the nominal effective exchange rate)
- *Securities market* (realised volatility of rate on the 3-month Treasury bills and on long-term government bonds)
- *Money market* (TED spread, inverted interest rate spread)

3.2 Transformation and Aggregation of Components into FSI

Each of the 5 components of the FSI is transformed before aggregation in order to facilitate measuring and cross-country comparison of financial stress levels by each FSI. Therefore, every observation at every point in time (year's quarter) for each indicator was assigned the value equal to the percentile it represents of the country-specific distribution function for this indicator. The values of thus transformed observations for each component range from 0 to 1 included. The individual stress components were designed in such a way that their higher values representing higher percentiles of their distributions signal increased financial stress levels.

The transformed variables are then aggregated in the FSI according to the following formula:

$$FSI_{i,t} = \sum_{j=1}^{5} w_j \cdot Ind_{j,i,t}$$

where *j* represents each indicator of the FSI, *i* indicates a country within the sample and *t* stands for the quarter an observation falls into. The FSI is thus a continuous measure at quarterly frequency that is calculated as a weighted average of the 5 transformed indicators for each country *i* at each quarter *t*. The weights are fixed for each component across all countries due to the cross-country character of the FSI and its homogenous composition.

Alternatively, unweighted FSI defined by the formula:

$$FSI_{i,t} = \frac{\sum_{j=1}^{5} Ind_{j,i,t}}{5}$$

would place equal weight to each FSI component but at the same time some market segments included into FSI calculation might be favoured over others. For the constructed FSI this means placing too much emphasis on indicators capturing stress in equity market (weight of 40% as two indicators pertain to this market) and equally lower significance to foreign exchange, securities and money markets (weight of 20% per market due to one included indicator from each market). As such, for purposes of this thesis market-equal weighting is chosen for indicators aggregation, i.e. placing a weight of 25% to each market represented within FSI. In this spirit, the distribution of weights among individual indicators is as follows:

- 12,5% for negative returns of the main equity index
- 12,5% for the realised volatility of the main equity index
- 25% for the realised volatility of the nominal effective exchange rate
- 25% for TED spread or inverted interest rate spread
- 25% for the realised volatility of the 3-month Treasury bill rate or long-term government bond yield volatility

Inclusion of economies at different stages of their development (both advanced and emerging) justifies the use of market-equal weighting scheme. Had this thesis attempted a country-specific case study of financial stress, this approach would not be accurate due to existence of large differences among countries within the sample and therefore different markets might adequately capture financial stress for each country. Hence, the market-equal weighting is preferred due to the cross-country nature of the model.

4 Resulting Financial Stress Indices for the Panel of Countries

The aim of this section is to present the results of author's calculations following the reasoning and the methodology offered in previous sections of the thesis. The calculated FSIs are presented for each country in the sample separately along with appended comments explaining the financial stress levels captured.

4.1 FSI for Argentina

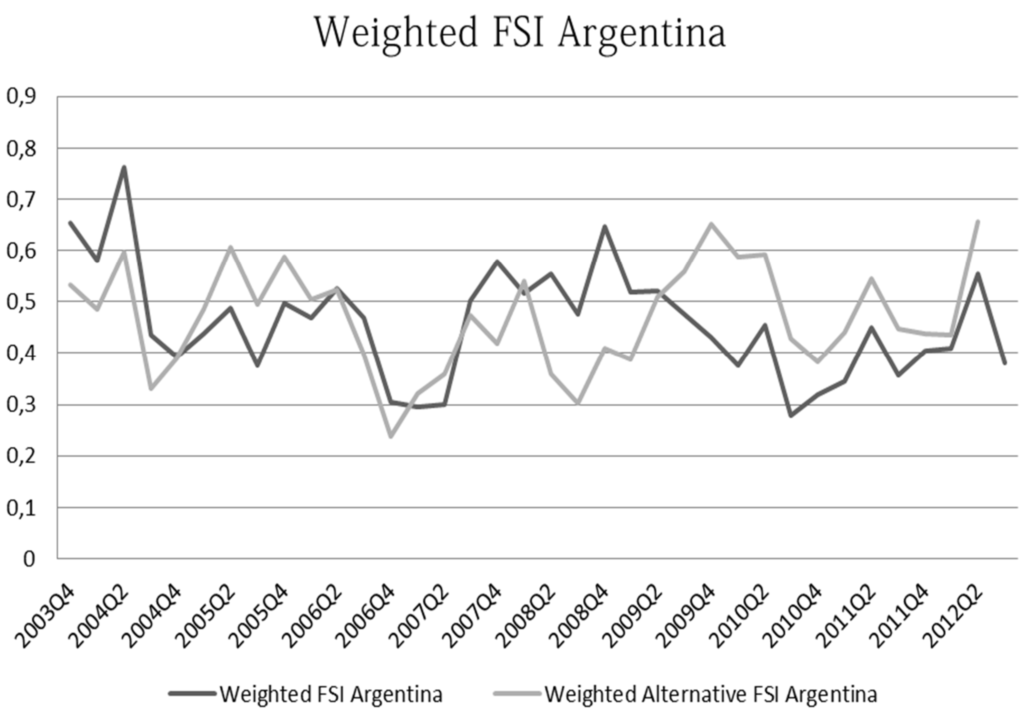


Figure 4.1: Weighted FSI for Argentina Source: author's own calculations

The figure 4.1 depicts the financial stress levels measured by the two types of FSI. The "Alternative FSI" differs from the principal FSI in the two components while both indices resulted from market-equal weighting of components as stated in the section about methodology above. Both stress measures capture the periods of elevated financial stress in a similar fashion.

The FSI reaches its highest values over the studied period at the beginning of the sample, a value which overcomes even the stress levels detected during the recent global crisis. As Lo Duca and Peltonen (2011) observed, in many emerging economies the level of financial stress was higher during some country-specific crisis, such as crisis in Argentina in 2001, than that detected during Global Financial Crisis.

According to crises database by Laeven and Valencia (2008) debt crisis, systemic banking crisis and currency crisis with starting dates of 2001, 2001 and 2002, respectively, occurred in Argentina. The crises originated by a bank run in March 2001 provoked by doubts about the sustainability of the currency board among others. Consequently, the FSI registers the highest stress in 2004.

4.2 FSI for Brazil

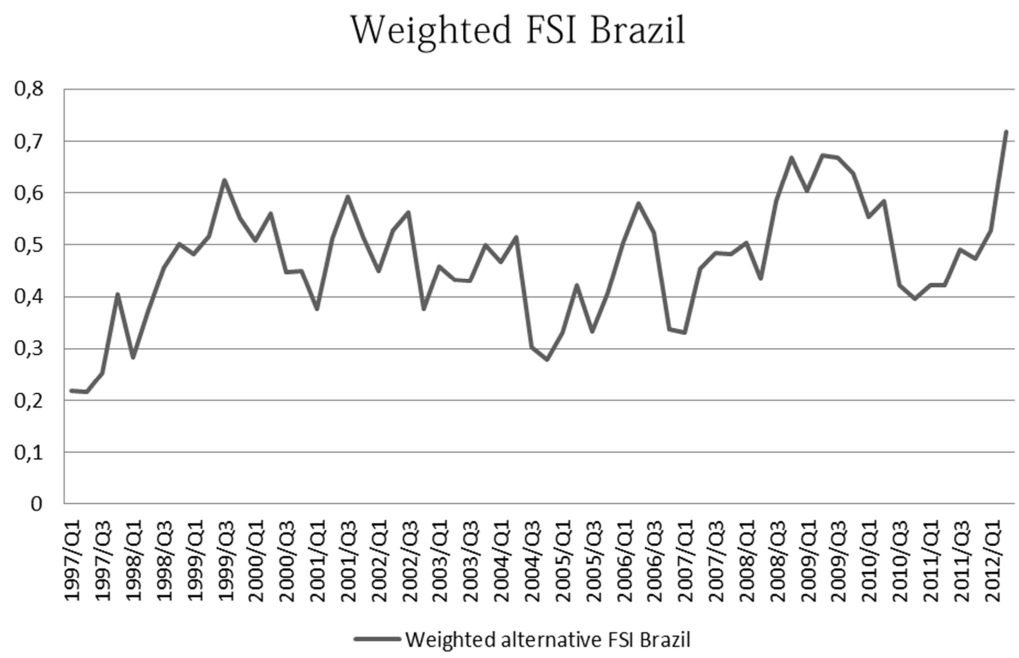


Figure 4.2: Weighted FSI for Brazil Source: author's own calculations

Due to restricted data availability FSI for Brazil was calculated using the alternative set of components as well as market-equal weighting was applied. The "alternative FSI" is shown to be a reliable measure of financial stress as demonstrated in the following calculations for individual countries. Moreover, Cardarelli, Elekdag and Lall (2011) observed that "FSI is quite robust in capturing the main financial stress episodes documented in narrative descriptions and in the literature".

The Brazilian FSI registers the highest stress during the recent crisis and towards the end of the sample. Elevated financial stress levels are, however, detected also around the turn of the millennia which coincides with the start of the Brazilian currency crisis according to Laeven and Valencia (2008).

4.3 FSI for the Czech Republic

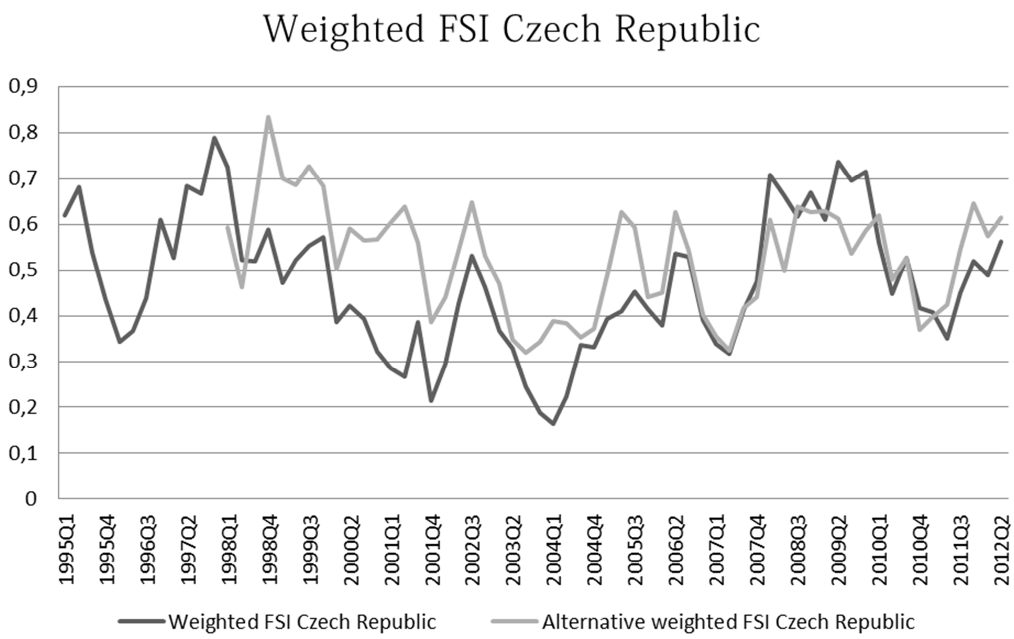


Figure 4.3: Weighted FSI for the Czech Republic Source: author's own calculations

As the main objective of this thesis is to develop a suitable EWS for the Czech Republic, FSI had to be calculated first and in line with the methodology. The FSI peaks in the last quarter of 1997 as it registers higher stress levels than during the recent crisis. The elevated stress at that time is associated with the systemic banking crisis which started in 1996 as a result of bank failures, runs at small banks and a subsequent bank restructuring (Laeven and Valencia, 2008).

4.4 FSI for Euro area

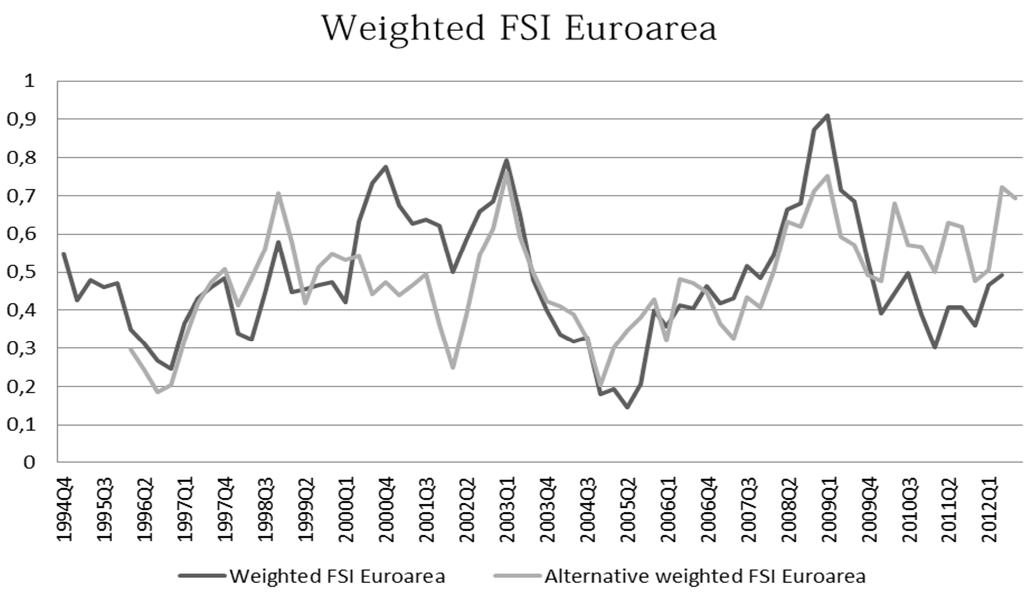


Figure 4.4: Weighted FSI for the Euro area Source: author's own calculations

Constructing FSI for a geographical region, the Euro area, is slightly particular as it is an aggregation of economies, both advanced and developing. As such, it is important to assess how well the FSI can capture the financial stress during the recent global crisis. It is observable from the figure 4.4 that the FSI attained its highest values during crisis period in 2008/2009.

4.5 FSI for Hungary

From the figure 4.5 below it is discernible that the FSI identified higher stress levels during the recent global crisis than at the beginning of the sample when the Hungarian country-specific crisis occurred. According to the documented crises database by Laeven and Valencia (2008) Hungary experienced apart from the recent crisis only one other crisis starting in 1991 which was a systemic banking one. The FSI thus correctly captures both instances of increased financial stress over the sample period.

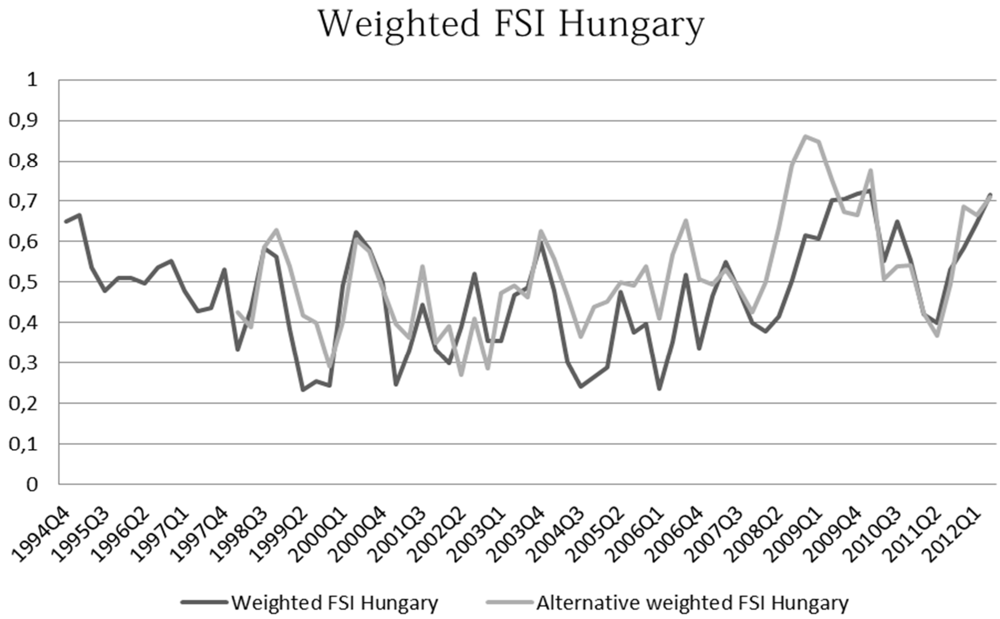


Figure 4.5: Weighted FSI for Hungary Source: author's own calculations

4.6 FSI for Japan

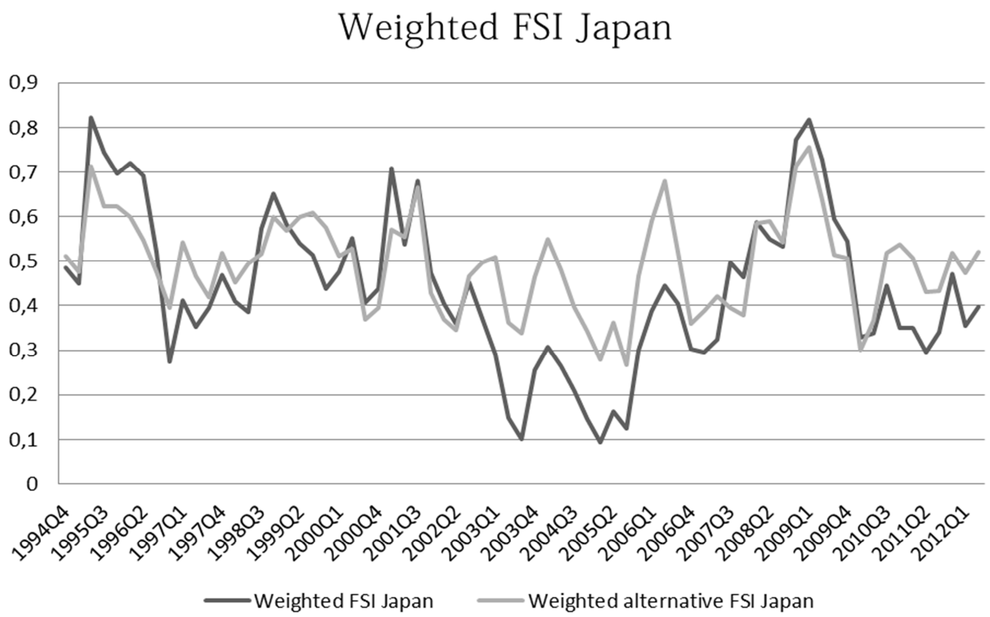


Figure 4.6: Weighted FSI for Japan Source: author's own calculations

Japan as an advanced economy experienced two periods of comparably high financial stress, i.e. during the recent global crisis and in the period immediately preceding the outbreak of the Japanese systemic banking crisis in 1997 (Laeven and Valencia, 2008). The underlying causes of this crisis constituted of a sharp decline in stock market and real estate prices followed by a dramatic increase in the value of banks' nonperforming loans.

4.7 FSI for the Republic of Korea

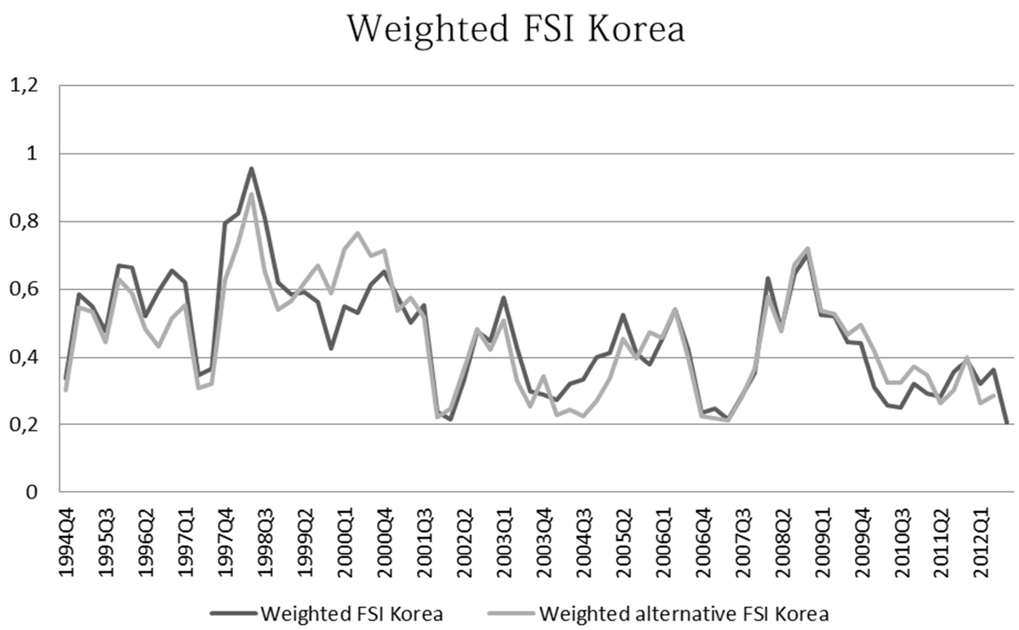


Figure 4.7: Weighted FSI for Korea Source: author's own calculations

The Republic of Korea is a good example of a country from the region of Asia that reflects well the Asian crisis of 1997 in its financial system. The value of the FSI nearly reached 1, the maximum, in the second quarter of 1998. Laeven and Valencia (2008) justify this finding by having identified the occurrence of the Korean systemic banking crisis with a starting point in 1997 followed by a currency crisis starting in 1998.

4.8 FSI for Mexico

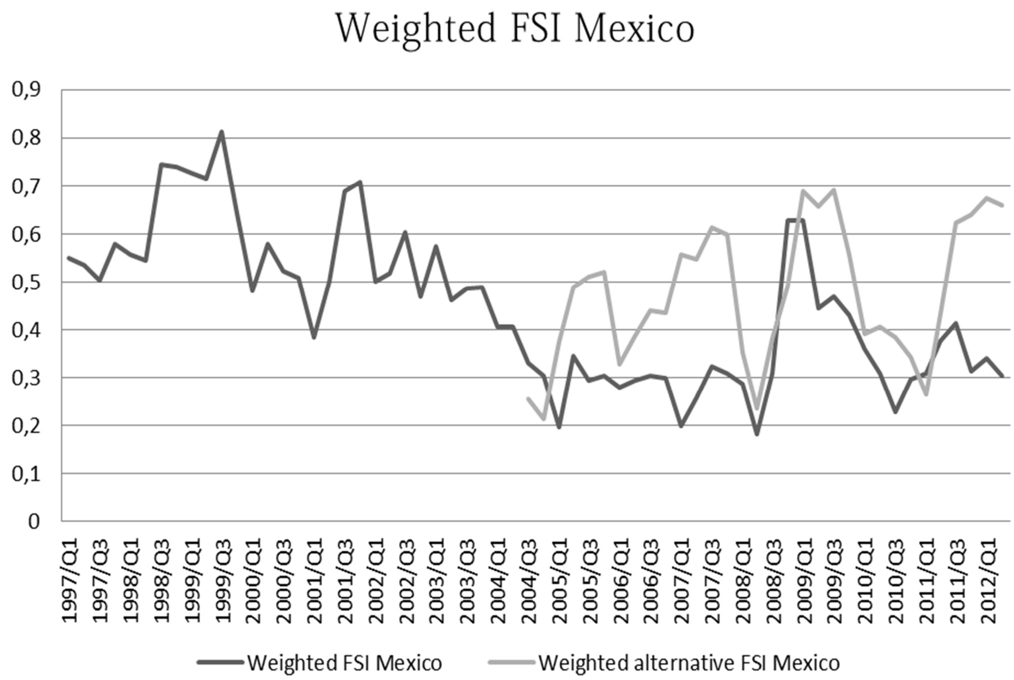


Figure 4.8: Weighted FSI for Mexico Source: author's own calculations

The crises database by Laeven and Valencia (2008) identified the start of the Mexican systemic banking crisis in 1994 followed by the currecy crisis in 1995. However, because of data restrictions the FSI covers only the period from 1997Q1 onwards. The highest stress measured by the constructed FSI was therefore in 1999Q3 potentially reflecting the fact that by 2000 many Mexican banks' assests were deemed insolvent hence resulting in foreign ownership of the 50% of them.

4.9 FSI for Poland

The figure 4.9 below identifies the largest financial stress in Poland at the beginning of the sample in 1994. Poland experienced systemic banking crisis starting in 1992 when seven out of nine Polish commercial banks suffered from solvency problems followed by the debt restructuring in 1994 (Laeven and Valencia, 2008).

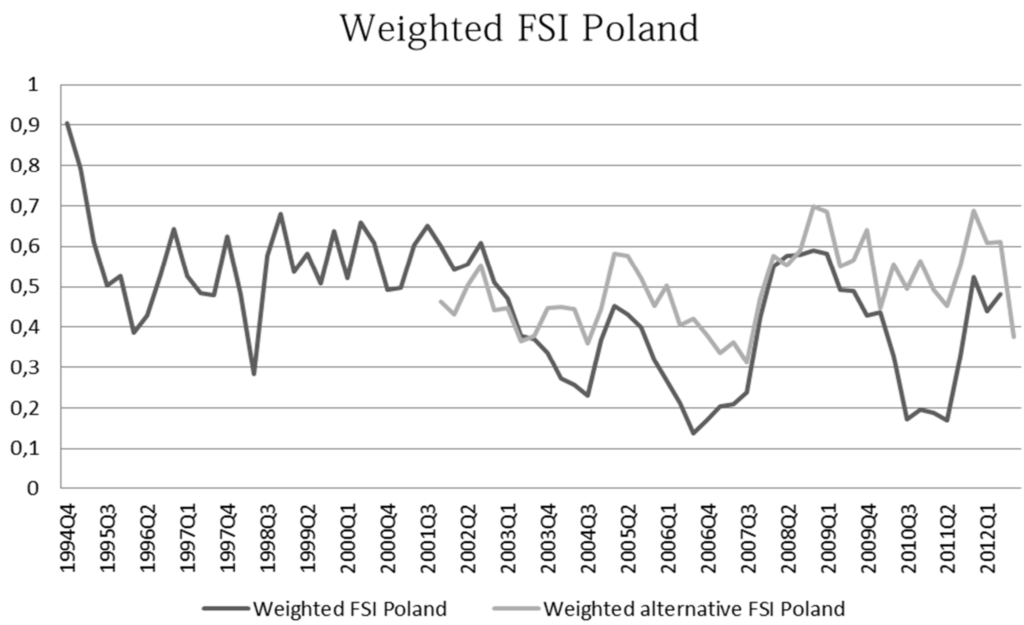


Figure 4.9: Weighted FSI for Poland Source: author's own calculations

4.10 FSI for the Russian Federation

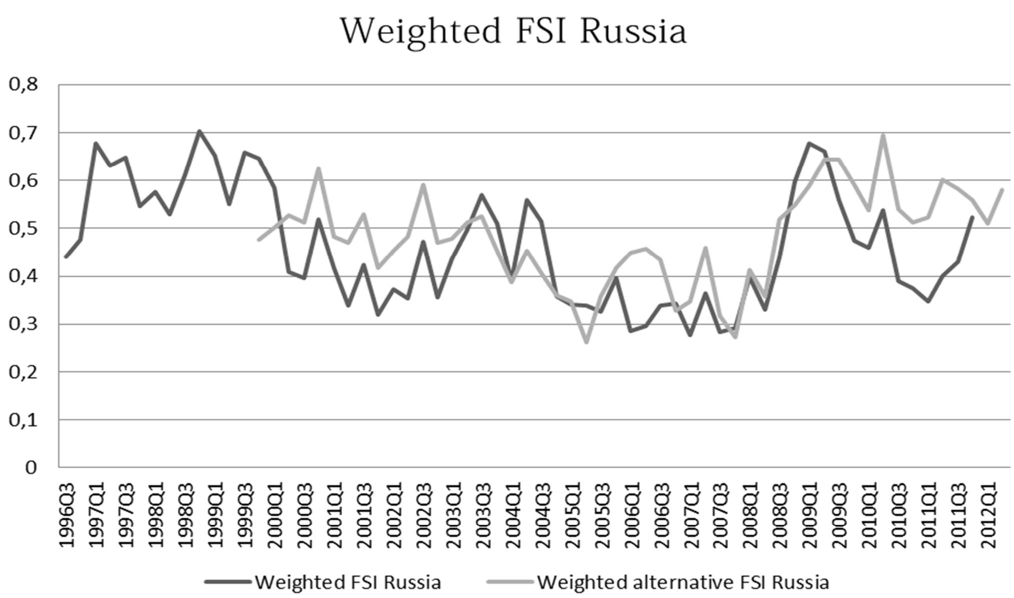


Figure 4.10: Weighted FSI for Russia Source: author's own calculations

The FSI captured the highest stress levels during the country-specific crisis, the Russian crisis of 1998, which encompassed systemic banking, currency and debt crises. This turbulence led to a large devaluation of ruble, loss of access to international capital markets and subsequent losses to the banking system (Laeven and Valencia, 2008).

4.11 FSI for Sweden

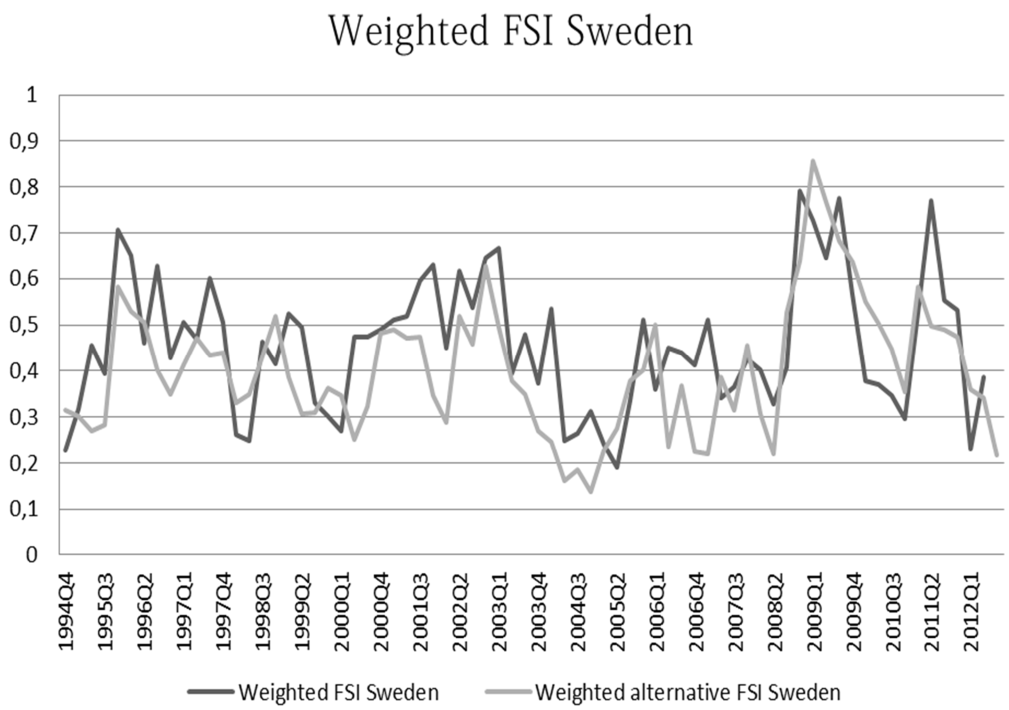


Figure 4.11: Weighted FSI for Sweden Source: author's own calculations

As is the case of many advanced economies, the Swedish FSI reached its highest point during the recent global crisis. Nevertheless, Sweden experienced a country-specific systemic banking crisis starting in 1991 and followed by a currency crisis in 1993. The Swedish FSI reflects this fact by reaching its second highest level in 1995.

4.12 FSI for Switzerland

Switzerland has not experienced any documented crises over the observed time period (Laeven and Valencia, 2008) apart from the recent global crisis when the FSI also reached its peak in 2009Q1.

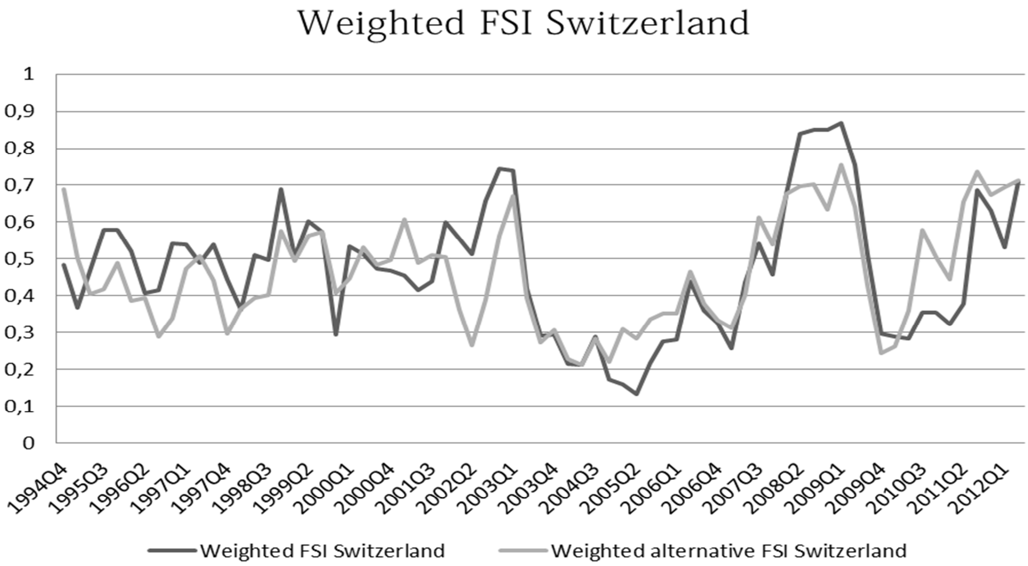


Figure 4.12: Weighted FSI for Switzerland Source: author's own calculations

4.13 FSI for Thailand

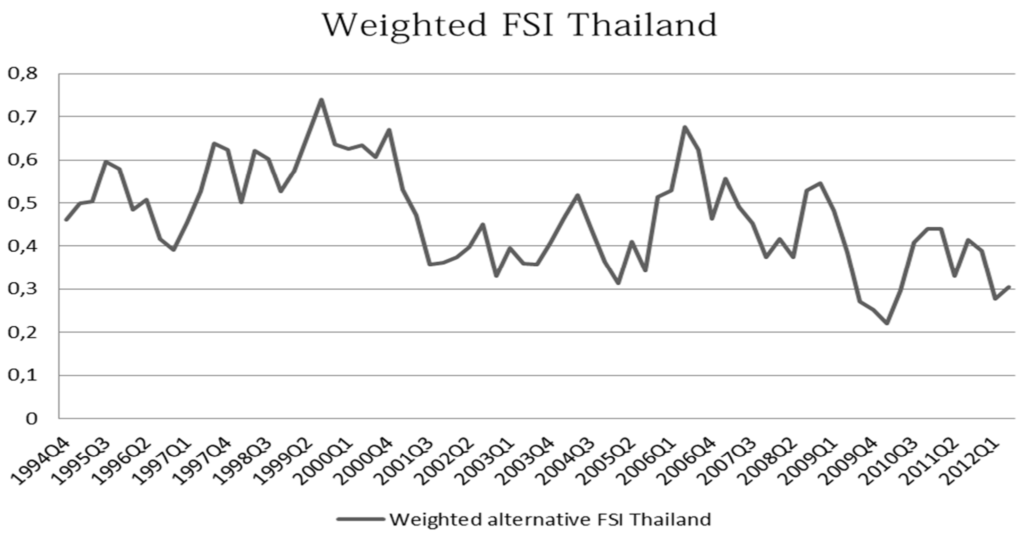


Figure 4.13: Weighted FSI for Thailand Source: author's own calculations

Due to data restrictions, the Thai FSI was constructed using the "alternative" set of indicators. Based on the database of documented crises the systemic banking crisis started in Thailand in 1997 followed by the currency crisis in 1998. The forces underlying the outbreak of the crisis were the pressures put on the fixed exchange rate regime eventually leading to currency floating and the transmission to the banking sector (Laeven and Valencia, 2008). Accordingly, the FSI peaked in Q3 1999.

4.14 FSI for Turkey

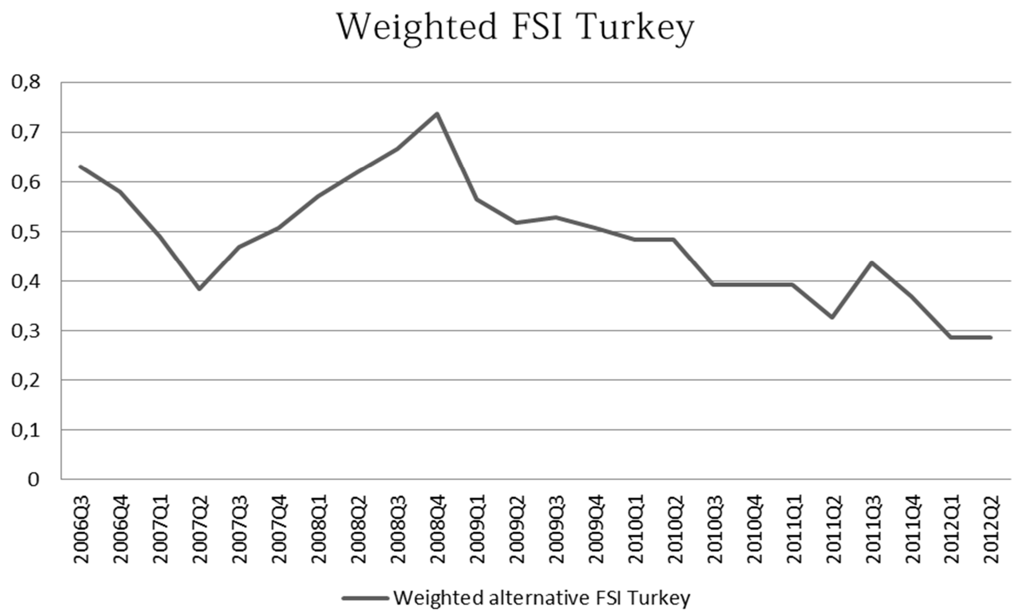


Figure 4.14: Weighted FSI for Turkey Source: author's own calculations

Due to data unavailability was not only the FSI constructed from the "alternative" set of indicators but also the observed period for financial stress is the shortest for Turkey within the panel of countries. Hence the Turkish systemic banking crisis of 2000 could not be captured and the FSI peaks at the end of 2008 in accordance with stress induced by the recent global crisis.

4.15 FSI for the United Kingdom

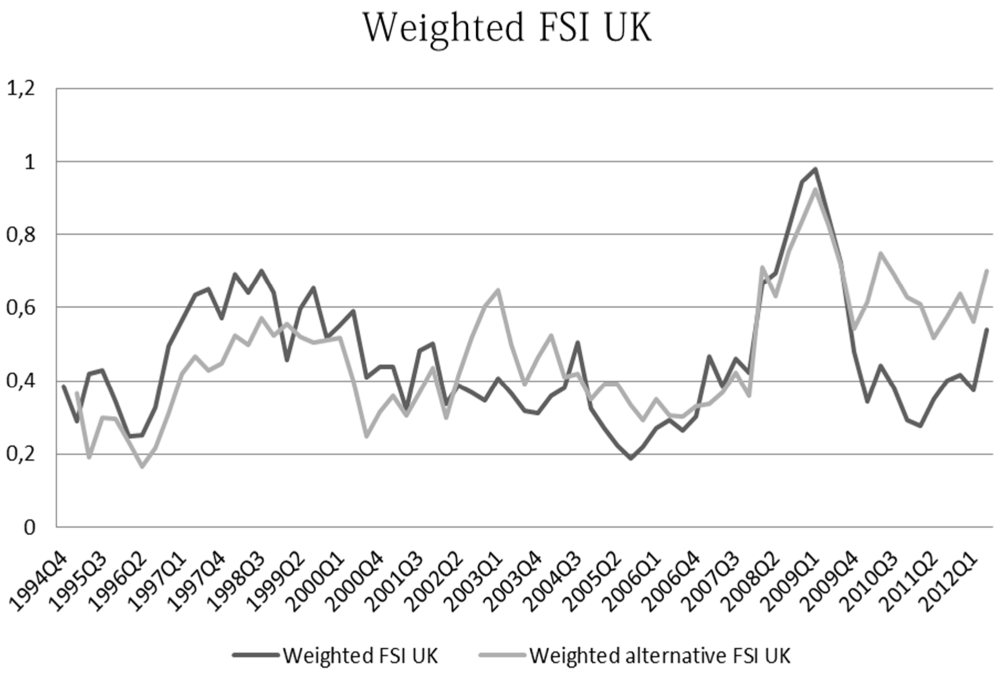


Figure 4.15: Weighted FSI for the United Kingdom Source: author's own calculations

According to the crises database by Laeven and Valencia (2008) there had not been a crisis detected in the UK prior to the current global crisis which demonstrated in the UK first in 2007 and was characterized as a systemic banking crisis. The start of the crisis is marked by a liquidity provision to a mortgage lender from the Bank of England. The UK FSI essentially tracks the growing financial stress from the beginning of 2007 which peaks in 2009Q1.

4.16 FSI for the United States of America

Over the observed period the USA experienced a systemic banking crisis with a starting point in 2007, an opening stage of the recent global crisis. The turbulences originated in the US subprime mortgage market and extended to the US banking system through severe writedowns of asset-backed securities. The situation further aggravated over 2007 and 2008. The calculated FSI in figure 4.16 coincides with these qualitative observations by Laeven and Valencia

(2008) as the FSI gradually increased over 2007 and 2008 and peaked in the fourth quarter of 2008.

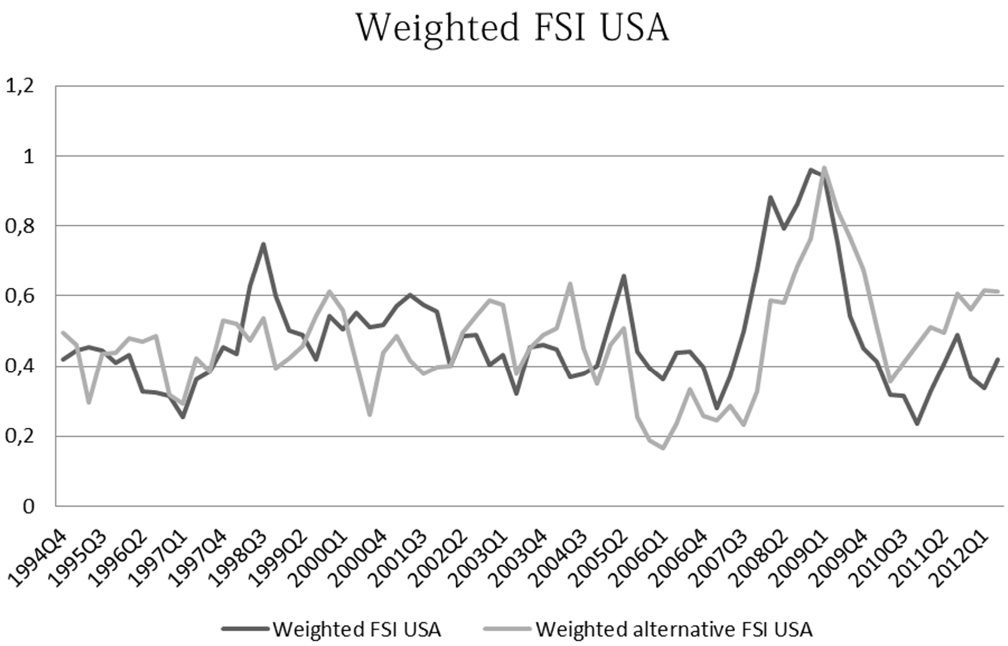


Figure 4.16: Weighted FSI for the United States Source: author's own calculations

Calculation of the systemic stress measures (FSI) for all countries within the panel as presented in this chapter allows for identification of starting dates of country-specific systemic financial crises. The description of this process and subsequent transformation of the FSI for EWS model is undertaken in the following chapter.

5 Systemic events identification

The aim of this chapter is to identify country-specific systemic event occurences from the measures of financial stress calculated and presented in the previous section for each country within the sample. Systemic events identification from financial stress measures, FSI, is crucial to the early warning system framework in this thesis as crisis occurence/absence will be used as a dependent variable within the EWS model.

Due to the fact that FSI was calculated as simple average of financial stress captured in different markets by selected indicators and expressed as a percentile value of these indicators‘ country distributions, it represents average attained levels of stress in the economy as a whole for each time period. Hence, it is possible to set a certain value of FSI as a threshold which, once exceeded, would signal the occurence of a systemic event. In this spirit, the threshold of 0,7 was chosen for systemic event occurence which in turn identifies 30% of highest stress periods for each country as crises. The FSI with highlighted systemic event episodes for each country can be found below.

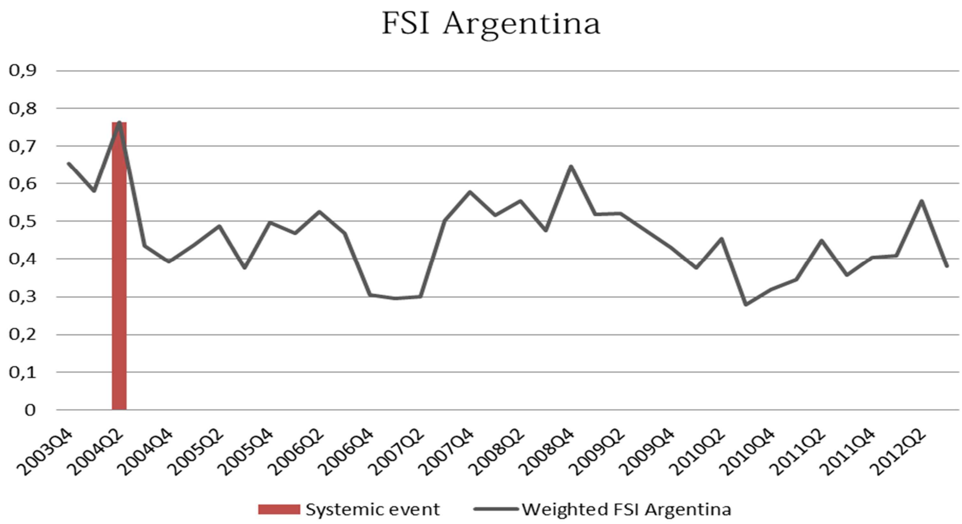


Figure 5.1: Identified systemic event episodes for Argentina, source: author's own calculations

Given the fact that FSI for Argentina covers a relatively short time period due to restricted data availability, the chosen threshold correctly identifies systemic event taking place in 2004Q2, near the time of Argentinian systemic banking crisis starting in 2001 (Laeven and Valencia, 2008).

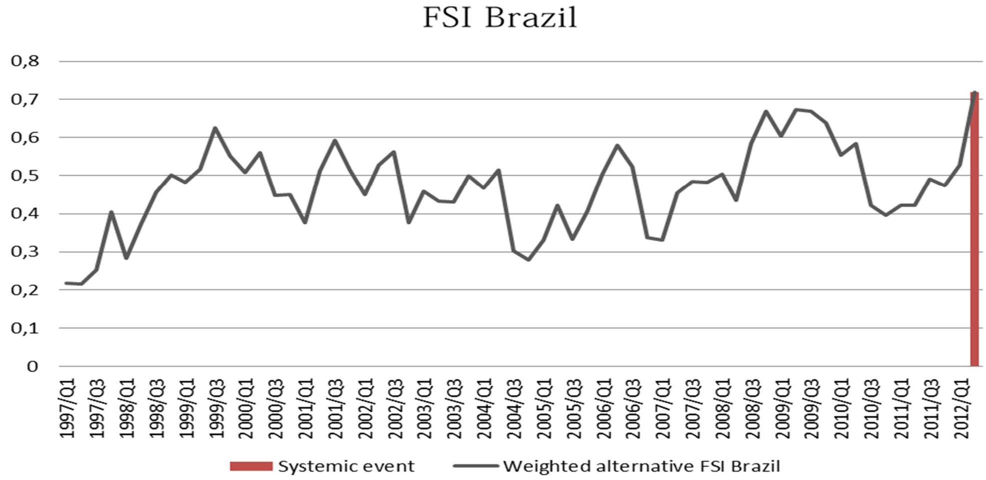


Figure 5.2: Identified systemic event episodes for Brazil, source: author's own calculations

For Brazil only one systemic event episode was identified in 2012Q2 and is associated with the global current crisis.

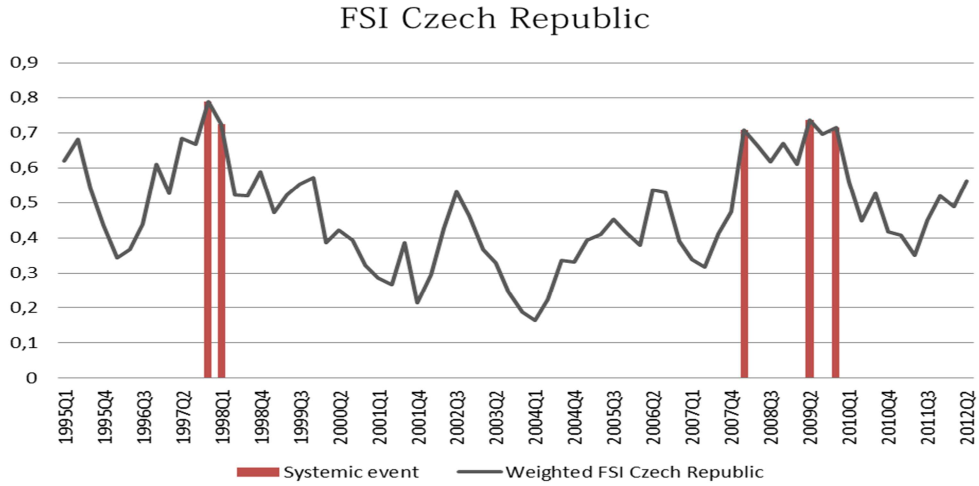


Figure 5.3: Identified systemic event episodes for the Czech Republic, source: author's own calculations

In line with the crises database by Laeven and Valencia (2008), the Czech FSI exceeded the set threshold in 1997Q4 and 1998Q1 during the country-specific systemic banking crisis. The other systemic event instances were identified in 2008 and 2009 during the recent crisis.

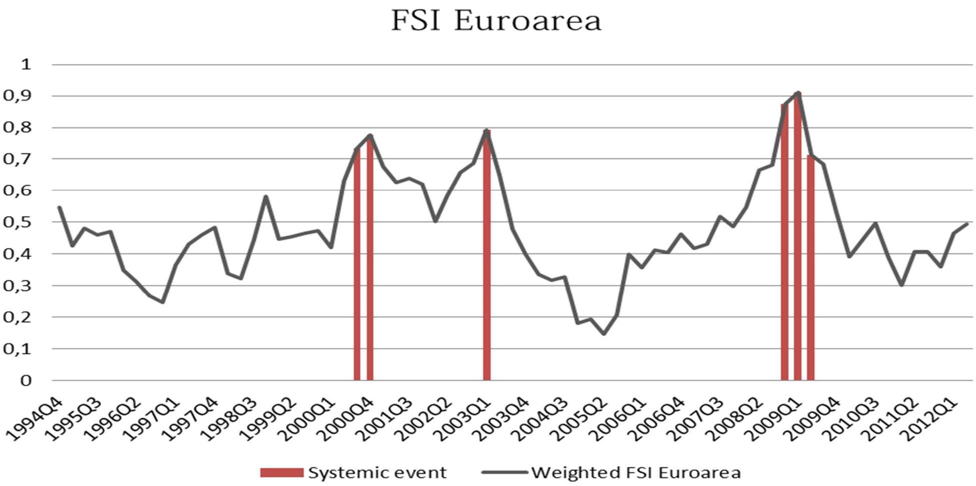


Figure 5.4: Identified systemic event episodes for the Euroarea, source: author's own calculations

For the Euro area as a whole FSI exceeded the drawn threshold in the second half of 2000, the beginning of 2003 and during the recent crisis.

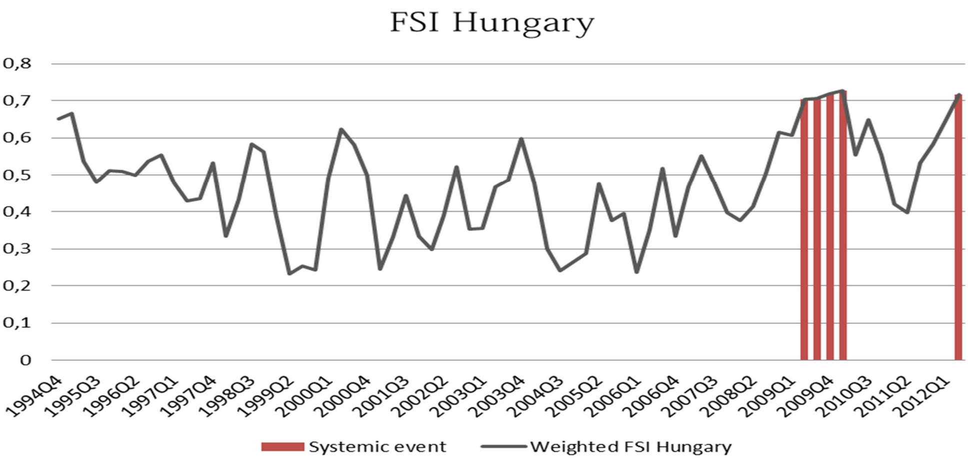


Figure 5.5: Identified systemic event episodes for Hungary, source: author's own calculations

As for Hungary the systemic event episodes were recognized during the recent crisis, in 2009, 2010Q1 and 2012Q2, which is in accordance with the turbulences detected by Laeven and Valencia (2008, 2012).

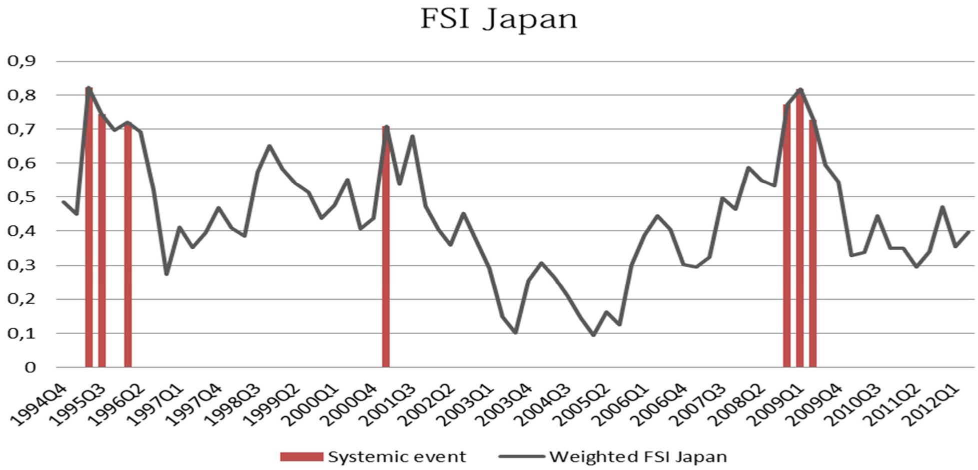


Figure 5.6: Identified systemic event episodes for Japan, source: author's own calculations

FSI exceeded the set threshold in the periods preceding the Japanese systemic banking crisis of 1997 (Laeven, Valencia, 2008) and at the end of this crisis, in 2001Q1. The remaining crisis instances fall in the period of 2008 and 2009.

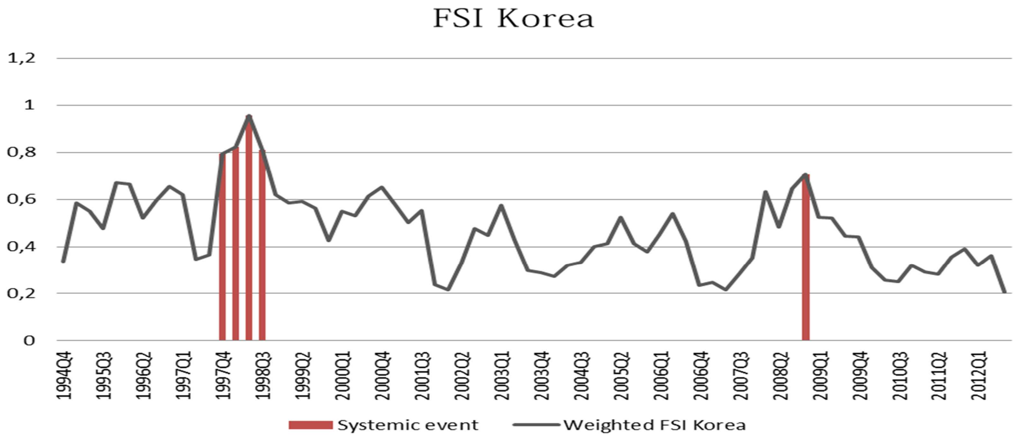


Figure 5.7: Identified systemic event episodes for the Republic of Korea, source: author's own calculations

The threshold identified the presence of systemic events at the end of 1997 and during the first three quarters of 1998 which falls into the Korean crisis period classified by Laeven and Valencia (2008). A systemic event episode was recognized during the global crisis as well.

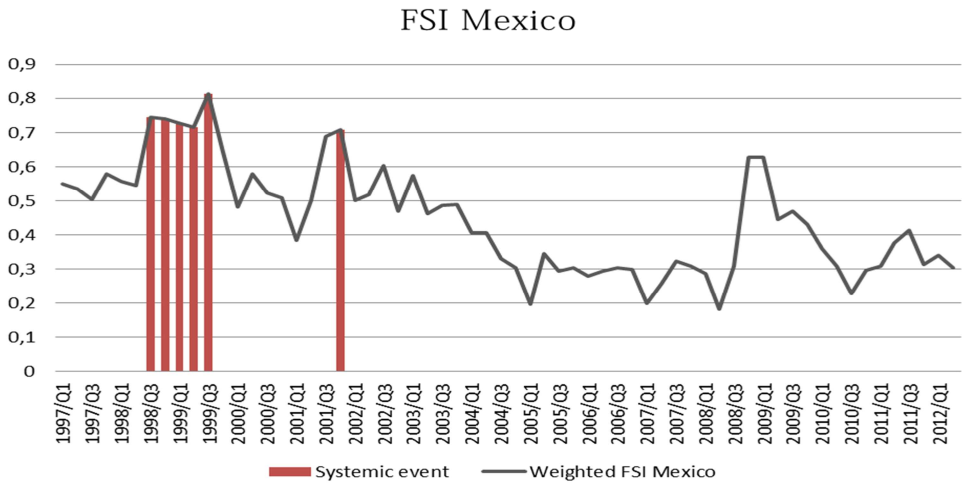


Figure 5.8: Identified systemic event episodes for Mexico, source: author's own calculations

For Mexico systemic events were identified in the wake of the Mexican systemic banking and currency crises, in 1998 and 1999.

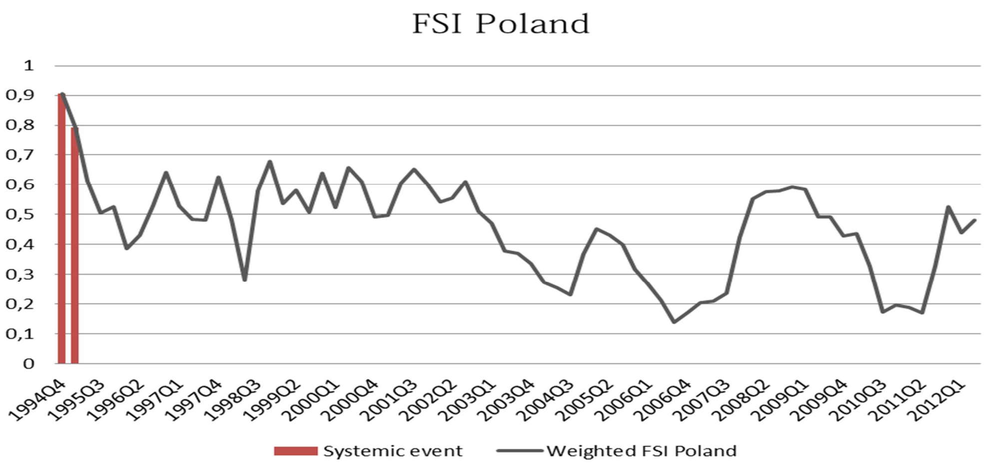


Figure 5.9: Identified systemic event episodes for Poland, source: author's own calculations

Identified systemic events at the end of 1994 and the beginning of 1995 coincide with the Polish systemic banking crisis classified by Laeven and Valencia (2008).

As for Russia, the recognized systemic event of 1998Q4 by the predefined threshold reflects the occurence of the Russian crisis in 1998.

Figure 5.10: Identified systemic event episodes for the Russian Federation, source: author's own calculations

For Sweden multiple systemic events were recognized - a systemic event in 1995Q4 coinciding with systemic banking crisis taking place at the time (Laeven, Valencia, 2008) as well as several instances identified throughout 2008, 2009 and 2011.

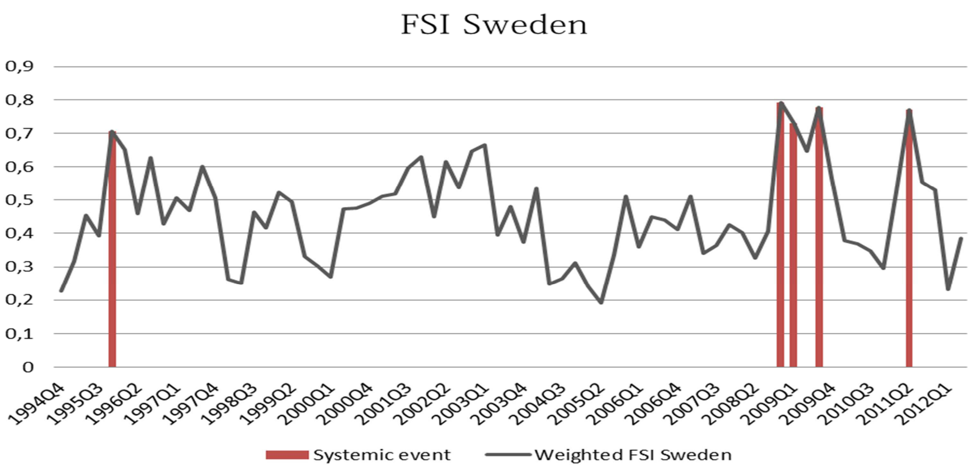


Figure 5.11: Identified systemic event episodes for Sweden, source: author's own calculations

Threshold-setting found in case of Switzerland systeming event episodes pertaining mainly to the recent global crisis as events were recognized in 2008, 2009 and in 2012Q2. Apart from this, FSI exceeded the threshold also in 2002/2003.

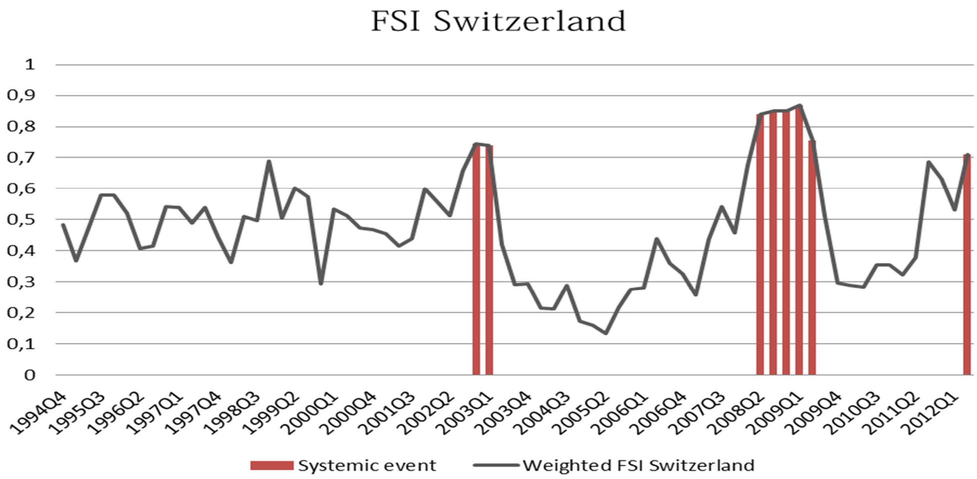


Figure 5.12: Identified systemic event episodes for Switzerland, source: author's own calculations

There was one systemic event identified for Thailand over the observed period, in 1999Q3. This event falls into the period of Thai systemic banking and currency crisis with the starting point in 1997 (Laeven, Valencia, 2008).

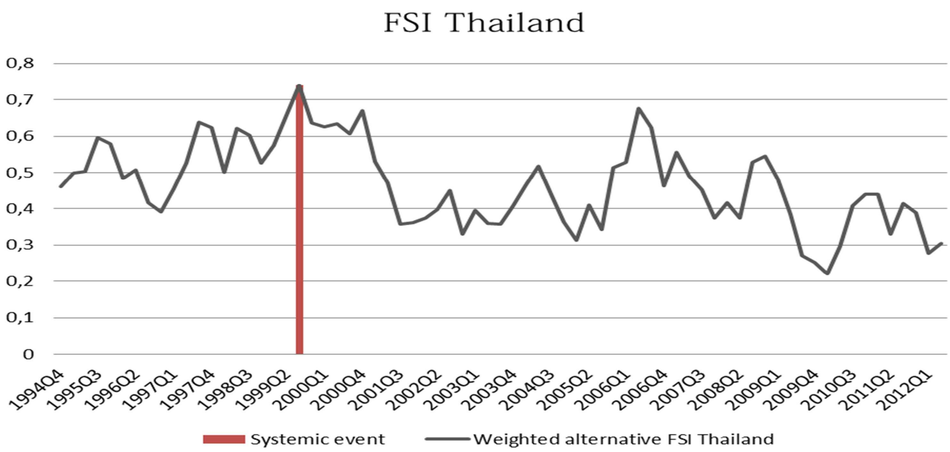


Figure 5.13: Identified systemic event episodes for Thailand, source: author's own calculations

Resulting from insufficient data availability for Turkey, only one systemic event was identified over the observed period, i.e. in 2008Q4 as shown in the figure 5.14 below.

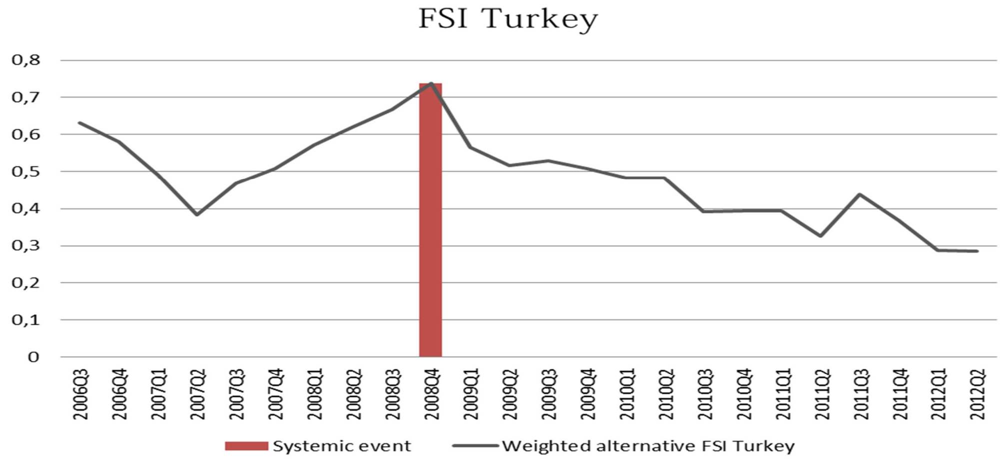


Figure 5.14: Identified systemic event episodes for Turkey, source: author's own calculations

Systemic events for the United Kingdom were found based on calculations in the second half of 2008 and most of 2009. These empirical findings fit with the crises classification by Laeven and Valencia (2008, 2012).

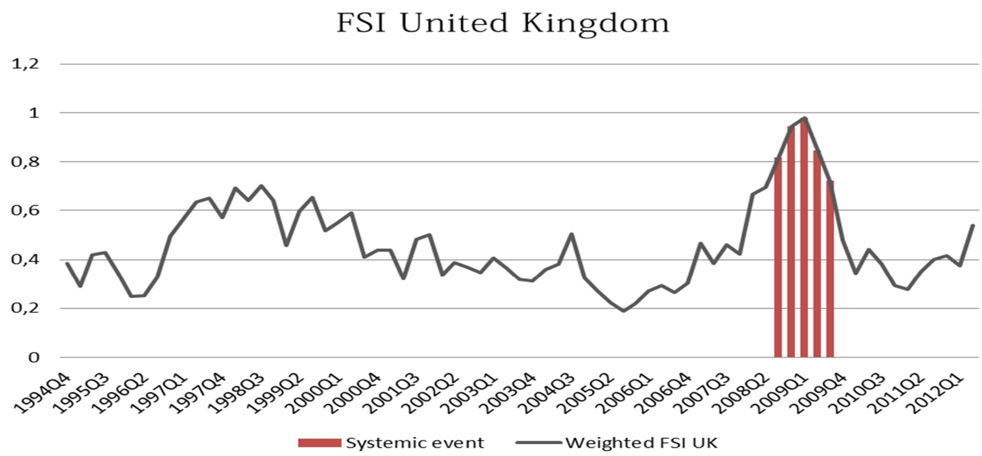


Figure 5.15: Identified systemic event episodes for the United Kingdom, source: author's own calculations

Similar to the United Kingdom, the FSI for the USA exceeded the set threshold during the entire 2008 and the first half of 2009 coinciding again with the current global crisis. Additionally, a systemic event was found in 1998Q3.

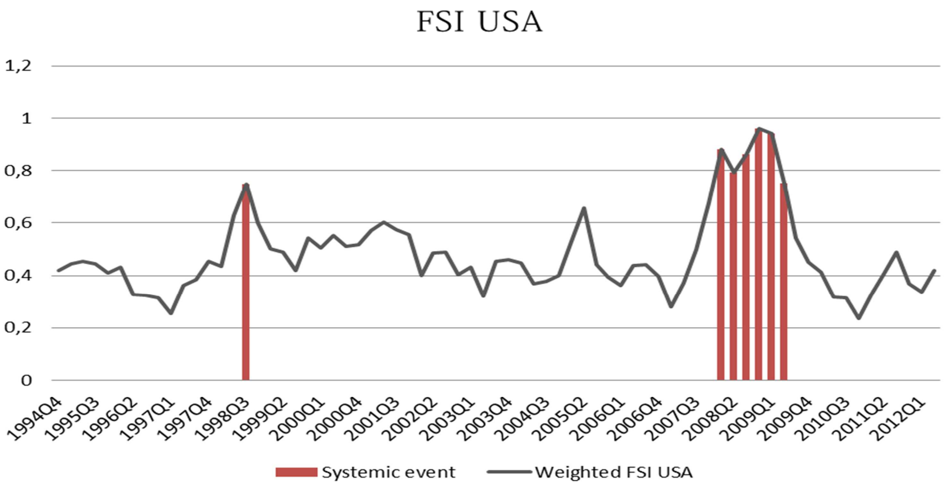


Figure 5.16: Identified systemic event episodes for the United States, source: author's own calculations

Now that systemic events for all countries within the panel were identified by means of exceeding a uniform predefined threshold of 0,7, the continuous FSIs can be converted into binary variables with 0 standing for a nonevent and 1 for an event occurrence. The next section describes this conversion in detail as FSI in its binary form will be used as a dependent in EWS model for probabilistic prediction of crisis occurrence that will be developed in the latter part of this thesis.

5.1 FSI transformation

For the subsequent empirical work whose objective is identification and prediction of systemic events via binary logit model, it is necessary to convert the calculated country-specific FSI indices into binary variables in such a way that FSI adopts value 1 in periods when it surpasses the predefined threshold of 0,7, as specified earlier in this chapter, and in a similar fashion gains value 0 in all other periods.

In order to ensure that FSI behaves as an appropriate early warning indicator by signalling upcoming systemic events, it needs to equal 1 in periods leading to the outbreak of these events. The horizon for signalling of upcoming systemic events of 2 different lenghts, short and long, is of interest to focus on in this work. In this view, two models (short and long) are to be built to account for appropriate upcoming crisis signalling over each of these horizons.

Therefore, in the short model FSI is set to 1 in 6 quarters leading to an event as this time length should be sufficient for policy makers to prepare adequate policy response (Peltonen and Lo Duca, 2011). Furthermore, in line with Peltonen, Lo Duca (2011) and Bussiere, Frantzscher (2006) the so-called periods of economic recovery, i.e. transitions from systemic events to tranquil periods, are excluded from the sample as during these times „economic variables go through an adjustment process before reaching again the path they have during tranquil periods“ which could consequently lead to a „post crisis bias“ (Bussiere and Frantzscher, 2006). In practice this means that FSI is set to 0 after a crisis outbreak, i.e. in periods during which it originally remained above the set threshold. Additionally, FSI is assigned 0 in all tranquil periods shorter than 6 quarters as any subsequent high stress periods could still be continuations of previous systemic events (Peltonen and Lo Duca, 2011).

As for the FSI transformation in the long model with the horizon of 12 quarters the very same reasoning was implemented for the binary transformation as described above. However, FSI is set to 1 in 12 quarters preceding a systemic event outbreak and to 0 in all other periods.

6 Leading Indicators for Systemic Events Detection

In regards to constructing a framework for assessment and probabilistic prediction of systemic events, it is essential to include among potential leading indicators variables with the capacity to capture presence of imbalances both within domestic and global economy that may lead to an outbreak of a systemic event. The initial set of variables in this thesis is based on indicators that tend to appear in early warning system mechanisms such as Peltonen and Lo Duca (2011), Babecky, Havranek et al. (2011), Jakubik and Slacik (2013).

In line with Peltonen and Lo Duca (2011) the set of potential leading indicators contains not only domestic and global variables but also interactions between selected domestic variables, between global variables and between domestic and global variables.

In this spirit, for each country in the panel growth in domestic asset prices is approximated by real annual growth of the local MSCI index while asset price valuations are expressed by the ratio of equity market capitalization/GDP. As for leverage, it is measured by the ratio of private credit/GDP while growth in a country's bank credit is approximated by private credit annual growth. Moreover, interaction between domestic asset price growth and asset price valuations as well as interaction between domestic credit growth and leverage levels is computed as product between the two variables that should capture the dynamics. The same set of variables and their interactions as for domestic economy was computed also for the global one. In an attempt to capture „additional fragilities that emerge when the overheating of the domestic economy coincides with the vulnerabilities in the global conditions" (Peltonen and Lo Duca, 2011), interactions between domestic and global variables were included as products of relevant variables. Global variables were approximated by GDP-weighted averages of four large economies within the sample, i.e. Euro area, Japan, United Kingdom and United States (Peltonen and Lo Duca, 2011).

Apart from these variables the set of potential leading indicators includes proxies for macroeconomic conditions on a domestic level as well as some on the global level. The short and long trends were derived from Hodrick-Prescott filter with values of the smoothing parameter of 1600 and 400 000, respectively. All indicators are in quarterly frequency. However, the variables from table 6.1 that are indicated as obtained from the World Bank (WB) were initially in annual frequency thus to ensure their quarterly frequency for the purposes of this analysis a decomposition by cubic-match method was applied (Babecky, Havranek et al., 2011). Real variables within the dataset were calculated by deflating a nominal variable by the consumer price index (CPI). Ultimately, the set of amassed variables covers the period between 1990Q1 and 2013Q1 for 14 countries altogether as Brazil and Poland had to be eventually excluded from the initial sample due to data restrictions.

The table 6.1 below presents the full set of aggregated potential indicators, their short descriptions and sources.

Table 6.1: Set of potential leading indicators, source: author based on listed sources

Indicator	Description	Source	Indicator	Description	Source
Real GDP	year-on-year change	OECD, NCB	**Real private credit annual growth**	interaction between global and domestic variables	author based on BIS
Real M2	year-on-year change	IMF, NCB	**Private credit/GDP**	interaction between global and domestic variables	author based on BIS
Real money	year-on-year change	IMF, NCB	**Real MSCI annual growth x Global market capitalization/GDP**	interaction between global and domestic variables	author based on WB, www.msci.com
M2	share of GDP	IMF, NCB	**Private credit growth x Global Private credit/GDP**	interaction between global and domestic variables	author based on BIS
Money	share of GDP	IMF, NCB	**CPI**	year-on-year change	IMF, OECD, NCB
Real domestic credit	year-on-year change	IMF	**Real effective exchange rate**	period-on-period change	BIS
Government deficit	share of GDP	IMF, NCB, Reuters	**Global real private credit**	year-on-year change	author based on BIS
Government debt	share of GDP	OECD, NCB, Reuters	**Global market capitalization**	share of global GDP	author based on WB
Private credit	share of GDP	BIS	**Global private credit**	share of global GDP	author based on BIS
Real MSCI index	deviation from HP trend (short)	www.msci.com	**Global private credit growth x Global private credit/GDP**	interaction between global variables	author based on BIS
Reserves	period-on - period change	IMF, OECD	**Global real GDP**	year-on-year change	author based on OECD, NCB
Trade balance	period-on - period change	IMF, OECD	**Global CPI**	year-on-year change	author based on IMF, OECD, NCB
Current account/GDP	share of GDP	OECD, NCB	**Real private credit**	year-on-year change	BIS
Unemployment rate	share of labour force	IMF, NCB	**Real MSCI index**	deviation from HP trend (long)	www.msci.com
Gross fixed capital formation	period-on-period change	IMF	**Real MSCI index**	year-on-year change	www.msci.com
Industrial production	period-on-period change	IMF, OECD, NCB	**Property price index**	year-on-year change	BIS, NCB

Market capitalization	share of GDP	WB	**Real MSCI annual growth x Market capitalization/GDP**	interaction between domestic variables	author based on WB, www.msci.com
Private credit growth x Private credit/GDP	interaction between domestic variables	author based on BIS	**Real MSCI annual growth**	interaction between global and domestic variables	author based on www.msci.com
Market capitalization/GDP	interaction between global and domestic variable	author based on WB	**Global real MSCI index**	year-on-year change	author based on www.msci.com
Non-performing loans	share of total loans	WB	**Global real MSCI annual growth x Global market capitalization/GDP**	interaction between global variables	author based on WB, www.msci.com

The set of potential leading indicators was prepared in a way to ensure stationarity of included variables, i.e. expressing indicators by mostly growth rates. Nevertheless, stationarity check was performed for each variable in the panel using Augmented Dickey-Fuller (ADF) test in order to investigate the presence of a unit root process. Moreover, as ADF test checks for stationarity in each cross-sectional unit separately, it would be prudent to also check stationarity of a variable across all units in the panel, which was performed via Im, Pesaran, Shin (2003) statistics and Choi (2001) tests. Im, Pesaran, Shin's test is based on the average of (augmented) Dickey-Fuller statistics computed for each group in the panel while Choi's approach combines p-values from a unit root test applied to each group in the panel data. The stationarity was rejected for the following variables: M2/GDP, Money/GDP, Government deficit/GDP, Government debt/GDP, domestic private credit/GDP, Current account/GDP, interaction of domestic private credit growth with domestic private credit/GDP, interaction between domestic and global private credit/GDP and real private credit annual growth. Stationarity was subsequently ensured by first differencing the original nonstationary variables.

Furthermore, as leading indicators are to be explanatory variables and FSI a dependent in latter analysis, avoidance of potential correlations between indicators of systemic events and the variables from the FSI composition needs to be kept in mind when building the set of indicators. Therefore, correlations were checked for critical indicators while those variables for which null of no correlation was rejected were ultimately excluded form the analysis. The list of excluded indicators for which correlations were statistically significant can be found on the right-hand side of the table 6.1 from the bottom and is as follows: deviation of real MSCI index from long Hodrick-Prescott trend (smoothing parameter of 400 000), annual growth of real MSCI index, property price index annual growth, interaction between domestic real MSCI index annual growth and domestic market capitalization/GDP, interaction between domestic and global real MSCI index annual growth, annual growth of global real MSCI index and finally interaction between global real MSCI index annual growth and global market capitalization/GDP. The results of stationarity testing as well as the correlation matrix of critical coefficients with the FSI can be found in the appendix.

6.1 Evaluation of the indicators based on signalling analysis

The crisis-detecting ability of indicators and hence their usefulness within the EWS can be assessed in a framework that takes into account missing systemic events, false signal emissions as well as policy-maker's preferences. This analysis follows the approach by Alessi and Detken (2011) which allows to find optimal early warning thresholds for indicators and thus rank them with respect to their crisis detecting usefulness.

In this spirit, the formula used to evaluate each indicator's utility in crises detection is as follows:

$$U = Min[\mu, 1-\mu] - \left(\mu * \left(\frac{C}{A+C}\right) + (1-\mu) * \left(\frac{B}{B+D}\right)\right)$$

The first term in the equation expresses the loss a policy maker experiences in case they disregard the signal from an indicator. The second term quantifies the loss they obtain if the indicator is considered in crises detection conditional on the policy maker's preferences μ towards either missing systemic events or issuing false signals. The proportion of missing signals (type I error), i.e. periods in which an indicator did not surpass the threshold so the signal was not issued even if a systemic event materialized, is expressed by $\left(\frac{C}{A+C}\right)$. Similarly, the proportion of false signals (type II error), i.e. periods in which an indicator surpassed the threshold and thus emitted a signal despite the absence of a systemic event, is given by

$\left(\frac{B}{B+D}\right)$. The table 6.2 below offers a more detailed overview of this reasoning:

	Systemic event materialization	Systemic event absence
Indicator above threshold (signal)	A (correct signal)	B (wrong signal)
Indicator below threshold (no signal)	C (missing signal)	D (correct absence of signal)

Table 6.2: Signalling analysis, source: Peltonen, Lo Duca (2011)

The objective of this analysis is to find a threshold for each indicator that maximizes the utility from the equation presented above. As neither of the two error types is considered more negligible than the other in this thesis, the policy maker's preferences μ were set to 0,5, the viewpoint of a neutral observer.

In order to find a country-specific optimal threshold for every potential indicator within the dataset, all the observations of each indicator were transformed into percentile values of an indicator's country-specific distribution function. Every such percentile value was then set as a threshold for which utility function was computed. The threshold which maximized the utility function, apart from minimum and maximum value of the country distribution, was consequently chosen as optimal.

The table 6.3 presents the results yielded from signalling analysis for potential indicators in the dataset. The set of indicators for which it was possible to calculate their utility functions is, however, reduced compared to the original dataset in table 6.1 as some time series were too short to cover both tranquil and crisis periods within a country's history. The crisis dating needed for these calculations was provided from the crises database by Laeven and Valencia (2008, 2012) while for Euro area and the global economy the crisis dating includes only one systemic event, i.e. global current crisis, within the observed period of 1990Q1-2013Q1.

Table 6.3: Average maximum utility of indicators across the panel, source: author's own calculations

Average maximum utility of indicators across the panel:			
Private credit/GDP	0,3233	Market capitalization/GDP	0,1113
Global CPI annual growth	0,2727	Government deficit/GDP	0,1101
M2/GDP	0,2655	Real M2 annual growth	0,1098
Government debt/GDP	0,2217	Global real annual GDP growth	0,1063
Money/GDP	0,2142	Trade balance change	0,1027
Unemployment rate	0,1821	Real money annual growth	0,0958
CPI annual growth	0,1678	Interaction Market capitalization/GDP	0,0715
Global real annual growth of private credit	0,1599	Real effective exchange rate growth	0,0698
Global private credit growth x Global private credit/GDP	0,1599	Gross fixed capital formation growth	0,0655
Reserves growth	0,1333		
Real domestic credit annual growth	0,1328	Private credit growth x Private credit/GDP	0,0653
Real MSCI index HP short trend	0,1278	Industrial production change	0,0551
Current account/GDP	0,1278	Global private credit/GDP	0,0400
Global market capitalization/GDP	0,1250	Real GDP annual growth	0,0185

The maximum average utility of an indicator across the panel of countries was calculated by averaging the maximum utility of the indicator obtained in each country as a country-specific threshold for utility maximisation was employed in line with Peltonen and Lo Duca (2011). All presented indicators have their utility measure higher than 0, i.e. a neutral observer would benefit from using these indicators rather than ignoring them. The best performing indicator of all resulting from the signalling analysis is the ratio of private credit over GDP which coincides with common findings in the literature (e.g. Alessi and Detken, 2011). There are two indicators for monetary aggregates among the top 5 indicators which, though quite useful in general, are not considered as well-performing as credit indicators according to the literature (Alessi and Detken 2011; Borio and Lowe 2004). Surprisingly, in contrast to Peltonen and Lo Duca (2011) global indicators and interactions between global and domestic indicators did not perform better than the top 5 indicators all of which are domestic. The best performing non-domestic indicators, ranked 8th and 9th, both of which are global indicators as well as credit indicators. In addition, both of these global indicators have the same maximum utility, i.e. global real annual growth of private credit and interaction between global private credit annual growth and global private credit over GDP are equally successful in crises signalling.

Due to the fact that the set of indicators for which it was possible to calculate maximum utility is quite constricted compared to the set of all amassed indicators in table 6.1, the signalling analysis can thus be viewed as an alternative or complementary technique to indicators selection into an EWS model. Therefore the selection of appropriate indicators itself will be more refined and undertaken in the rest of this chapter.

6.2 Lags Selection for the Potential Leading Indicators

Optimal lags selection for the indicators to be included in early warning models poses a serious question as different indicators might be able to discern the probability of occurance of a systemic event with a varying lead time length. In this view, various indicators would be capable of issuing either a late warning for a 1-3Q horizon ahead or an early warning for 4-8Q ahead of a systemic event materialization as specified in Babecky, Havranek et al. (2012). Generally, in research works the indicator lags selection is conditional upon researchers' expert opinion (Kaminsky and Reinhart, 1999) or to allow for publication lags of selected indicators (Peltonen and Lo Duca, 2011). In this thesis a quantitative approach towards lag selection is undertaken, inspired by Babecky, Havranek et al. (2012), who chose panel vector autoregression model to account for differing dynamics of the indicators in regards to systemic event occurences.

However, as opposed to the mentioned paper, in this work important lags for each indicator were obtained from a univariate logit model with FSI as a dependent (transformed into binary form after having applied transformation detailed in the previous chapter) and an indicator along with its lags from 1 to 8 (in quarters) as independent variables. This setting investigates the dynamics of each indicator and FSI separately with the aim to extract lags that are relevant in explanation of systemic events' occurences as defined by binary FSI. Moreover, logit model was chosen for this purpose in order to maintain consistency throughout the entire analysis as ultimately logit model will be applied within EWS to assess the probability of crises occurences.

From this initial univariate model setting for each indicator those lags were omitted whose coefficients displayed high p-values as well as for which Wald test statistic did not allow rejection of the null of the coefficient equal to zero on 5% significance level. All the while Akaike information criterion was attempted to be kept as low as possible and likelihood ratio's chi-squared statistic, testing joint significance of all variables within the model or which, in other words, tests if the current model fits the data better than the model containing an intercept only, was aimed to be rejected. Lags of each indicator that emerged significant from these univariate logit models were included in further analysis. The described method for relevant lag selection was performed twice with the same set of initial indicators from table 6.1, once for FSI in the short form, i.e. flashing 1 in the six quarters preceding the identified outbreak of a systemic event, and once for FSI in the long form, i.e. flashing 1 in the twelve quarters preceding the identified outbreak of a systemic event. All calculations pertaining to lags selection can be found in the appendix.

Finally, after the inclusion of the relevant lags the set of potential indicators expanded from 33 as presented in table 6.1 to 78 for the short model, i.e. with FSI in the short form, and to 74 for the long model with FSI in the long form. From these two broad sets of potential indicators only the indicators with the highest usefulness for the construction of systemic event assessment and prediction framework need to be extracted for each model which is the topic of the following section.

6.3 Selection of Leading Indicators for the EWS

With the objective of creating a parsimonious framework for systemic risks evaluation and systemic events prediction in mind, the identification of useful indicators among the numerous indicators preselected in the previous section and their subsequent inclusion in the final model should be done in a systematic and concise manner. For this purpose the Bayesian model averaging technique is applied to the sets of data containing lagged variables from section 6.2 and the computation is performed in R using „BMS“ package by

Feldkircher and Zeugner (2009). This approach was utilized to address model uncertainty among others also in the area of financial stability research by Babecky, Havranek et al. (2012).

In the presence of many potential variables the issue of discerning and selecting only the meaningful ones arises. When attempting to deal with the problem some hindrances materialize (Koop, 2003). First of all, including large number of potential variables in one regression might lead to large standard errors, a consequence of the presence of irrelevant variables. Another hindrance in testing for inclusion of relevant variables only is connected to inadvertent omission of an important variable during the sequential testing. The Bayesian model averaging is designed to circumvent these issues as it selects the best performing combination of potential indicators from among all combinations. The following model is considered:

$$y = \alpha_\gamma + X_\gamma \beta_\gamma + \varepsilon \quad \varepsilon \sim (0, \sigma^2 I)$$

where y is FSI in a binary form, α_γ a constant, β_γ a vector of coefficients, ε an error term and X_γ a subset of all explanatory variables. The potential models space size depends on the number of indicators included, i.e. in case of K indicators there will be 2^K potential models. Thus the model space cointains 2^{78} potential models to choose from for the short model. In case of the long model the model space is slightly smaller and constitutes 2^{74} potential models.

Across the models the gathered information is then averaged using posterior model probabilities from the Bayes' theorem as follows:

$$p(M_\gamma | y, X) \propto p(y | M_{\gamma,} X) p(M_\gamma)$$

where $p(M_\gamma | y, X)$ is the posterior model probability, $\propto$ a sign of proportionality, $p(y | M_{\gamma,} X)$ the marginal likelihood of the model and $p(M_\gamma)$ the prior probability of the model. The posterior model distribution of any statistic θ is then obtained from model weighting as follows:

$$p(\theta | M_\gamma, y, X) = \sum_{\gamma=1}^{2^K} p(\theta | M_\gamma, y, X) \frac{p(M_\gamma | y, X) p(M_\gamma)}{\sum_{i=1}^{2K} p(y | M_i, X) p(M_i)}$$

To express the lack of prior knowledge about the parameters and models uniform priors were used. For the vector of coefficients β_γ the Zellner's g prior is used as the application of the uniform model prior and the unit information prior to the parameters in the model performs well when forecasting (Eicher et al., 2010).

Posterior inclusion probability (PIP) which is also part of the Bayesian model averaging output denotes the robustness extent of a particular variable with respect to the dependent variable (binary FSI). PIP therefore indicates the pobability with which a variable is included in the regression:

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

Due to a large number of potential variables (and their lags) to be input into the Bayesian model averaging in this thesis, enumeration of all potential combinations of variables becomes not only time consuming but with increasing variable numbers even infeasible (Feldkircher and Zeugner, 2009). Therefore, Markov Chain Monte Carlo (MCMC) samplers developed by Madigan and York (1995) are used to amass results on the most important part of the posterior model distribution and thus deliver as precise estimates as possible. The quality of the MCMC approximation to the actual posterior distribution, i.e. the correlation of MCMC approximation results and the analytical ones, is linked to the number of draws the sampler is set to go through during the estimation process (iterations). However, as the MCMC sampler might start sampling from models that might not yield the best results and only after some time converge to models with high posterior model probabilities, it is advisable to discard these initial iterations (burn-ins).

For both models, i.e. both sets of potential indicators, in this thesis the number of iterations is set to 45 000 000 after the initial 2 000 000 were discarded as burn-ins. The correlations obtained between the MCMC and analytical results for the short and the long model model are 0,9496 and 0,7937, respectively which could be considered a sufficient convergence. The figure 6.1 below details these results as well as it shows prior and posterior model size distributions for both models:

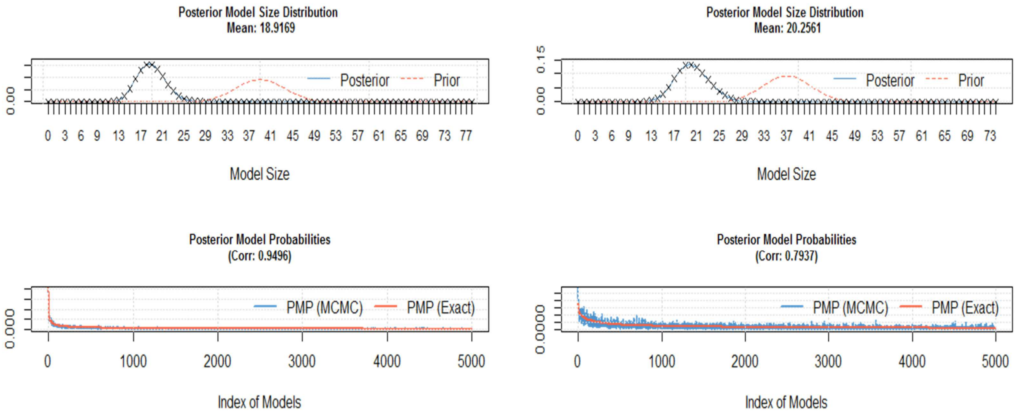
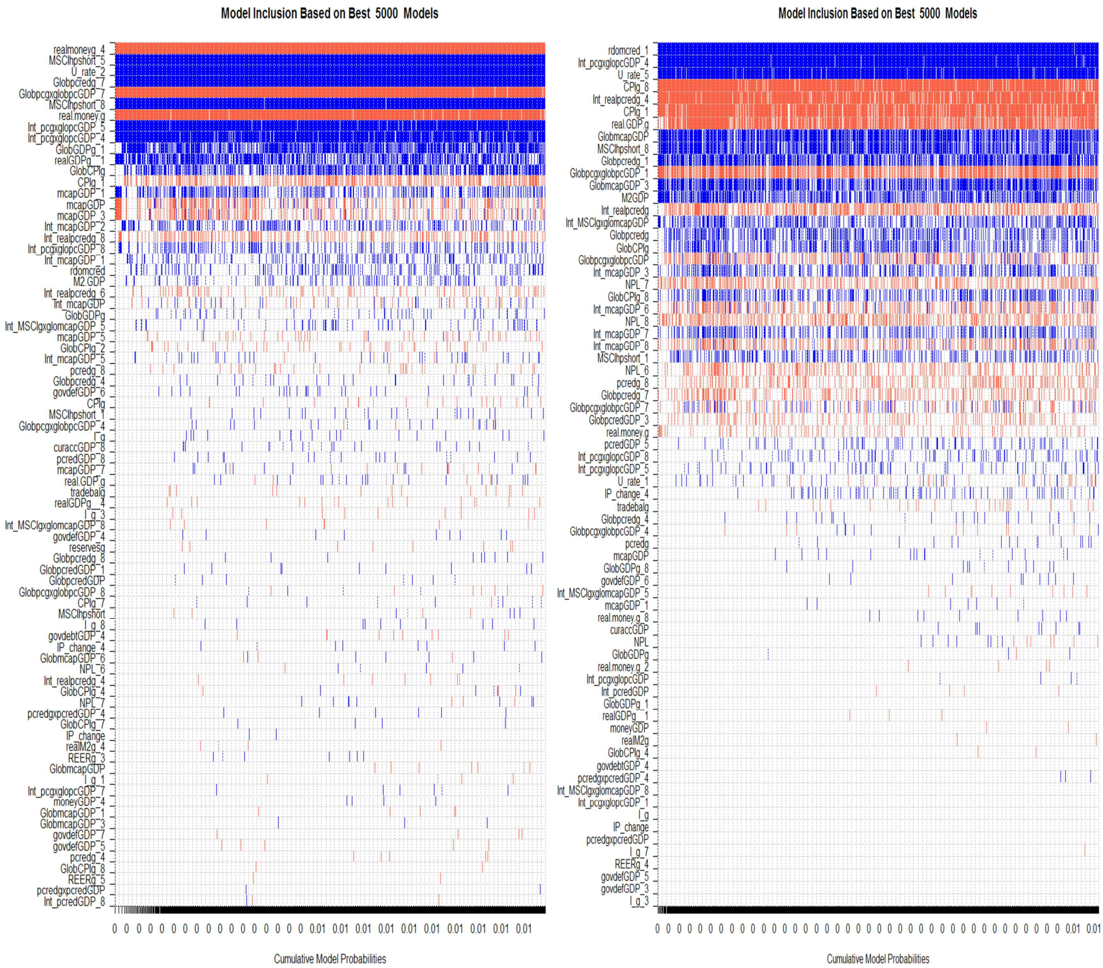


Figure 6.1: Convergence and model size distributions for the short and the long model, source: author's own calculations

As is discernible from figure 6.1 uniform model prior was employed in the computations therefore expected prior model parameter size equals half the number of potential indicators entered into the Bayesian model averaging. However, after having updated the model prior with data it yields a smaller expected posterior model parameter size as parsimonious models are preferred.

The figure 6.2 below reports results for the 5000 best models gained from the Bayesian model averaging (BMA) method; results for the potential leading indicators in the short model are on the left while those for indicators in the long model are on the right.

Figure 6.2: Posterior inclusion probabilities of potential leading indicators in the short (left) and the long (right) model, source: author's own calculations



Note: the number following each indicator states an indicator‘s lag (in quarters)

Rows in the figure 6.2 represent individual potential indicators that were input into the BMA method for each model. In columns (horizontal axis) models are ordered from left to right in descending order by their posterior model probability. Red colour for an indicator indicates a negative sign of its coefficient while blue stands for a positive sign. Blank cells in figure 6.2 indicate absence of indicators from a particular model. Tables 6.4 and 6.5 below detail MCMC sampling results for all entered potential indicators in both models from among which only those with posterior inclusion probability (PIP) of 0,5 and greater are deemed to be useful for the explanation of the binary FSI, i.e. systemic event detection, and consequently to be retained for the final regression.

Table 6.4: Results from BMA MCMC sampling for the short model, source: author's own calculations

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
U_rate_2	0.99999538	3.688196e+00	6.451157e-01	1.00000000	23
realmoneyg_4	0.99988980	-1.055056e+00	2.140828e-01	0.00000000	6
MSCIhpshort_5	0.99498580	5.764964e-01	1.468689e-01	1.00000000	18
Globpcredg_7	0.91783518	6.641394e+01	3.450507e+01	0.99988211	61
real.money.g	0.90586962	-6.095432e-01	2.812152e-01	0.00000000	5
Int_pcgxglopcGDP_5	0.90182173	1.859043e+00	8.705682e-01	1.00000000	50
GlobpcgxglobpcGDP_7	0.89507287	-1.634550e+01	9.063810e+00	0.07532941	70
MSCIhpshort_8	0.82283771	2.785996e-01	1.608481e-01	0.99999271	19
Int_pcgxglopcGDP_4	0.70617040	1.165444e+00	9.083116e-01	0.99999959	49
GlobGDPg_1	0.61793373	2.021066e+00	1.889016e+00	0.99930942	73
GlobCPIg	0.59505118	5.112959e+00	5.011135e+00	0.99949700	74
CPIg_1	0.46564198	-1.074449e+00	1.339264e+00	0.00053365	54
realGDPg__1	0.44571778	8.954631e-01	1.144566e+00	0.99933326	2
mcapGDP_1	0.34217831	5.608837e-01	1.158618e+00	0.96535101	31
Int_realpcredg_8	0.32383298	-6.996839e+00	1.202700e+01	0.00048763	45
mcapGDP	0.29887729	-3.512866e-01	7.652164e-01	0.20662289	30
mcapGDP_3	0.28744100	-1.745721e-01	4.748373e-01	0.25296847	32
Int_pcgxglopcGDP_8	0.26686211	3.696046e-01	7.255735e-01	0.99893070	52
M2.GDP	0.25454916	3.844335e-02	7.678808e-02	0.99999240	7
Int_mcapGDP_2	0.25232722	1.885353e-02	2.660970e-01	0.90482068	39
Globpcredg_4	0.24145627	1.061494e+01	2.840924e+01	0.99058297	60
Globpcredg_8	0.23121118	1.544175e+01	3.492713e+01	0.96354329	62
GlobpcgxglobpcGDP_4	0.23017224	-2.629830e+00	7.351607e+00	0.39959746	69
Int_mcapGDP_1	0.22894702	1.025682e-01	5.041053e-01	0.89717175	38
GlobpcgxglobpcGDP_8	0.22688578	-3.967863e+00	9.036691e+00	0.17274135	71
GlobGDPg	0.22538409	6.171636e-01	1.441511e+00	0.95045238	72
rdomcred	0.20752904	1.026928e-01	2.383028e-01	0.99957661	9
MSCIhpshort_1	0.20281047	6.174728e-02	1.535729e-01	0.99447399	17
Int_mcapGDP	0.18326476	-7.028770e-02	3.004985e-01	0.33486283	37
Int_realpcredg_6	0.18162516	-2.504938e+00	6.402291e+00	0.00373235	44
CPIg	0.16401713	-2.152798e-01	8.143758e-01	0.15501104	53
mcapGDP_5	0.16400367	-2.773095e-02	1.735535e-01	0.22944961	33
Int_MSCIgxglomcapGDP_5	0.14816193	1.231931e-01	3.626787e-01	0.99995425	47
MSCIhpshort	0.14810440	-3.872731e-02	1.240074e-01	0.06855930	16
govdefGDP_6	0.14631240	8.198796e-02	2.422534e-01	0.99999681	12
pcredg_8	0.14154724	-1.066504e-01	3.252464e-01	0.00028479	59
pcredGDP_8	0.13018502	2.102093e-02	6.875706e-02	0.99765633	15
Int_mcapGDP_5	0.12984089	1.078362e-02	7.122289e-02	0.74892484	40
GlobpcredGDP_1	0.12604976	4.154989e-02	1.490374e-01	0.94611704	68
curaccGDP_8	0.12069016	1.933134e-01	6.564652e-01	1.00000000	22
GlobmcapGDP_6	0.11723556	4.101931e-02	1.930266e-01	0.83909508	66
GlobCPIg_2	0.11181169	-5.069413e-01	2.007310e+00	0.06265395	75
mcapGDP_7	0.11106676	7.245340e-03	7.935516e-02	0.49159865	34
GlobmcapGDP_3	0.11000500	4.336602e-02	2.754532e-01	0.73835290	65
real.GDP.g	0.10758967	1.007958e-01	4.806086e-01	0.83733733	1
I_g	0.10630200	1.581512e-02	6.532460e-02	0.99904089	24
realGDPg__4	0.10405776	-9.079742e-02	3.609173e-01	0.02302162	3
GlobpcredGDP	0.09744920	2.667157e-02	1.204224e-01	0.92269568	67
tradebalg	0.09598413	-5.801589e-05	2.354933e-04	0.00000000	21
GlobmcapGDP_1	0.09551911	-2.321032e-02	2.702694e-01	0.32986232	64
govdebtGDP_4	0.09507649	-2.008445e-02	8.552246e-02	0.00563242	14
GlobmcapGDP	0.09069631	-1.679102e-02	1.810686e-01	0.28197398	63
Int_realpcredg_4	0.09026738	-9.650826e-01	5.355454e+00	0.15150201	43
GlobCPIg_4	0.08867720	2.265512e-01	1.917176e+00	0.71708524	76
Int_pcgxglopcGDP_7	0.08757371	5.752580e-02	2.842989e-01	0.92804614	51
GlobCPIg_7	0.08747436	2.847436e-01	1.543461e+00	0.89430934	77
Int_MSCIgxglomcapGDP_8	0.08247484	-4.444654e-02	2.270320e-01	0.05779621	48
I_g_3	0.08208433	-8.160594e-03	3.941128e-02	0.01563379	26
govdefGDP_4	0.08067213	2.905154e-02	1.399815e-01	0.99922595	10
IP_change_4	0.07974389	3.024565e-02	1.518504e-01	0.99090561	29
reservesg	0.07965942	-1.213973e-02	6.001195e-02	0.00264515	20

GlobCPIg_8	0.07914353	-2.307614e-01	1.332427e+00	0.10412278	78
I_g_8	0.07431616	4.426538e-03	4.907964e-02	0.89440938	27
NPL_6	0.06985529	5.659242e-02	5.282321e-01	0.88978199	41
CPIg_7	0.06863771	9.606882e-03	2.892453e-01	0.59042859	55
REERg_3	0.06576673	2.427737e-02	1.507525e-01	0.99551175	56
NPL_7	0.06561287	-5.353140e-03	4.869281e-01	0.71627482	42
Int_pcredGDP_8	0.06096209	-1.363777e-02	1.352507e-01	0.23704495	46
pcredg_4	0.06031649	-2.041127e-02	1.643186e-01	0.07831616	58
IP_change	0.05979311	1.195311e-02	1.109852e-01	0.88664506	28
realM2g_4	0.05901407	-2.031672e-03	7.432848e-02	0.41232618	4
pcredgxpcredGDP_4	0.05825569	2.045787e-03	2.472487e-02	0.77916129	36
govdefGDP_5	0.05610469	-8.973118e-03	9.532338e-02	0.12285961	11
govdefGDP_7	0.05574829	-8.922520e-03	9.812728e-02	0.12026478	13
I_g_1	0.05473887	-1.928382e-03	2.671986e-02	0.15950519	25
moneyGDP_4	0.05280916	4.563065e-03	5.321461e-02	0.89982377	8
pcredgxpcredGDP	0.05145840	7.196915e-04	1.683219e-02	0.67516199	35
REERg_5	0.04986333	-2.666771e-03	1.060855e-01	0.36130000	57

Note: the number following each indicator states an indicator‘s lag (in quarters)

Table 6.4 reports PIPs, posterior means and posterior standard deviations for all entered variables. Column conditional posterior sign records if a coefficient for each variable was mostly positive (value of either 1 or close to 1) throughout the best 5000 models or if it was negative (value 0 or close to 0). The top 11 variables whose PIPs are larger than 0,5 are judged the most useful and are to be included within the short model (Babecky, Havranek et al., 2012). However, this outcome based on MCMC sampling slightly differs from reported analytical likelihoods for the short model variables which include among the variables with PIP larger than 0,5 apart from the same 11 variables also the 12th one; first lag of real domestic GDP annual growth. This phenomenon could be explained by he fact that analytical PIPs are slightly larger than those obtained from the MCMC sampling as they do not account for many models with not-so-useful variables which are factored into MCMC results. In this thesis variables will be included into the final model based on their analytical likelihoods similar to Fernandez et al. (2001b) and results can be found in the appendix. In this view there are 12 useful variables to be chosen from all 78 potential indicators in the short model.

Table 6.5 below presents in the same manner results of BMA method for potential variables in the long model.

Table 6.5: Results from BMA MCMC sampling for the long model, source: author's own calculations

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
rdomcred_1	0.95265722	9.307394e-01	3.475656e-01	1.00000000	9
Int_pcgxglopcGDP_4	0.92995198	2.365919e+00	9.877975e-01	1.00000000	50
U_rate_5	0.88104822	3.103029e+00	1.920336e+00	0.99991528	23
CPIg_8	0.82845473	-2.557157e+00	1.574146e+00	0.00000000	54
CPIg_1	0.82632773	-3.438961e+00	2.126189e+00	0.00000164	53
Int_realpcredg_4	0.80372778	-2.730366e+01	1.706450e+01	0.00032385	43
GlobmcapGDP	0.76910787	8.223777e-01	5.621752e-01	0.99939928	62
Globpcredg_1	0.71048442	8.699517e+01	6.685432e+01	0.99283146	59
GlobpcgxglobpcGDP_1	0.71006778	-2.314010e+01	1.782491e+01	0.01743430	66
real.GDP.g	0.66624404	-1.757571e+00	1.501918e+00	0.00133681	1
GlobmcapGDP_3	0.62716342	7.521649e-01	6.865189e-01	0.99703437	63
MSCIhpshort_8	0.61075087	1.887241e-01	1.761336e-01	0.99962782	18
M2GDP	0.52397698	1.062911e-01	1.180903e-01	1.00000000	7
Int_realpcredg	0.48159664	-1.519547e+01	1.844655e+01	0.00182324	42
GlobCPIg	0.43166242	4.630646e+00	6.102457e+00	0.98364663	72
Globpcredg	0.39340056	2.123112e+01	4.434857e+01	0.99135346	58
GlobpcgxglobpcGDP	0.37157171	-5.001751e+00	1.156775e+01	0.47363282	65
Int_MSCIgxglomcapGDP	0.35095622	4.334748e-01	6.816549e-01	0.99904072	45
MSCIhpshort_1	0.34754196	1.062357e-01	1.710779e-01	0.99834245	17
pcredg_8	0.33448456	-3.970065e-01	6.520407e-01	0.00002378	57
GlobCPIg_8	0.33201658	2.823075e+00	4.887034e+00	0.99096437	74
NPL_7	0.32128136	-6.243023e-01	1.566421e+00	0.01646712	40
NPL_8	0.31257484	-5.003267e-01	1.114552e+00	0.02895257	41
Int_mcapGDP_3	0.30320887	1.313033e-01	2.955407e-01	0.99500381	34
NPL_6	0.26477380	-3.927582e-01	1.272991e+00	0.07950266	39
Int_mcapGDP_7	0.26266580	1.244508e+00	3.166096e+00	0.97051412	36
Int_mcapGDP_6	0.25980664	-7.914295e-01	2.047525e+00	0.42037989	35
real.money.g	0.25025827	-1.047021e-01	2.137508e-01	0.00007903	4
Globpcredg_7	0.24872009	-6.530008e+00	1.949157e+01	0.08379647	61
Int_mcapGDP_8	0.24623411	-5.332827e-01	1.388830e+00	0.37567663	37
GlobpcgxglobpcGDP_7	0.24370744	1.563853e+00	5.152034e+00	0.54403673	68
U_rate_1	0.24290787	-1.136723e-01	1.818880e+00	0.50655740	22
pcredGDP_5	0.24007091	4.535133e-02	9.472141e-02	0.99999898	16
Int_pcgxglopcGDP_8	0.22686231	1.921423e-01	4.187659e-01	0.99872199	52
IP_change_4	0.20037878	1.409856e-01	3.363921e-01	0.99997250	29
Int_pcgxglopcGDP_5	0.18769684	1.798208e-01	4.494631e-01	0.99951044	51
tradebalg	0.17606122	-1.475610e-04	3.817893e-04	0.00000000	20
GlobGDPg_8	0.17359871	3.486944e-01	9.618622e-01	0.96610932	71
GlobpcredGDP_3	0.16703600	-1.144247e-01	3.233730e-01	0.03354513	64
GlobGDPg	0.15477069	1.079006e-01	1.035880e+00	0.59614877	69
Globpcredg_4	0.14764667	5.390649e+00	2.161712e+01	0.86544348	60
GlobpcgxglobpcGDP_4	0.14459309	-1.357890e+00	5.645483e+00	0.39469060	67
real.money.g_8	0.13834460	3.179526e-02	1.020278e-01	0.97636626	6
Int_MSCIgxglomcapGDP_5	0.13736744	-1.103527e-01	3.493660e-01	0.00866079	46
GlobGDPg_1	0.12080751	-1.842256e-01	7.418455e-01	0.11010868	70
pcredg	0.11953829	9.420821e-02	3.344305e-01	0.98951503	56
mcapGDP	0.11724524	1.181090e-02	9.647118e-02	0.82117939	30
mcapGDP_1	0.11545598	-9.852291e-03	1.206249e-01	0.61964108	31
curaccGDP	0.11132360	1.383336e-01	5.031975e-01	0.99999900	21
Int_pcgxglopcGDP	0.10945749	8.100297e-02	3.336174e-01	0.91848058	48
govdefGDP_6	0.10691713	4.416448e-02	1.659296e-01	0.99998836	13
NPL	0.10434384	7.516265e-02	5.154661e-01	0.74647261	38
realGDPg__1	0.09277704	3.964230e-03	4.924322e-01	0.54298968	2
real.money.g_2	0.08380604	-1.468239e-02	7.490865e-02	0.05813078	5
GlobCPIg_4	0.08374831	1.232721e-01	1.512754e+00	0.62635505	73
Int_pcredGDP	0.08246524	-4.181777e-02	2.279351e-01	0.10938642	44
moneyGDP	0.07444458	-1.704656e-02	1.037480e-01	0.12218306	8
Int_pcgxglopcGDP_1	0.06976536	2.158467e-02	1.708232e-01	0.79018462	49
pcredgxpcredGDP_4	0.06512509	2.951305e-03	2.909070e-02	0.77126480	33
realM2g	0.06364227	2.357211e-03	8.161622e-02	0.52738641	3
pcredgxpcredGDP	0.06282440	-2.056526e-03	2.486908e-02	0.34434180	32
govdefGDP_3	0.06258176	1.202094e-02	8.976497e-02	0.95546483	10
IP_change	0.06245216	2.220694e-03	1.351651e-01	0.69190673	28
govdebtGDP_4	0.06007451	-4.361239e-03	4.684445e-02	0.20389975	14
I_g_7	0.06002998	-4.045856e-03	3.714176e-02	0.03758159	26
Int_MSCIgxglomcapGDP_8	0.05925511	9.726272e-03	1.431197e-01	0.70949716	47
I_g	0.05868947	4.146829e-03	3.809993e-02	0.95554947	24

REERg_4	0.05712687	1.318279e-02	1.213039e-01	0.96046694	55
I_g_3	0.05559931	-1.254077e-03	3.460895e-02	0.15202267	25
govdefGDP_5	0.05450136	-5.268373e-03	8.257535e-02	0.21095092	12
govdebtGDP_6	0.05374773	1.643173e-03	4.144173e-02	0.63338030	15
I_g_8	0.05252627	-6.598721e-05	3.340977e-02	0.72655543	27
govdefGDP_4	0.05151789	-1.517713e-03	7.681583e-02	0.40247897	11
reservesg_8	0.05058513	7.723865e-04	3.299659e-02	0.65924332	19

Note: the number following each indicator states an indicator‘s lag (in quarters)

In the case of the long model the top 13 variables from table 6.5 have PIPs greater than 0,5 and are hence considered useful. Analytical results in this case report these same variables with PIPs exceeding 0,5 and no additional ones. As such MCMC sampling and analytical results do not diverge for the long model variables apart from their ordering based on PIPs. Analytical results for the long model can be found in the appendix as well.

To summarize, BMA technique thus identified the following 12 indicators as useful in crisis signalling over the short horizon of 6 quarters (short model): real money growth and its 4th lag, the 5th and 8th lags of real MSCI deviation from short Hodrick-Prescott trend, the 2nd lag of unemployment rate, the 7th lag of global private credit annual growth, the 7th lag of interaction between global private credit annual growth and global private credit/GDP, the 4th and 5th lag of interaction between private credit annual growth and global privated credit/GDP, the 1st lag of global real GDP annual growth, the 1st lag of real GDP annual growth and global CPI annual growth.

The identified useful indicators for systemic event prediction over the short horizon are broadly in line with the most useful indicators identified by Peltonen, Lo Duca (2011) as follows:

- From among domestic indicators they identified domestic asset prices as one of the top useful. These are expressed by the deviation of real MSCI index from short Hodrick-Prescott trend and appear among useful indicators here even twice (lags 5 and 8).
- From among global variables and their interactions with domestic ones, global GDP, global private credit indicators and their interactions were identified in Peltonen, Lo Duca (2011) as the most useful from among all indicators. In this thesis the most useful indicators belonging in this category

are global private credit annual growth, interaction between global private credit annual growth and global private credit/GDP, interaction between domestic private credit annual growth and global private credit/GDP which appears twice (lags 4 and 5) and global GDP annual growth.

As for other selected variables domestic GDP annual growth, unemployment rate, real money growth and global CPI growth are also considered informative and will be therefore included in the final short model.

For the EWS over the long horizon of 12 quarters the following 13 variables were selected as the most informative: the 1st lag of real domestic credit annual growth, the 4th lag interaction between domestic private credit annual growth and global private credit/GDP, the 5th lag of unemployment rate, the 1st and 8th lag of domestic CPI annual growth, the 4th lag of interaction between domestic and global real private credit annual growth, real domestic GDP annual growth, global market capitalization/GDP and its 3rd lag, the 8th lag of MSCI deviation from short Hodrick-Prescott trend, the 1st lag of global private credit annual growth, the 1st lag of interaction between global private credit annual growth and global private credit/GDP and ratio M2/GDP.

As is common in the literature (Alessi and Detken, 2011) and also identified by Peltonen and Lo Duca (2011), credit and private credit indicators both domestic and global as well as their interactions were found useful for the model over the long horizon as well. Overall 5 credit indicators are to be included into EWS over the long horizon. Moreover, global market capitalization/GDP was selected even twice which coincides with the finding by Peltonen, Lo Duca (2011) that it is the most useful global indicator, i.e. most useful indicator overall, in their study. As for asset prices they are an important indicator here similarly to short model, though only their 8th lag appears.

Same as for the short model indicators, domestic GDP, CPI growth and unemployment rate were selected for the model. When it comes to money aggregates the ratio of M2/GDP was selected for the long model as opposed to real money growth that appears in the short model.

Now that the key indicators were identified the next chapter focuses on estimation and performance of the EWS over short and long horizon.

7 Systemic Events Probability Framework

Having selected appropriate indicator lags and indicators themselves previously, this chapter focuses on estimating the joint impact of useful indicators on the probability of a systemic event. In other words, the probability of a systemic event is hence defined as a function of indicators deemed useful for systemic risk assessment and crisis prediction. As the dependent variable for this framework is the leading indicator for risk assessment and events prediction, i.e. FSI in a binary form, a logistic regression is applied to the data to ascertain the relation between useful indicators of vulnerabilities and crisis probability. The use of logit model for this purpose is in line with other research works in early warning system setting such as Peltonen and Lo Duca (2011) as well as advocated by Demirguc-Kunt and Detragiache (2005, pp. 5-9).

7.1 Logit model

Logit model falls into the category of discrete probability models. More specifically, due to the binary nature of the dependent variable, FSI, binary logit model is applied in this thesis. The specification of the logit model is as follows:

$$Probability_{i,t}\left[Dependent_{i,t} = 1\right] = \frac{e^{X_{it}\beta}}{1 + e^{X_{it}\beta}}$$

where $Probability_{i,t}\left[Dependent_{i,t} = 1\right]$ is a probability of a systemic event outbreak for a country i at time t within next several quarters defined by a binary FSI set to 1 in six quarters before a crisis outbreak (short model) and to 0 in all other periods or in case of the long model set to 1 in twelve quarters before the crisis outbreak. X_{it} is a set of useful indicators observed in a country i at the time t.

To estimate logit model maximum likelihood estimation technique is used which yields coefficient estimates that are consistent and asymptotically efficient as well as asymptotic standard errors of the coefficient estimates (Cramer, 2003).

Model estimation should be accompanied by diagnostic testing in order to assess its quality in regards to describing the data. Next, those statistical tests suitable for logit model are to be presented which will be employed for evaluation of the model fit to the data in this work. Specific outcomes from logit model and its testing will be presented later in this chapter.

First of all, Likelihood Ratio (LR) test is based on comparison of maximum value of the loglikelihood with and without restrictions. In other words, LR tests the joint significance of all variable coefficients in a model and compares it to the null model, i.e. model with intercept only and no other independent variable. The null hypothesis of the fitted model being not significantly different from the null model is often rejected. Thus the test explains only that the fitted model is better than nothing and does not provide any additional information about the model fit to the data. The LR test can be thought of as an equivalent of the F test in OLS regression (Cramer, 2003).

Wald test is used within the maximum likelihood setting "to test the restrictive hypothesis of a zero coefficient" (Cramer, 2003). In upcoming analysis it is about to be used to verify if a variable displaying high collinearity could be omitted from the model which follows the advice by Cramer (2003) that in cases of severe collinearity one or two regressors can be omitted.

Goodness-of-fit tests are another class of statistical tests that could be employed in the validation of logit models. One such test, the Hosmer-Lemeshow test, orders individual observations into G groups by their estimated probability. Thus for each group the expected frequency of successes equals sum of the estimated probabilities which is then compared to actual frequency. For the group the estimated probability then equals the mean of probabilities. This test, however, is not recommended for unbalanced samples which is the case in this thesis as it may lead to a very uneven distribution of observations over the groups and test statistic might thus show erratic behaviour (Cramer, 2003). In place of the Hosmer-Lemeshow goodness-of-fit test, other methods are thus employed to ensure model validation.

One of these measures for detection of model performance is the percentage correctly predicted (PCP). Unlike the dependent variable entered into logit model a probability estimate output from logit model is not binary. Therefore to evaluate model performance a cut-off value for probability is chosen and model fit success is obtained from the match count of predicted and observed outcomes. Cramer (2003) advises to set the cut-off equal to the mean value of logit predicted probabilities in case of unbalanced samples as cut-off = 0,5 gives "nonsense results". Apart from this PCP method proposed by Cramer (2003) the PCP was evaluated for logit models in this thesis also by means of utilizing as a cut-off such observed probability value that maximizes the utility statistic of a model as presented in chapter 6 for individual potential indicators. The PCP results obtained from the utility maximization method and from setting the cut-off equal to the observed probability mean do not differ significantly. However, later in this chapter the results for logit models are to be reported based on utility maximization.

Last but not least, logit model validation can be executed by means of the Receiver Operating Characteristics (ROC) curve. In general the ROC curve is used to represent the quality of probabilistic detection and forecasts systems (Mason and Graham, 2002) while it originated in the field of radar-signal detection theory. In probabilistic forecasts the probability at which the warning is emitted varies across different thresholds. For each such threshold the hit rate (portion of events for which the warning is correctly issued) and the false-alarm rate (portion of nonevents for which the warning is incorrectly issued) can be observed and as they create a two-dimensional coordinate in a ROC space they can be subsequently plotted drawing altogether the ROC curve. Thus the ROC curve plot exhibits a false-alarm rate on the horizontal axis and a hit rate on the vertical axis for each probability threshold. In this spirit, the area under the ROC curve indicates the quality of a model forecast by its ability to correctly predict both the occurrence and the non-occurrence of defined events (Mason and Graham, 2002). Moreover, Mason (1982) and Mason and Graham (1999) showed that when the forecast has some skill then the area under the ROC curve exceeds 0,5. In order to evaluate how well a model fits the data, i.e. "to assess the significance of forecast event probabilities for cases where events actually occurred with those where events did not occur" (Mason and Graham, 2002), the Mann-Whitney U-statistic is used. In the upcoming analysis the ROC curve is derived for the fitted short and long models on full data as well as for the in-sample predictions for models on truncated data and their out-of-sample predictions. Next, the areas under these ROC curves are to be assessed via the Mann-Whitney U-statistic for which the p-value is generated to verify the extent of the forecast's skill. All calculations are performed in R using package "verification" that follows the process outlined in Mason and Graham (2002).

7.2 Short Model Estimation and Performance

The short logit model contains in this analysis binary FSI with values of 1 in 6 quarters preceding the pre-defined outbreak of a systemic event and 0 in all other periods on the left-hand side, i.e. dependent variable, and on its right-hand side the 12 useful indicators, the outcome of BMA technique. However, this model displayed high collinearity between 2 indicators, the seventh lag of global annual private credit growth (Globpcredgl7) and the seventh lag of the interaction between global annual private credit growth and global private gredit over GDP (GlobpcgxglobpcGDPl7). Therefore, in order to achieve noncollinearity among independent variables the seventh lag of the interaction between global annual private credit growth and global private gredit over GDP (GlobpcgxglobpcGDPl7) was omitted from the model based on the Wald test statistic with p-value of 0,595818, which is higher than the respective p-value for the seventh lag of global annual private credit growth (Globpcredgl7) equalling 0,488666. Results of collinearity testing can be found in the appendix.

All in all, the final short model composition includes 11 indicators and is to be fitted to all available data, data till 2011 as well as until 2006. For each model in-sample predictions are computed same as out-of-sample predictions for period of 2011Q1- 2013Q1 and for pre-crisis period of the Global crisis, i.e. 2006Q1-2008Q1.

In this section, indicator coefficients are estimated for each model specification followed by in-sample and out-of-sample performance of short logit models.

Due to the nature of logit model, the coefficient estimates for independent variables are log-odds ratios. Logit regression estimates thus in this case express how the log-odds of a systemic event occurrence change with a unit change in an independent variable. The sign of log-odds ratios indicates either a positive or a negative relationship between an explanatory variable and the likelihood of a systemic event occurrence. However, in order to estimate more precisely the extent of the change in likelihood given a change in an independent variable, an exponential of the log-odds ratio would indicate actual odds of materialization of an event. For a negative relationship between an explanatory and the dependent variable odds lie between 0 and 1, in case of a positive relationship they exceed 1.

Table 7.1: Short model estimation on all available data, source: author's own calculations

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-2,26005	0,452736	-4,9920	5,98e-07	***
realmoneygl4	-12,5276	2,26024	-5,5426	2,98e-08	***
MSCIhpshortl5	5,34506	1,51967	3,5172	0,00044	***
Uratel2	22,1122	6,88392	3,2122	0,00132	***
Globpcredgl7	40,2897	10,0369	4,0142	5,97e-05	***
MSCIhpshortl8	1,85216	0,928	1,9959	0,04595	**
realmoneyg	-7,32671	2,27894	-3,2150	0,00130	***
Int_pcgxglopcGDPl4	11,6145	9,21088	1,2610	0,20732	
Int_pcgxglopcGDPl5	23,2149	9,92291	2,3395	0,01931	**
GlobGDPgl1	14,747	9,168	1,6085	0,10772	
realGDPgl1	20,7753	6,63864	3,1294	0,00175	***
GlobCPIg	31,2841	19,104	1,6376	0,10151	

Mean dependent var	0,192453	S.D. dependent var	0,394599
McFadden R-squared	0,452249	Adjusted R-squared	0,406020
Log-likelihood	-142,1812	Akaike criterion	308,3624
Schwarz criterion	359,6369	Hannan-Quinn	328,4320

Likelihood ratio test: Chi-square(11) = 234,783 [0,0000]

Note: the number following each indicator states an indicator's lag (in quarters)

Table 7.1 above presents coefficient estimates of the 11 independent variables included in the short model, their standard errors as well as their Wald test statistics z and their significance where one asterix represents significance on 10% level of significance, two on 5% and three significance on 1% significance level. Only one variable, real money growth (realmoneyg) and its fourth lag (realmoneygl4), have a negative relationship with the likelihood of an event occurence, i.e. for a one-unit change in this variable the odds of a crisis occurence are less than 1. A unit change in all other independent variables (the 5th lag of real MSCI deviation from short

Hodrick-Prescott trend, the 2nd lag of unemployment rate, the 7th lag of the global real private credit annual growth, the 8th lag of real MSCI deviation from short Hodrick-Prescott trend, the 4th and the 5th lags of the interaction between real private credit annual growth and the global private credit over GDP, the 1st lag of the global real GDP annual growth, the 1st lag of real GDP annual growth and the annual growth of the global CPI) increases the odds of a crisis by more than 1.

One way of evaluating robustness of the model is by comparing the coefficient estimates for the variables and their significance in the model estimated on the data of differing length. In this spirit, the coefficient estimates will be compared among the short model estimated on all available data (1990Q1-2013Q1), on truncated data till 2011 (1990Q1-2010Q4) and truncated until 2006 (1990Q1-2005Q4).

Table 7.2: Short model estimation on data truncated till 2011, source: author's own calculations

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-2,70507	0,535742	-5,0492	4,44e-07	***
realmoneygl4	-15,8406	2,77313	-5,7122	1,12e-08	***
MSCIhpshortl5	5,78253	1,62348	3,5618	0,00037	***
Uratel2	29,0217	8,70531	3,3338	0,00086	***
Globpcredgl7	40,8864	11,2972	3,6192	0,00030	***
MSCIhpshortl8	3,36033	1,39108	2,4156	0,01571	**
realmoneyg	-10,18	2,98776	-3,4072	0,00066	***
Int_pcgxglopcGDPl4	12,6909	11,0692	1,1465	0,25159	
Int_pcgxglopcGDPl5	29,3057	12,2007	2,4020	0,01631	**
GlobGDPgl1	20,0809	11,0036	1,8249	0,06801	*
realGDPgl1	21,6318	7,6804	2,8165	0,00485	***
GlobCPIg	34,0579	21,0526	1,6177	0,10572	

Mean dependent var	0,191898	S.D. dependent var	0,394214
McFadden R-squared	0,535229	Adjusted R-squared	0,482902
Log-likelihood	-106,5829	Akaike criterion	237,1657
Schwarz criterion	286,9730	Hannan-Quinn	256,7629

Likelihood ratio test: Chi-square(11) = 245,481 [0,0000]

Note: the number following each indicator states an indicator's lag (in quarters)

The short model estimated on truncated data till 2011 in table 7.2 does not differ substantially from the model estimated on full data in terms of significance. In fact, the 1st lag of the global real annual GDP growth is even marked as significant on 10% significance level unlike the full data model. As for the coefficient estimates a negative relationship is again estimated only between the 4th lag of real money growth and the real money growth and the dependent. A two-digit percentage change in coefficient estimates between the full data model and the truncated model until 2011 is observable only for the 4th lag of real money growth (-26,5%), the 2nd lag of unemployment rate (31,2%), the 8th lag of real MSCI deviation from short Hodrick-Prescott trend (81,4%), real money growth (-39%), the 5th lag of the interaction between the annual growth of real private credit and the global private credit over GDP (26,2%) and the 1st lag of the global real GDP annual growth (36,2%). For this model the changes in estimates are not substantial as the truncated model includes most of the observations of the model estimated on full data.

Table 7.3: Short model estimation on data truncated till 2006, source: author's own calculations

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-5,90711	2,24227	-2,6344	0,00843	***
realmoneygl4	-14,8745	6,53198	-2,2772	0,02278	**
MSCIhpshortl5	8,32458	4,61138	1,8052	0,07104	*
Uratel2	5,67351	20,1237	0,2819	0,77800	
Globpcredgl7	6,50544	46,9437	0,1386	0,88978	
MSCIhpshortl8	-0,43757	3,99908	-0,1094	0,91287	
realmoneyg	0,701325	3,4461	0,2035	0,83873	
Int_pcgxglopcGDPl4	-21,8695	39,1745	-0,5583	0,57667	
Int_pcgxglopcGDPl5	102,949	50,9079	2,0223	0,04315	**
GlobGDPgl1	193,446	98,1902	1,9701	0,04882	**
realGDPgl1	-11,875	20,5154	-0,5788	0,56270	
GlobCPIg	-337,811	203,492	-1,6601	0,09690	*

Mean dependent var	0,067358	S.D. dependent var	0,251292
McFadden R-squared	0,507179	Adjusted R-squared	0,255198
Log-likelihood	-23,46943	Akaike criterion	70,93886
Schwarz criterion	110,0911	Hannan-Quinn	86,79428

Likelihood ratio test: Chi-square(11) = 48,3064 [0,0000]

Note: the number following each indicator states an indicator‘s lag (in quarters)

The situation is, however, different even at first glance when comparing the model estimated on all data and the one estimated on data until 2006, as shown in table 7.3 above. Resulting from a large chunk of the data omitted (all observations from 2006Q1 onwards), the coefficient estimates differ substantially from those in table 7.1 as well as their significance levels which decreased markedly. Some variables even experienced a relationship reversal with the dependent variable, from a positive one to the negative. This is the case of the 8th lag of real MSCI deviation from the short Hodrick-Prescott trend, the 4th lag of the interaction between real annual private credit growth and the global private credit over GDP, the 1st lag of the real GDP growth and the annual growth of the global CPI. On the other hand, the real money growth reverted to the positive relationship with its unit change increasing the odds of a crisis by slightly more than 2.

Table 7.4 below provides a more comprehensive picture of the short logit model in-sample performance when applied on all available data, on truncated data till 2011 and till 2006.

In-sample performance of short logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Short truncated till 2006	0,436	0,812	87,56	100	0,133	0,959	1,75E-08
Short truncated till 2011	0,372	0,756	88,70	84,44	0,122	0,937	2,66E-38
Short on full data	0,335	0,805	89,43	73,53	0,092	0,908	6,38E-38

Table 7.4: In-sample performance of short logit models, source: author's own calculations

As shown in table 7.4 the short model performance was measured by several indicators:

- *maximum utility measure (U)* which was calculated using the model's in-sample predictions and applying the same formula as in chapter 6 when assessing the usefulness of individual potential indicators.
- *threshold* for which the model's utility is maximized.
- *percentage correctly predicted (PCP)* calculated as the number of matches between observed and predicted outcomes over the number of all predicted outcomes (the utility-maximizing threshold is used as a cut-off).
- *percentage of crises predicted* calculated as number of periods when signal was correctly issued over the number of periods in which the signal should have been issued (sum of "correct

signal" periods and "missing signal" periods) or $\frac{A}{(A+C)}$ from table 6.2 in chapter 6.

- *Noise to Signal ratio (NtS ratio)* equals the share of wrong signals as a ratio of all periods in which no signal should be issued divided by the number of correct signals as a ratio to all periods in which a signal should be issued $\frac{B}{(B+D)} \Big/ \frac{A}{(A+C)}$

  A useful indicator is supposed to have a NtS of less than 1. A value of 1 would result if an indicator provides purely random signals (Kaminsky et al., 1998).
- *ROC area* is an area under the Receiver Operating Characteristics curve indicating a forecast's accuracy. A value of 1 indicates a perfect model while a random forecast would have the ROC area equal to 0,5. The ROC area calculation follows Mason and Graham (2002).
- *p-value* helps estimate the adequacy of a model forecast via ROC area and is related to Mann-Whitney U statistics. The statistics tests the null of the area under the ROC curve equal to 0,5 or the forecast has no skill.

According to these calculations the best-performing in-sample short model is the one estimated on truncated data until 2006. It has the highest U measure, the percentage of crises predicted and area under ROC curve which is also highly significant with p-value of 1,75E-08. On the other hand, the model's NtS ratio is the largest out of the compared in-sample short models while the percentage correctly predicted is the lowest. On the whole, the in-sample performance of the short model appears to be more than satisfactory as it is among other verifiable by low p-values, signifying strong rejection of the null of no forecast skill for all three fittings of the short model.

Areas under ROC curves presented in table 7.4 were obtained from ROC curve plots in figure 7.1 below. The further the ROC curve for a model is from the diagonal, the larger the discrimination (analogy with Gini coefficient as a measure of inequality), i.e. the higher the forecast's skill to anticipate correctly the occurrence or non-occurrence of pre-defined events.

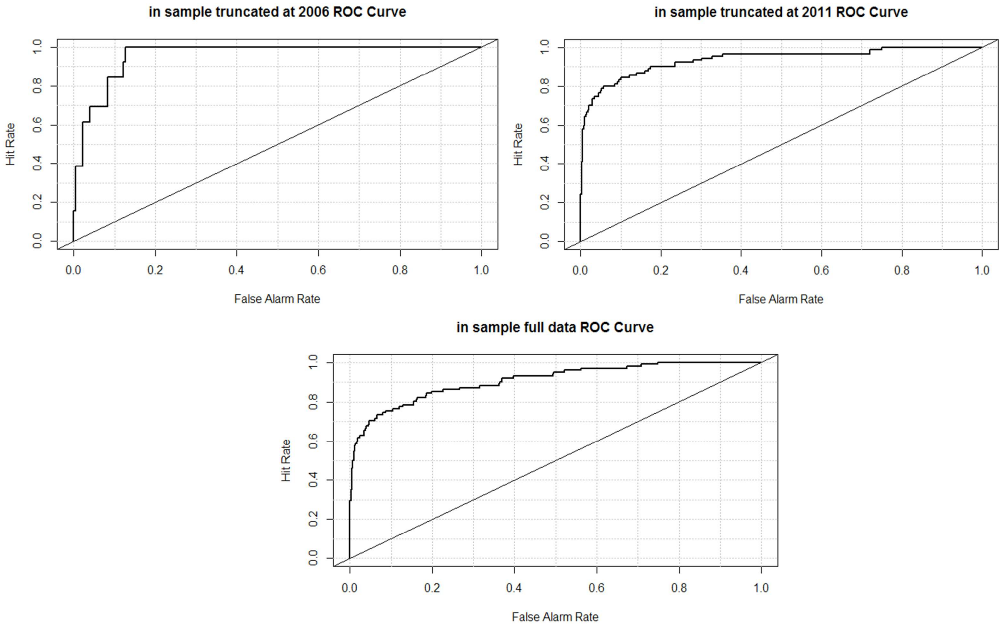


Figure 7.1: ROC curve plots for in-sample performance of short logit model estimated on data until 2006, until 2011 and on all available data, source: author's own calculations

Once the in-sample performance of the short logit model is validated, it is time to assess its performance out-of-sample. This check is performed to estimate a model's forcasting ability. The results of forecasts for the model on truncated data till 2011 over the period of 2011Q1-2013Q1 and those of the model on truncated data until 2006 over pre-crisis period of 2006Q1-2008Q1 are summarized in table 7.5 below.

Out-of-sample performance of short logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Short truncated till 2006	0,197	0,796	75	44,68	0,145	0,691	0,00019
Short truncated till 2011	0,159	0,666	68,85	58,33	0,490	0,599	0,150506

Table 7.5: Out-of-sample performance of short logit models, source: author's own calculations

As expected the out-of-sample performance of the model is lower compared to its in-sample results. The maximum utility is about half of that for in-sample performance as well as all other performance measures decreased (apart from NtS ratio which increased) indicating weaker performance in general.

The better out-of-sample performance is for the model on truncated data till 2006 due to having higher utility measure, PCP, lower NtS ratio and a larger area under ROC curve which is significant on 0,02% significance level. However, its percentage of crises predicted is lower than that for the model on data truncated till 2011. The worse out-of-sample performing short model, on data truncated until 2011, does not differ dramatically in terms of performance measures from the better one apart from NtS ratio that is almost 0,5 and the area nder ROC curve of 0,599 which is significant only on 16% significance level even if the model itself is not a random forecast (area of 0,599 still being larger than 0,5).

The short model on truncated data until 2006 is ranked as the best performing by its U measure both in-sample and out-of-sample. However, out-of-sample the model experienced almost 55% fall in its utility, 14,5% decline in its PCP, the fall of 55,3% in its percentage of crises predicted, 9% rise in its NtS ratio while the area under ROC curve shrank by 28%.

In comparison, the out-of-sample performance of the worse model, estimated on data up till 2011, declined from its in-sample performance by 57% for U, 22,4% for PCP, 31% for percentage of crises predicted and by 36% for ROC area while its NtS ratio shot up by 302% to the level of almost 0,5.

Overall, the best ranked model, estimated on truncated data till 2006, appears to be more stable when estimated out-of-sample than the second best ranked short model.

Figure 7.2 below offers ROC curve plots for out-of-sample performance of the short model from which areas under ROC curve were computed as presented in table 7.5.

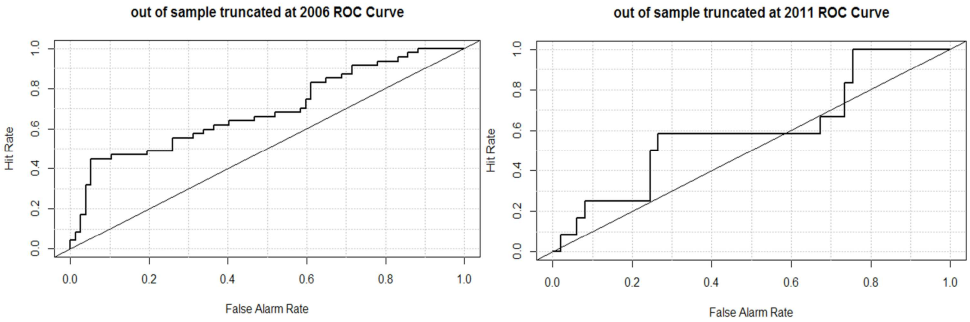


Figure 7.2: ROC curve plots for out-of-sample performance of short logit model estimated on data up till 2006 and till 2011, source: author's own calculations

7.3 Long Model Estimation and Performance

As for the long model, its dependent variable is the binary FSI with values of 1 in 12 quarters preceding the pre-defined occurence of a systemic event and 0 in all other periods on the left-hand side, i.e. dependent variable, and on its right-hand side there are the 13 indicators, deemed useful from BMA technique. Similarly to the short model, the long model also displayed high collinearity between 2 indicators, i.e. the first lag of global annual private credit growth (Globpcredgl1) and the first lag of the interaction between global annual private credit growth and global private gredit over GDP (GlobpcgxglobpcGDPl1). Thus, to ensure noncollinearity among explanatory variables the first lag of the interaction between global annual private credit growth and global private gredit over GDP (GlobpcgxglobpcGDPl1) was omitted in the spirit of the short model analysis. The decision is justified by the Wald test statistic for this variable with p-value of 0,154462, which is again higher than the respective p-value for the first lag of global annual private credit growth (Globpcredgl1) that equals 0,152273. Results of collinearity testing are detailed in the appendix.

After this adjustment final long model contains 12 indicators and is to be fitted, as in case of the short model, to all available data, data truncated till 2011 and truncated till 2005. For each model in-sample predictions are calculated as well as out-of-sample predictions for period of 2011Q1- 2013Q1 and for pre-crisis period of the Global crisis, i.e. 2005Q1-2008Q2.

Next, the analysis resumes the structure of that for the short model. As such, indicator coefficients are estimated for each of the above specifications followed by in-sample and out-of-sample performances of long logit models.

Table 7.6: Long model estimation on all available data, source: author's own calculations

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-10,9152	1,23256	-8,8557	8,31e-019	***
rdomcredl1	-1,07904	2,10306	-0,5131	0,60790	
Int_pcgxglopcGDPl4	50,8465	13,926	3,6512	0,00026	***
Uratel5	8,77642	5,82841	1,5058	0,13212	
CPIgl8	4,54716	4,36299	1,0422	0,29731	
Int_realpcredgl4	-309,252	109,757	-2,8176	0,00484	***
CPIgl1	-54,7731	8,75562	-6,2558	3,96e-010	***
realGDPg	-14,7407	5,81822	-2,5335	0,01129	**
GlobmcapGDP	5,26878	1,47088	3,5821	0,00034	***
MSCIhpshortl8	1,59052	0,949851	1,6745	0,09403	*
Globpcredgl1	2,48314	10,0189	0,2478	0,80425	
GlobmcapGDPl3	7,26515	1,38609	5,2415	1,59e-07	***
M2GDP	2,06582	0,844418	2,4464	0,01443	**

Mean dependent var	0,275362	S.D. dependent var	0,447102
McFadden R-squared	0,459095	Adjusted R-squared	0,419078
Log-likelihood	-175,7201	Akaike criterion	377,4402
Schwarz criterion	433,5163	Hannan-Quinn	399,3503

Likelihood ratio test: Chi-square(12) = 298,286 [0,0000]

Note: the number following each indicator states an indicator‘s lag (in quarters)

From long model estimation on the full data sample in table 7.6, it is observable that 4 independent variables, the 1st lag of real domestic credit growth, the 4th lag of interaction between domestic and global real private credit growth, the 1st lag of CPI annual growth and annual growth of real GDP, have a negative relationship with the dependent, a likelihood of a systemic event occurence. A unit change in all other explanatory variables, i.e. the 4th lag of interaction between annual real private credit growth and global private credit over GDP, the 5th lag of unemployment rate, the 8th lag of growth in CPI, global market capitalization over GDP, the 8th lag of real MSCI deviation from short Hodrick-Prescott trend, the 1st lag of global private credit real annual growth, the 3rd lag of global market capitalization over GDP and ratio of M2 over GDP, increases the odds of a crisis occurence by a factor of more than 1.

The model validation will be performed in spirit of that for the short model by comparing coefficient estimates in the long model estimated on data samples of varying length, i.e. model on full data versus model estimated on truncated data till 2011 and model on all available data versus that on truncated data till 2005.

Table 7.7: Long model estimation on truncated data till 2011, source: author's own calculations

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-11,1426	1,29634	-8,5955	8,29e-018	***
rdomcredl1	-1,16733	2,17077	-0,5377	0,59075	
Int_pcgxglopcGDPl4	51,5749	14,1533	3,6440	0,00027	***
Uratel5	12,4662	6,09056	2,0468	0,04068	**
CPIgl8	3,97843	4,34414	0,9158	0,35976	
Int_realpcredgl4	-311,475	109,404	-2,8470	0,00441	***
CPIgl1	-55,115	8,85072	-6,2272	4,75e-010	***
realGDPg	-17,0746	5,95434	-2,8676	0,00414	***
GlobmcapGDP	5,26932	1,56424	3,3686	0,00076	***
MSCIhpshortl8	1,36051	1,07355	1,2673	0,20505	
Globpcredgl1	3,00204	10,149	0,2958	0,76739	
GlobmcapGDPl3	7,30192	1,39814	5,2226	1,76e-07	***
M2GDP	1,87015	0,837352	2,2334	0,02552	**

Mean dependent var	0,296593	S.D. dependent var	0,457214
McFadden R-squared	0,459947	Adjusted R-squared	0,417095
Log-likelihood	-163,8342	Akaike criterion	353,6684
Schwarz criterion	408,4323	Hannan-Quinn	375,1595

Likelihood ratio test: Chi-square(12) = 279,066 [0,0000]

Note: the number following each indicator states an indicator‘s lag (in quarters)

Even at first glance the coefficient estimates from table 7.7 appear quite similar to those estimated in the model on all data. The explanatory variable estimate that experienced the largest change (42% increase) is the one for the 5th lag of unemployment rate. A two-digit change in estimates compared to those in the full data model was recorded only for four other variables; the 8th lag of CPI annual growth (-12,5%), growth in real annual GDP (-15,8%), the 8th lag of real MSCI deviation from short Hodrick-Prescott trend

(-14,5%) and the 1st lag of global real private credit annual growth (21%). Moreover, positive and negative relationships between explanatory and the dependent variable were preserved for all coefficient estimates as well.

As for significance of the estimates, estimate for the 5th lag of unemployment rate is significant here on 5% significance level while it was not deemed significant in the model on all data. Similarly, in the model on truncated data till 2011 the coefficient for the 8th lag of real MSCI deviation from short Hodrick-Prescott trend is not significant while it was significant in the model on full sample data. All in all, the estimates in this model differ very slightly from those in table 7.6.

Table 7.8: Long model estimation on truncated data till 2005, source: author's own calculations

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-27,5137	17,0472	-1,6140	0,10653	
rdomcredl1	-41,5825	26,1191	-1,5920	0,11138	
Int_pcgxglopcGDPl4	-225,882	108,031	-2,0909	0,03654	**
Uratel5	-104,799	47,5432	-2,2043	0,02750	**
CPIgl8	66,89	24,883	2,6882	0,00718	***
Int_realpcredgl4	1958,88	808,417	2,4231	0,01539	**
CPIgl1	-312,411	113,642	-2,7491	0,00598	***
realGDPg	-206,379	88,2257	-2,3392	0,01932	**
GlobmcapGDP	13,4723	22,8443	0,5897	0,55536	
MSCIhpshortl8	13,0697	9,21997	1,4175	0,15632	
Globpcredgl1	4,05476	45,2316	0,0896	0,92857	
GlobmcapGDPl3	29,9438	11,9057	2,5151	0,01190	**
M2GDP	-2,82985	7,17879	-0,3942	0,69344	

Mean dependent var	0,082840	S.D. dependent var	0,276460
McFadden R-squared	0,703149	Adjusted R-squared	0,433859
Log-likelihood	-14,33056	Akaike criterion	54,66112
Schwarz criterion	95,34980	Hannan-Quinn	71,17335

Likelihood ratio test: Chi-square(12) = 67,8893 [0,0000]

Note: the number following each indicator states an indicator's lag (in quarters)

The model estimated in table 7.8 on truncated data until 2005 substantially differs from the one in table 7.6 estimated on all data in terms of both coefficient estimates and their significance. Moreover, several variables experienced a reversal in the nature of their relationship with the dependent, i.e. mostly from a positive one to a negative (the 4th lag of interaction between real private credit annual growth and global private credit over GDP, the 5th lag of unemployment rate and ratio of M2 over GDP) and in the case of the 4th lag of interaction between domestic and global real private credit annual growth there was a switch from a negative relationship to a positive one.

As for significance, only two variables are significant here on 1% level of significance, i.e. the 8th lag of CPI annual growth which was not significant in the other two long models at all and the 1st lag of the same variable whose significance remained unchanged. On the whole, long model estimated on truncated data until 2005 dramatically differs from the same model estimated on either full data or data truncated till 2011 analogically to the short model estimated on data up till 2006. Table 7.9 summarizes other measures of in-sample performance of the above mentioned long logit models.

In-sample performance of long logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Long truncated till 2005	0,461	0,845	92,31	100	0,084	0,984	1,04E-09
Long truncated till 2011	0,339	0,726	87,37	75	0,099	0,905	1,18E-46
Long on full data	0,334	0,753	87,86	73,03	0,089	0,905	2,44E-49

Table 7.9: In-sample performance of long logit models, source: author's own calculations

In the spirit of the short model analysis, the best in-sample performing long model is the one estimated on data up till 2005. This model boasts the highest PCP, percentage of crises predicted as well as area under ROC curve (which is strongly significant) while it has the lowest NtS ratio of only 0,084.

All in all, the differences in performance measures between the best performing long model in-sample and the second best are not very substantial with the largest difference of 36% for U measure. The plot of ROC curves for in-sample performance of the model is presented in figure 7.3.

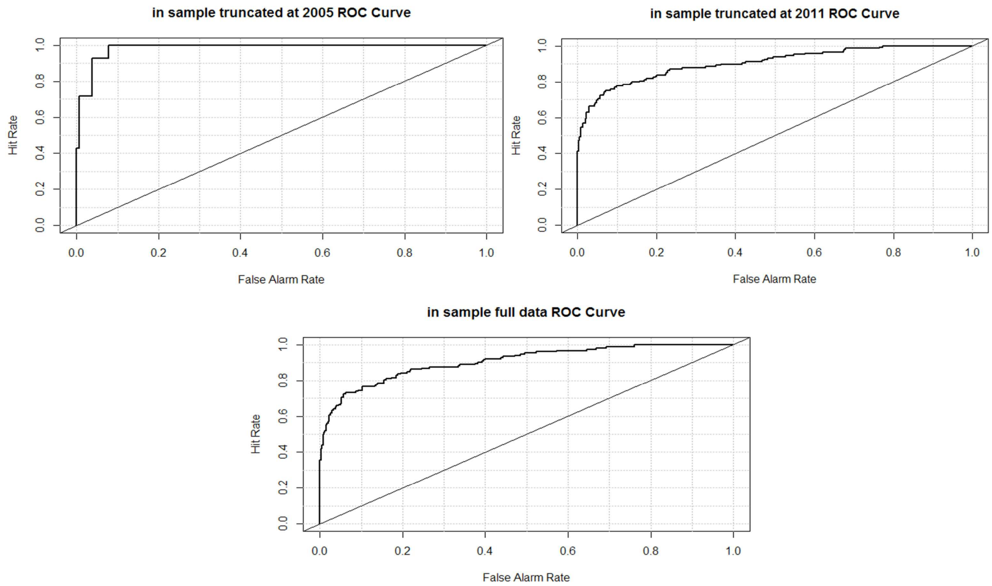


Figure 7.3: ROC curve plots for in-sample performance of long logit model estimated on data up till 2005, till 2011 and on all available data, source: author's own calculations

Now that long model's performance was assessed in-sample, it is of interest to analyse its performance out-of-sample and to detect the differences. Table 7.10 below presents the out-of sample results over the period of 2011Q1-2013Q1 for the long model estimated on data up till 2011 and for the model on data up until 2005 projected over the pre-crisis period of 2005Q1-2008Q2.

Out-of-sample performance of long logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Long truncated till 2011	0,327	0,596	66,04	100	0,367	0,765	0,041465
Long truncated till 2005	0,166	0,365	67,89	76,79	0,584	0,639	0,000579

Table 7.10: Out-of-sample performance of long logit models, source: author's own calculations

The first look reveals that the better performing long model is not the one estimated on data up till 2005 as was the case for short models but the one estimated on data till 2011 and projected over the last couple of years till present. The U measure of the better performing model is double of that for worse performing one. The percentage of crises predicted for this model is 23% higher than that of its counterpart while NtS ration is 37% lower and area under ROC curve is almost 20% larger. However, despite the larger ROC area the better out-of-sample model is significant only on 5% level while the worse model's ROC area is significant on 0,06%.

In comparison to the in-sample performance of the model estimated on data up till 2011, its out-of-sample performance measures declined by 3,7% for U, 24,4% for PCP and 15,5% for area under ROC curve. Other measures increased out-of-sample, namely percentage crises predicted by 25% and NtS ratio by 270%.

As for the worse out-of-sample performing model but the best one in-sample, estimated on data up till 2005, its U measure fell by 64%, PCP by 26,5%, percentage of crises predicted by 24,2%, its area under ROC curve by 35% while its NtS ratio rocketed by 595% to almost 0,6, all out-of-sample.

Figure 7.4 presents ROC curve plots for out-of-sample performance of the long model.

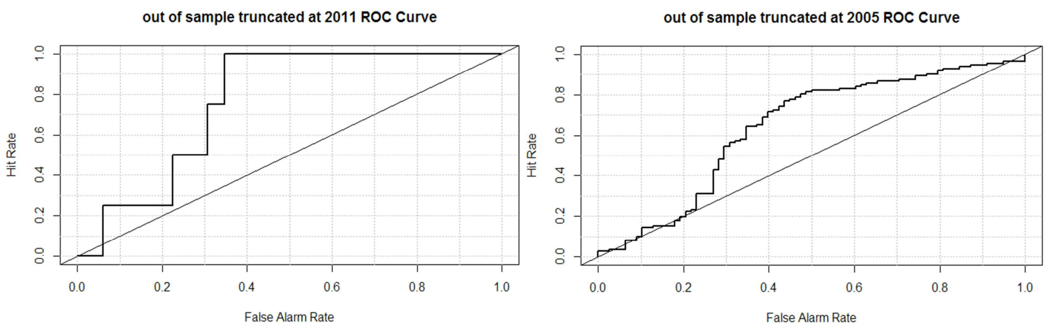


Figure 7.4: ROC curve plots for out-of-sample performance of long logit model estimated on data up until 2011 and till 2005

To conclude, comparatively it appears that out-of-sample performance of the model estimated on data up till 2011 deteriorated less than that of the model estimated on truncated data till 2005 making the better model more stable when estimated both in-sample and out of it.

8 Model Application to the Czech Republic

In addition to the problem of collinearity, which is also often the case in linear regression, discrete data regressions can also become unstable from separation. Separation or perfect prediction arises when some linear combination of the predictors is perfectly predictive of the outcome (Albert and Anderson, 1984 and Lesaffre and Albert, 1989). In order to solve separation, independent variables are gradually removed until the final model is identifiable. However, according to Zorn (2005) this approach may result in removing the strongest predictors from the model. Therefore the technique to employ in case of perfect prediction is Bayesian inference. The Bayesian estimation of logistic regression is used in applying both, the short and the long model, on Czech data as the traditional maximum likelihood estimation suffered from perfect prediction which demonstrated by producing abnormally large coefficient as well as standard error estimates while p-value for coefficient significance equalled 1 for all coefficient estimates.

To yield stable coefficient estimates for logit models via Bayesian inference the “arm” package in R, built to accompany the paper by Gelman, Jakulin, Pittau and Su (2008), was used for the calculations.

Gelman, Jakulin, Pittau and Su (2008) adapt the classical maximum likelihood algorithm within logit model in a way to obtain approximate posterior inference for the coeffcients β, in the form of an estimate $\hat{\beta}$ and covariance matrix V_β. The standard logistic regression algorithm, upon which this technique expands, proceeds by approximately linearizing the derivative of the log-likelihood, solving using weighted least squares, and then iterating this process, each step evaluating the derivatives at the latest estimate $\hat{\beta}$ (McCullagh and Nelder, 1989). At each iteration, the algorithm determines pseudo-data z_i and pseudo-variances $(\sigma_i^z)^2$ based on the linearization of the derivative of the log-likelihood as follows:

$$z_i = X_i\hat{\beta} + \frac{\left(1+e^{X_i\hat{\beta}}\right)^2}{e^{X_i\hat{\beta}}}\left(y_i - \frac{e^{X_i\hat{\beta}}}{1+e^{X_i\hat{\beta}}}\right),\ (\sigma_i^z)^2 = \frac{1}{n_i}\frac{\left(1+e^{X_i\hat{\beta}}\right)^2}{e^{X_i\hat{\beta}}}$$

Then the algorithm performs weighted least squares, regressing z on X with weight vector $(\sigma^z)^{-2}$. The resulting estimate $\hat{\beta}$ is used to update the computations, and the iteration proceeds until approximate convergence.

Moreover, in Gelman, Jakulin, Pittau and Su (2008) in regards to a prior distribution the goal is a somewhat informative prior distribution, i.e. to be used as a baseline on top of which the real prior information can be added as necessary (as opposed to Jeffrey's noninformative prior). In this view, Gelman, Jakulin, Pittau and Su (2008) believe that for logistic regression a change of 5 on the logistic scale in an independent variable moves a probability from 0,01 to 0,5 or from 0,5 to 0,99 which is the range where the actual effects tend to fall. Thus their prior distribution assigns low probabilities to changes of 10 on the logistic scale in predictors. In this thesis, in the logit model estimation for the Czech Republic no additional information about prior distribution was introduced.

As for prior distribution for the coefficients of explanatory variables, Gelman, Jakulin, Pittau and Su (2008) employ the Cauchy distribution as "the Cauchy prior distribution outperforms the normal, on average, because it allows for occasional large coefficients while still performing a reasonable amount of shrinkage for coefficients near zero".

Now that the theoretical background of the estimation method in this chapter was introduced, the next 2 sections present the estimation results for the short and the long logit model, respectively, when applied to Czech data only as well as evaluate their in-sample performance.

8.1 Estimation and Performance of the Short Model for the Czech Republic

The short model from section 7.2 with 11 independent variables and an intercept was estimated by Bayesian inference on the full Czech data from 1990Q1 till 2013Q1 as well as only on truncated data up until 2011 with the objective of evaluating its fit, i.e. the quality of its in-sample forecasting performance. This is executed via various performance statistics which were also used to evaluate the model's performance on a panel of countries. In addition, coefficient estimates resulting from fitting the short model on data of different length will be compared for the purpose of observing their stability.

Table 8.1: Short model estimation on all available Czech data, source: author's own calculations

	coef estimate	coef st. error
(Intercept)	-0,59	5,3
realmoneygl4	19,45	18,2
MSCIhpshortl5	4,67	4,77
Uratel2	-44,6	61,1
Globpcredgl7	45,47	34,02
MSCIhpshortl8	-0,52	3,26
realmoneyg	3,6	15,3
Int_pcgxglopcGDPl4	37,16	42,07
Int_pcgxglopcGDPl5	-22,76	42,79
GlobGDPgl1	5,67	31,88
realGDPgl1	55,7	30,7
GlobCPIg	9,22	99,61
n=38,k=12 residual deviance=9,3 null deviance=36,3 (difference=27)		

Note: the number following each indicator states an indicator's lag (in quarters)

From table 8.1 above it is apparent that the Bayesian estimation of the logit model provides only coefficient estimates and their standard errors and excluding information about their significance. A negative relationship is detected only between three independent variables, i.e. the 2^{nd} lag of unemployment rate, the 8^{th} lag of real MSCI deviation from the short Hodrick-Prescott trend and the 5^{th} lag of interaction between real private credit annual growth and the global private credit over GDP, and the binary dependent. Thus a unit change in either of these three variables increases the odds of a crisis materialization between 0 and 1. Moreover, the fitted model appears to explain the data quite well compared to a model with intercept only as the reduction in deviance (difference between the null and the residual deviance) is quite large.

Table 8.2: Short model estimation on truncated data up till 2011 for the Czech Republic, source: author's own calculations

	coef estimate	coef st. error
(Intercept)	-0,7	4,84
realmoneygl4	20,43	19,64
MSCIhpshortl5	4,44	4,52
Uratel2	-41,93	58,9
Globpcredgl7	46,38	34,26
MSCIhpshortl8	-0,88	3,83
realmoneyg	3,45	15,26
Int_pcgxglopcGDPl4	37,12	41,49
Int_pcgxglopcGDPl5	-21,73	41,51
GlobGDPgl1	5,47	30,72
realGDPgl1	51,34	29,73
GlobCPIg	4,22	95,32
n=33, k=12 residual deviance=9,5 null deviance=34,1 (difference=24,6)		

Note: the number following each indicator states an indicator‘s lag (in quarters)

The short model estimated on data till 2011 from table 8.2 preserves the signs of the estimated coefficients, i.e. the relationships with the likelihood of the crisis occurrence. The coefficient estimates themselves differ only slightly (a one-digit percentage change) from those estimated on full data in table 8.1, apart from the estimates for the 8^{th} lag of real MSCI deviation from the short Hodrick-Prescott trend (-69% change) and for annual growth in global CPI (change of -54%). All in all, the coefficient estimates in these two regressions do not differ substantially from each other, confirming model stability when estimated on data of differing lengths. However, the model might be a slightly worse fit to truncated data than the full sample given that the difference in deviance here is lower than for the model in table 8.1.

Now the same measures that were employed to assess the model's performance on panel data are also applied here. Table 8.3

summarizes the in-sample performance of the short model estimated on both sets of data.

In-sample performance of the short model for the Czech Republic							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Short full data	0,484	0,783	94,74	100	0,065	0,9954	1,58E-07
Short truncated till 2011	0,481	0,75	93,94	100	0,077	0,9945	4,68E-07

Table 8.3: In-sample performance of the short model for the Czech Republic, source: author's own calculations

As evidenced from table 8.3 the short model estimated on all available data for the Czech Republic performs better in all performance statistics than the model on truncated data. The model successfully predicts 94,74% of observations as well as 100% of systemic events. The worse of the two regressions, on truncated data, predicts observations only 0,8% less successfully while it also predicts 100% of systemic events. The quality of in-sample forecast is also captured here by the area under ROC curve and no discrimination line (the diagonal) which attains for both almost maximum (1) while its p-value is quite low, indicating almost perfect forecasting skill of both models. Figure 8.1 below attests to these findings.

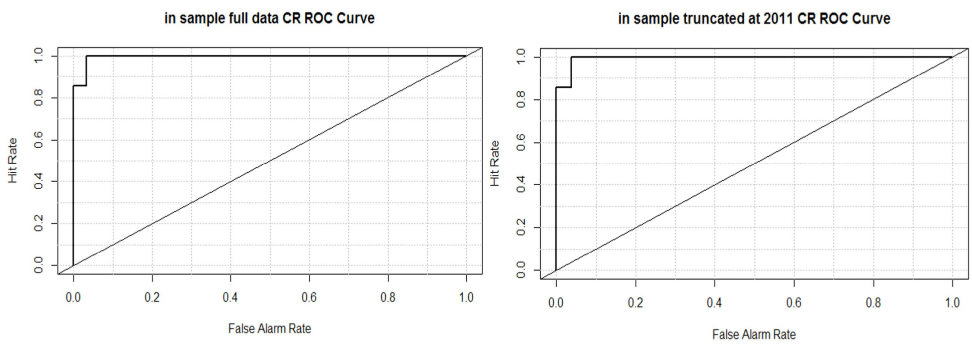


Figure 8.1: ROC curves for in-sample performance of the short logit model on full data and truncated data for the Czech Republic, source: author's own calculations

8.2 Estimation and Performance of the Long Model for the Czech Republic

Bayesian inference was used for the Long model estimation on the Czech data as well. In similar fashion to the short model estimation for the Czech Republic, long model from section 7.3 with 12 most useful indicators from BMA technique is applied to all available Czech data as well as to truncated data only up till 2011. The objective is the same as for short model estimation on Czech data, to assess model's fit to the data, i.e. its in-sample predicting ability. For this purpose, a set of performance measures will be applied to evaluate model's prediction of the binary dependent while model's stability will be discussed by comparing coefficient estimates from full data regression with those from truncated sample.

Table 8.4: Long model estimation on all available Czech data, source: author's own calculations

	coef estimate	coef st. error
(Intercept)	-27,62	13,63
rdomcredl1	-3,05	12,39
Int_pcgxglopcGDPl4	3,73	79,4
Uratel5	1,5	67,82
CPIgl8	-17,12	46,81
Int_realpcredgl4	24,82	348,26
CPIgl1	-17,67	45,42
realGDPg	9,39	30,16
GlobmcapGDP	31,47	14,58
MSCIhpshortl8	0,02	3,62
Globpcredgl1	13,25	58,6
GlobmcapGDPl3	0,87	5,66
M2GDP	-1,22	13,25
n=37, k=13 residual deviance=2,6 null deviance=48 (difference=45,4)		

Note: the number following each indicator states an indicator's lag (in quarters)

As shown in table 8.4 there is a negative relationship between 4 indicators and the likelihood of a crisis occurrence, namely the 1st lag of real domestic credit annual growth, the 1st and the 8th lag of annual CPI growth and ratio of M2 over GDP. A unit change in all other 8 indicators increases odds of a crisis occurrence by more than

1. As for the usefulness of the fitted model as a whole, its deviance decreased by 45,2 - a large change from a model containing an intercept only.

Table 8.5: Long model estimation on truncated data up till 2011 for the Czech Republic, source: author's own calculations

	coef estimate	coef st. error
(Intercept)	-28,07	14,26
rdomcredl1	-2,78	12,15
Int_pcgxglopcGDPl4	3,52	76,66
Uratel5	1,7	66,42
CPIgl8	-15,7	47,14
Int_realpcredgl4	22,67	335,93
CPIgl1	-15,56	44,07
realGDPg	8,56	29,43
GlobmcapGDP	31,84	15,17
MSCIhpshortl8	-0,41	4,48
Globpcredgl1	12,8	56,71
GlobmcapGDPl3	0,77	5,46
M2GDP	-1,96	13,72
n=33, k=13 residual deviance=2,5 null deviance=44,3 (difference)=41,8		

Note: the number following each indicator states an indicator's lag (in quarters)

Even at first glance coefficient estimates from model on truncated data appear to be quite similar to those in table 8.4. All coefficient estimates preserve their sign apart from the estimate for the 8th lag of real MSCI deviation from the short Hodrick-Prescott trend which was a small positive number in model estimated on full data. Apart from this sign reversal most changes in estimates are in a one-digit percentage range (or up to 13,3% for the 5th lag of unemployment rate). The only exception is the estimate for the ratio of M2 over GDP which decreased on truncated data by 61%. Similarly to the short model, the long model on truncated data brings lower reduction in deviance from the intercept-only model than model estimated on full data sample, indicating a slightly worse fit.

Table 8.6 assesses the long model in-sample performance for the Czech Republic on both truncated and full data.

In-sample performance of the long model for the Czech Republic							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Long full data	0,5	0,638	97,30	100	0,042	1	2,81E-10
Long truncated till 2011	0,5	0,593	96,97	100	0,05	1	1,74E-09

Table 8.6: In-sample performance of the long model for the Czech Republic, source: author's own calculations

According to performance measures the long model on both full sample and truncated one performs very well for the Czech Republic. In-sample both models reach the maximum utility value of 0,5, predict 100% of systemic events and thus maximize area under ROC curve to 1 for which p-value is quite low. Based on ROC area measure it can be said that the long model on Czech data yields perfect in-sample predictions. However, according to PCP there is some noise within the forecast as the model on full data successfully predicts only 97,3% observations and its Noise-to-Signal ratio is not 0 either, though it is very low. As for the slightly worse performing model, the one on truncated data, it correctly predicts 0,3% of observations less than the full data model while its NtS ratio is 19% higher.

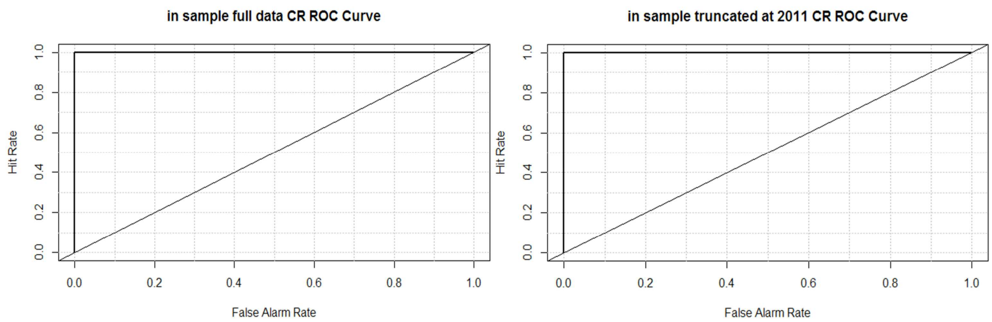


Figure 8.2: ROC curves for in-sample performance of the long logit model on full data and truncated data for the Czech Republic, source: author's own calculations

The following table 8.7 ranks and offers overview of in-sample performances of both short and long models for the Czech Republic.

In-sample performance of logit models for the Czech Republic							
Model	U	Threshold	PCP	%crisis predicted	NtS ratio	ROC area	p-value
Long full data	0,5	0,638	97,30	100	0,042	1	2,81E-10
Long truncated till 2011	0,5	0,593	96,97	100	0,05	1	1,74E-09
Short full data	0,484	0,783	94,74	100	0,065	0,9954	1,58E-07
Short truncated till 2011	0,481	0,75	93,94	100	0,077	0,9945	4,68E-07

Table 8.7: In-sample performance of logit models for the Czech Republic, source: author's own calculations

The highest ranking model for the Czech Republic is thus the long model on all available data followed by the long model on truncated data. The short model on all data performed as third best while its estimation on truncated data ranked last.

Ultimately, the long model, designed to be able to anticipate crises within long horizon of 12 quarters (3 years) performed better than the short model with the horizon of 1,5 years. Overall both models performed very well in-sample with the difference between long and short model on full data in terms of utility of 3,3%, PCP of 2,7%, percentage of crises predicted of 0%, NtS ratio of 35,4% and finally area under ROC curve of 0,5%.

9 Conclusions

The aim of this thesis was to develop an EWS framework for monitoring systemic risks and predicting systemic events over the short horizon of 6 quarters as well as over the long horizon of 12 quarters on the panel of 14 countries and subsequently apply the constructed model to the Czech Republic for which its in-sample performance was observed.

First of all, the Financial stress index (FSI) measuring the level of financial stress within the financial system was constructed for each country within the panel. To aggregate individual subindices from equity, foreign exchange, money and securities markets into the composite measure, FSI, a market-equal weighting was employed due to the cross-country nature of the analysis. FSI thus reports average level of systemic stress in the economy at each point in time (quarter). Moreover, the constructed FSIs were used for identification of starting dates of country-specific systemic events.

Secondly, uncertainty in regards to the inclusion of potential leading indicators that best explain crisis occurrences into EWS was resolved by Bayesian model averaging (BMA) technique while the assumption of a common fixed horizon at which all potential indicators issue early warning signals was relaxed and indicators' relevant lags for signal emission were detected by univariate logit models. For the short model BMA identified as useful both domestic and global indicators as well as their interactions. From among domestic indicators asset prices, unemployment rate, real money growth and real GDP growth were selected. All other useful indicators apart from global GDP growth are credit indicators measuring either leverage, credit growth or their interactions and are at the same time either global or global interacting with domestic credit indicators.

As for the BMA results over the long horizon, again credit and private credit indicators both domestic and global as well as their interactions were found useful. Overall 5 credit indicators were included into EWS with the aim of signaling crises over the long horizon. In addition, two lags for global market capitalization/GDP were selected which coincides with the empirical finding by Peltonen and Lo Duca (2011) that market capitalization/GDP is the most useful global indicator, even the most useful indicator overall. Same as for the short horizon, domestic GDP, CPI growth and unemployment rate were deemed most useful while M2/GDP ratio replaced over the long horizon real money growth. Overall, the selected indicators for both horizons are in accordance with the literature which identifies credit indicators as the most useful (Alessi and Detken 2011; Borio and Lowe 2004) as well as their domestic and their global and domestic interactions (Peltonen and Lo Duca, 2011).

Next, a binary logit model incorporating the most useful indicators was estimated for both horizons on the panel. Over the short horizon the best performing model both in-sample as well as out-of-sample was the one estimated on data till 2006 with its out-of-sample performance tested over the pre-crisis period of the global recent crisis (2006Q1-2008Q1). As expected for all models, out-of-sample the best model experienced significant deterioration in all its performance statistics though it still proved to be substantially better than random forecast.

As for the long horizon of 12 quarters, the best performing model in-sample was the one estimated on data till 2005 while out-of-sample it was the one estimated on data until 2011 and projected over the last two years till present. However, comparatively it was revealed that out-of-sample performance of the model estimated on data until 2011 deteriorated less than that of the model estimated on truncated data until 2005 which makes the model with better out-of-sample performance more stable.

Finally, after having tested skill of the developed EWS framework on Czech data, in terms of in-sample performance the highest ranking model was the model over the long horizon estimated on all available. The long model designed to anticipate crises within the horizon of 3 years managed to correctly predict 100% of systemic events, maximized the utility measure for the Czech Republic as well as the area under ROC curve which indicates perfect in-sample prediction skill of the model. Moreover, the short model structured to anticipate crises within the horizon of 1 and a half year also performed very well in-sample for the Czech Republic with only negligible decline in performance compared to the long model.

To conclude, with respect to mostly global indicators and their interactions that emerged useful from BMA method in this thesis it can be observed that monitoring risks and mitigating systemic events by means of solely domestic vulnerabilities and national policy actions is not sufficient. Due to the nature of systemic risks' sources being often global, international cooperation and policy coordination are of impotance in preserving global financial stability as confirmed by Babecky, Havranek et al. (2011) and Peltonen, Lo Duca (2011).

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Appendix

1. Indicators Stationarity Testing in chapter 6

Real GDP annual g:

Augmented Dickey-Fuller test for
real_GDP_p_a__g
including 8 lags of (1-
L)real_GDP_p_a__g
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 78, lag order = 8
estimated value of (a - 1): -0,130982
test statistic = -2,6321 [0,0865]

Unit 2, T = 53, lag order = 8
estimated value of (a - 1): -0,0995064
test statistic = -1,59008 [0,4877]

Unit 3, T = 53, lag order = 8
estimated value of (a - 1): -0,112311
test statistic = -1,67553 [0,4438]

Unit 4, T = 57, lag order = 8
estimated value of (a - 1): -0,130866
test statistic = -2,76142 [0,0639]

Unit 5, T = 61, lag order = 8
estimated value of (a - 1): -0,325839
test statistic = -2,3742 [0,1492]

Unit 6, T = 77, lag order = 8
estimated value of (a - 1): -0,376023
test statistic = -2,97117 [0,0377]

Unit 7, T = 65, lag order = 8
estimated value of (a - 1): -0,0899266
test statistic = -2,41562 [0,1374]

Unit 8, T = 25, lag order = 8
estimated value of (a - 1): -0,254253
test statistic = -1,88951 [0,3376]

Unit 9, T = 65, lag order = 8
estimated value of (a - 1): -0,146908
test statistic = -2,16001 [0,2213]

Unit 10, T = 77, lag order = 8
estimated value of (a - 1): -0,181787
test statistic = -3,41525 [0,0105]

Unit 11, T = 67, lag order = 8
estimated value of (a - 1): -0,198508
test statistic = -1,67692 [0,4431]

Unit 12, T = 45, lag order = 8
estimated value of (a - 1): -0,0711402
test statistic = -1,598 [0,4836]

Unit 13, T = 77, lag order = 8
estimated value of (a - 1): -0,0578154
test statistic = -1,47485 [0,5466]

Unit 14, T = 76, lag order = 8
estimated value of (a - 1): -0,114321
test statistic = -1,74331 [0,4093]

H0: all groups have unit root

N = 14, Tmin = 25, Tmax = 78
Im-Pesaran-Shin W_tbar = -3,0594
[0,0011]

Choi meta-tests:
Inverse chi-square(28) = 48,1701
[0,0103]
Inverse normal test = -2,87578
[0,0020]
Logit test: t(74) = -2,85156 [0,0028]

Real M2 annual g:

Augmented Dickey-Fuller test for
real_M2_p_a_
including 8 lags of (1-L)real_M2_p_a_
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 45, lag order = 8
estimated value of (a - 1): -0,185384
test statistic = -1,87687 [0,3436]

Unit 2, T = 67, lag order = 8
estimated value of (a - 1): -0,441291
test statistic = -3,70116 [0,0041]

Unit 3, T = 53, lag order = 8
estimated value of (a - 1): -0,104085
test statistic = -1,27481 [0,6436]

Unit 4, T = 74, lag order = 8
estimated value of (a - 1): -0,0956587
test statistic = -1,29444 [0,6345]

Unit 5, T = 76, lag order = 8
estimated value of (a - 1): -0,179017
test statistic = -2,60952 [0,0910]

Unit 6, T = 77, lag order = 8
estimated value of (a - 1): -0,0540515
test statistic = -1,15453 [0,6961]

Unit 7, T = 77, lag order = 8
estimated value of (a - 1): -0,411332
test statistic = -2,91447 [0,0437]

Unit 8, T = 56, lag order = 8
estimated value of (a - 1): -0,138176
test statistic = -2,13903 [0,2294]

Unit 9, T = 45, lag order = 8
estimated value of (a - 1): -0,223843
test statistic = -1,63571 [0,4642]

Unit 10, T = 77, lag order = 8
estimated value of (a - 1): -0,202638
test statistic = -2,50979 [0,1131]

Unit 11, T = 79, lag order = 8
estimated value of (a - 1): -0,0919824
test statistic = -1,43358 [0,5674]

Unit 12, T = 77, lag order = 8
estimated value of (a - 1): -0,191231
test statistic = -1,96842 [0,3011]

Unit 13, T = 79, lag order = 8
estimated value of (a - 1): -0,138043
test statistic = -1,79425 [0,3838]

Unit 14, T = 77, lag order = 8
estimated value of (a - 1): -0,142183
test statistic = -2,03203 [0,2731]

H0: all groups have unit root

N = 14, Tmin = 45, Tmax = 79
Im-Pesaran-Shin W_tbar = -2,4561
[0,0070]

Choi meta-tests:
Inverse chi-square(28) = 43,5777
[0,0306]
Inverse normal test = -2,17968
[0,0146]
Logit test: t(74) = -2,2393 [0,0141]

Real Money annual g:

Augmented Dickey-Fuller test for
real_money_p_a_
including 8 lags of (1-
L)real_money_p_a_
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 78, lag order = 8
estimated value of (a - 1): -0,281437
test statistic = -2,95379 [0,0394]

Unit 2, T = 67, lag order = 8
estimated value of (a - 1): -0,323222
test statistic = -3,82789 [0,0026]

Unit 3, T = 54, lag order = 8

estimated value of (a - 1): -0,257791
test statistic = -1,83196 [0,3653]

Unit 4, T = 47, lag order = 8
estimated value of (a - 1): -0,101047
test statistic = -1,07535 [0,7278]

Unit 5, T = 79, lag order = 8
estimated value of (a - 1): -0,119341
test statistic = -1,62218 [0,4712]

Unit 6, T = 78, lag order = 8
estimated value of (a - 1): -0,3419
test statistic = -2,39271 [0,1438]

Unit 7, T = 79, lag order = 8
estimated value of (a - 1): -0,220991
test statistic = -3,88621 [0,0021]

Unit 8, T = 71, lag order = 8
estimated value of (a - 1): -0,219591
test statistic = -2,927 [0,0423]

Unit 9, T = 58, lag order = 8
estimated value of (a - 1): -0,00660865
test statistic = -0,0977628 [0,9480]

Unit 10, T = 78, lag order = 8
estimated value of (a - 1): -0,256158
test statistic = -2,54479 [0,1049]

Unit 11, T = 79, lag order = 8
estimated value of (a - 1): -0,250606
test statistic = -2,84999 [0,0514]

Unit 12, T = 79, lag order = 8
estimated value of (a - 1): -0,221353
test statistic = -1,95243 [0,3084]

Unit 13, T = 79, lag order = 8
estimated value of (a - 1): -0,116416
test statistic = -2,02903 [0,2744]

Unit 14, T = 79, lag order = 8
estimated value of (a - 1): -0,0704899
test statistic = -1,50078 [0,5335]

H0: all groups have unit root

N = 14, Tmin = 47, Tmax = 79
Im-Pesaran-Shin W_tbar = -3,3445 [0,0004]

Choi meta-tests:
Inverse chi-square(28) = 61,7257 [0,0002]
Inverse normal test = -3,28074 [0,0005]
Logit test: t(74) = -3,53361 [0,0004]

M2/GDP – nonstationary – 1st differences applied:

Augmented Dickey-Fuller test for d_M2_GDP
including 8 lags of (1-L)d_M2_GDP
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 48, lag order = 8
estimated value of (a - 1): 0,0592256
test statistic = 0,19439 [0,9723]

Unit 2, T = 56, lag order = 8
estimated value of (a - 1): -1,22652
test statistic = -2,69539 [0,0748]

Unit 3, T = 60, lag order = 8
estimated value of (a - 1): -0,454322
test statistic = -2,53162 [0,1079]

Unit 4, T = 60, lag order = 8
estimated value of (a - 1): -1,74524
test statistic = -4,01696 [0,0013]

Unit 5, T = 63, lag order = 8
estimated value of (a - 1): -0,867271
test statistic = -2,35668 [0,1543]

Unit 6, T = 80, lag order = 8
estimated value of (a - 1): -0,668522
test statistic = -2,96505 [0,0383]

Unit 7, T = 68, lag order = 8
estimated value of (a - 1): -1,24763
test statistic = -3,65218 [0,0049]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -1,17159
test statistic = -1,78047 [0,3907]

Unit 9, T = 47, lag order = 8
estimated value of (a - 1): -0,815444
test statistic = -2,09456 [0,2470]

Unit 10, T = 80, lag order = 8
estimated value of (a - 1): -0,655648
test statistic = -3,05973 [0,0297]

Unit 11, T = 70, lag order = 8
estimated value of (a - 1): -0,849604
test statistic = -2,1792 [0,2141]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): -0,912518
test statistic = -2,08943 [0,2491]

Unit 13, T = 80, lag order = 8
estimated value of (a - 1): -0,493499
test statistic = -2,37164 [0,1499]

Unit 14, T = 79, lag order = 8
estimated value of (a - 1): -0,410698
test statistic = -1,87313 [0,3454]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 80
Im-Pesaran-Shin W_tbar = -3,92827 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 67,3546 [0,0000]
Inverse normal test = -3,98033 [0,0000]
Logit test: t(74) = -4,14711 [0,0000]

Money/GDP – nonstationary – 1st differences applied:

Augmented Dickey-Fuller test for d_money_GDP
including 8 lags of (1-L)d_money_GDP
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 81, lag order = 8
estimated value of (a - 1): 0,446381
test statistic = 1,17053 [0,9981]

Unit 2, T = 56, lag order = 8
estimated value of (a - 1): -2,04195
test statistic = -3,92389 [0,0019]

Unit 3, T = 60, lag order = 8
estimated value of (a - 1): -0,66516
test statistic = -2,25526 [0,1869]

Unit 4, T = 48, lag order = 8
estimated value of (a - 1): -1,99079
test statistic = -3,79844 [0,0029]

Unit 5, T = 64, lag order = 8
estimated value of (a - 1): -0,741551
test statistic = -2,07916 [0,2533]

Unit 6, T = 80, lag order = 8
estimated value of (a - 1): -1,76944
test statistic = -3,82867 [0,0026]

Unit 7, T = 68, lag order = 8
estimated value of (a - 1): -0,789447
test statistic = -2,33532 [0,1608]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -2,16351
test statistic = -2,32634 [0,1636]

Unit 9, T = 60, lag order = 8
estimated value of (a - 1): -0,497103
test statistic = -1,42957 [0,5693]

Unit 10, T = 80, lag order = 8
estimated value of (a - 1): -0,622786
test statistic = -2,55968 [0,1015]

Unit 11, T = 70, lag order = 8
estimated value of (a - 1): -1,74037
test statistic = -2,86016 [0,0502]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): -1,6399
test statistic = -2,73318 [0,0684]

Unit 13, T = 80, lag order = 8
estimated value of (a - 1): -0,297036
test statistic = -1,93417 [0,3167]

Unit 14, T = 79, lag order = 8
estimated value of (a - 1): -0,164705
test statistic = -1,23937 [0,6596]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 81
Im-Pesaran-Shin W_tbar = -3,54751 [0,0002]

Choi meta-tests:
Inverse chi-square(28) = 69,6548 [0,0000]
Inverse normal test = -3,57444 [0,0002]
Logit test: t(74) = -3,76342 [0,0002]

Real domestic credit annual g:

Augmented Dickey-Fuller test for real_domestic_c
including 8 lags of (1-L)real_domestic_c
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 78, lag order = 8
estimated value of (a - 1): -0,266777
test statistic = -2,21752 [0,2001]

Unit 2, T = 66, lag order = 8
estimated value of (a - 1): -0,09366
test statistic = -1,34653 [0,6099]

Unit 3, T = 48, lag order = 8
estimated value of (a - 1): -0,0759112
test statistic = -0,919106 [0,7828]

Unit 4, T = 78, lag order = 8
estimated value of (a - 1): -0,0820936
test statistic = -1,23535 [0,6614]

Unit 5, T = 77, lag order = 8
estimated value of (a - 1): -0,353386
test statistic = -2,59875 [0,0932]

Unit 6, T = 78, lag order = 8
estimated value of (a - 1): -0,0601997
test statistic = -0,816432 [0,8140]

Unit 7, T = 78, lag order = 8
estimated value of (a - 1): -0,425351
test statistic = -2,65226 [0,0826]

Unit 8, T = 63, lag order = 8
estimated value of (a - 1): -0,202673
test statistic = -1,7918 [0,3851]

Unit 9, T = 78, lag order = 8
estimated value of (a - 1): -0,161194
test statistic = -2,18445 [0,2121]

Unit 10, T = 78, lag order = 8
estimated value of (a - 1): -0,196835
test statistic = -1,9532 [0,3080]

Unit 11, T = 78, lag order = 8
estimated value of (a - 1): -0,0660574
test statistic = -1,91444 [0,3259]

Unit 12, T = 78, lag order = 8
estimated value of (a - 1): -0,551868
test statistic = -3,33678 [0,0133]

Unit 13, T = 78, lag order = 8
estimated value of (a - 1): -0,107334
test statistic = -1,83154 [0,3655]

Unit 14, T = 75, lag order = 8
estimated value of (a - 1): -0,209897
test statistic = -2,53809 [0,1064]

H0: all groups have unit root

N = 14, Tmin = 48, Tmax = 78
Im-Pesaran-Shin W_tbar = -2,14734 [0,0159]

Choi meta-tests:
Inverse chi-square(28) = 40,4035 [0,0608]
Inverse normal test = -1,87894 [0,0301]
Logit test: t(74) = -1,86622 [0,0330]

Government deficit/GDP – nonstationary- 1st differences applied:

Augmented Dickey-Fuller test for d_gov_deficit_G
including 8 lags of (1-L)d_gov_deficit_G
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 57, lag order = 8
estimated value of (a - 1): -2,31853
test statistic = -2,11397 [0,2392]

Unit 2, T = 44, lag order = 8
estimated value of (a - 1): -3,36943
test statistic = -2,77753 [0,0615]

Unit 3, T = 40, lag order = 8
estimated value of (a - 1): -1,59037
test statistic = -2,97415 [0,0374]

Unit 4, T = 44, lag order = 8
estimated value of (a - 1): -8,13363
test statistic = -3,32232 [0,0139]

Unit 5, T = 64, lag order = 8
estimated value of (a - 1): -5,85325
test statistic = -3,21252 [0,0193]

Unit 6, T = 71, lag order = 8
estimated value of (a - 1): -0,237499
test statistic = -2,95377 [0,0394]

Unit 7, T = 68, lag order = 8
estimated value of (a - 1): -9,17765
test statistic = -5,11697 [0,0000]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -2,35959
test statistic = -2,12532 [0,2347]

Unit 9, T = 44, lag order = 8
estimated value of (a - 1): -1,70185
test statistic = -2,5151 [0,1118]

Unit 10, T = 59, lag order = 8
estimated value of (a - 1): -0,0973982
test statistic = -1,91045 [0,3277]

Unit 11, T = 65, lag order = 8
estimated value of (a - 1): -3,28059
test statistic = -2,75629 [0,0647]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): -1,90376
test statistic = -1,96561 [0,3024]

Unit 13, T = 44, lag order = 8
estimated value of (a - 1): -0,956687
test statistic = -1,27985 [0,6412]

Unit 14, T = 19, lag order = 8
estimated value of (a - 1): -0,979147
test statistic = -1,12362 [0,7088]

H0: all groups have unit root

Choi meta-tests:
Inverse chi-square(28) = 79,5852 [0,0000]
Inverse normal test = -4,75609 [0,0000]
Logit test: t(74) = -5,35903 [0,0000]

Government debt/GDP – nonstationary – 1st differences applied:

Augmented Dickey-Fuller test for d_gov_debt_GDP
including 8 lags of (1-L)d_gov_debt_GDP
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 69, lag order = 8
estimated value of (a - 1): -1,02104
test statistic = -2,67772 [0,0779]

Unit 2, T = 40, lag order = 8
estimated value of (a - 1): -0,630539
test statistic = -1,77976 [0,3911]

Unit 3, T = 40, lag order = 8
estimated value of (a - 1): -0,403264
test statistic = -1,82863 [0,3669]

Unit 4, T = 40, lag order = 8
estimated value of (a - 1): -2,32396
test statistic = -3,44683 [0,0095]

Unit 5, T = 64, lag order = 8
estimated value of (a - 1): -1,04217
test statistic = -2,29458 [0,1737]

Unit 6, T = 80, lag order = 8
estimated value of (a - 1): -0,0504118
test statistic = -2,00893 [0,2831]

Unit 7, T = 56, lag order = 8
estimated value of (a - 1): -0,0905028
test statistic = -1,62778 [0,4683]

Unit 8, T = 19, lag order = 8
estimated value of (a - 1): -0,628624
test statistic = -1,35492 [0,6059]

Unit 9, T = 68, lag order = 8
estimated value of (a - 1): -0,734669
test statistic = -3,31687 [0,0142]

Unit 10, T = 80, lag order = 8
estimated value of (a - 1): -0,0344016
test statistic = -1,61664 [0,4740]

Unit 11, T = 54, lag order = 8
estimated value of (a - 1): -1,11987
test statistic = -2,75971 [0,0642]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): -0,518521
test statistic = -1,8708 [0,3465]

Unit 13, T = 60, lag order = 8
estimated value of (a - 1): -0,220763
test statistic = -1,85951 [0,3519]

Unit 14, T = 59, lag order = 8
estimated value of (a - 1): -0,245746
test statistic = -1,46275 [0,5527]

H0: all groups have unit root

Choi meta-tests:
Inverse chi-square(28) = 47,7368 [0,0114]
Inverse normal test = -2,70629 [0,0034]
Logit test: t(74) = -2,74131 [0,0038]

Private credit/GDP – nonstationary – 1st differences applied:

Augmented Dickey-Fuller test for d_private_credi
including 8 lags of (1-L)d_private_credi
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 81, lag order = 8
estimated value of (a - 1): -0,184674
test statistic = -1,28695 [0,6380]

Unit 2, T = 56, lag order = 8
estimated value of (a - 1): -0,232101
test statistic = -1,5366 [0,5152]

Unit 3, T = 44, lag order = 8
estimated value of (a - 1): -0,626284
test statistic = -2,31517 [0,1671]

Unit 4, T = 60, lag order = 8
estimated value of (a - 1): -0,872915
test statistic = -2,24535 [0,1903]

Unit 5, T = 64, lag order = 8
estimated value of (a - 1): -0,792713
test statistic = -2,20733 [0,2038]

Unit 6, T = 80, lag order = 8
estimated value of (a - 1): -0,50746
test statistic = -2,88908 [0,0466]

Unit 7, T = 68, lag order = 8
estimated value of (a - 1): -0,283766
test statistic = -1,81403 [0,3741]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -1,07709
test statistic = -2,24792 [0,1894]

Unit 9, T = 68, lag order = 8
estimated value of (a - 1): -0,382314
test statistic = -2,31149 [0,1683]

Unit 10, T = 80, lag order = 8
estimated value of (a - 1): -0,751176
test statistic = -2,51498 [0,1118]

Unit 11, T = 69, lag order = 8
estimated value of (a - 1): -0,502027
test statistic = -1,96613 [0,3021]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): 0,102442
test statistic = 0,538597 [0,9880]

Unit 13, T = 80, lag order = 8
estimated value of (a - 1): -0,580504
test statistic = -1,71343 [0,4245]

Unit 14, T = 79, lag order = 8
estimated value of (a - 1): -0,344615
test statistic = -2,26472 [0,1837]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 81
Im-Pesaran-Shin W_tbar = -2,04048 [0,0207]

Choi meta-tests:
Inverse chi-square(28) = 39,1955 [0,0778]
Inverse normal test = -1,78768 [0,0369]
Logit test: t(74) = -1,59326 [0,0577]

MSCI HP short deviation:

Augmented Dickey-Fuller test for MSCIhp_short
including 8 lags of (1-L)MSCIhp_short
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 33, lag order = 8
estimated value of (a - 1): -0,555744
test statistic = -2,19729 [0,2074]

Unit 2, T = 40, lag order = 8
estimated value of (a - 1): -0,449233
test statistic = -2,57781 [0,0976]

Unit 3, T = 56, lag order = 8
estimated value of (a - 1): -0,3439
test statistic = -2,94641 [0,0402]

Unit 4, T = 40, lag order = 8
estimated value of (a - 1): -0,438908
test statistic = -2,57002 [0,0993]

Unit 5, T = 83, lag order = 8
estimated value of (a - 1): -0,367611
test statistic = -3,49547 [0,0081]

Unit 6, T = 83, lag order = 8
estimated value of (a - 1): -0,511769
test statistic = -3,54941 [0,0068]

Unit 7, T = 83, lag order = 8
estimated value of (a - 1): -0,304725
test statistic = -6,41738 [0,0000]

Unit 8, T = 74, lag order = 8
estimated value of (a - 1): -0,112988
test statistic = -3,56263 [0,0065]

Unit 9, T = 83, lag order = 8
estimated value of (a - 1): -0,383965
test statistic = -3,99139 [0,0015]

Unit 10, T = 83, lag order = 8
estimated value of (a - 1): -0,292146
test statistic = -3,13086 [0,0244]

Unit 11, T = 84, lag order = 8
estimated value of (a - 1): -0,51301
test statistic = -3,54624 [0,0069]

Unit 12, T = 83, lag order = 8
estimated value of (a - 1): -0,289099
test statistic = -3,07268 [0,0287]

Unit 13, T = 83, lag order = 8
estimated value of (a - 1): -0,300334
test statistic = -3,16186 [0,0223]

Unit 14, T = 83, lag order = 8
estimated value of (a - 1): -0,305521
test statistic = -3,40115 [0,0109]

H0: all groups have unit root

N = 14, Tmin = 33, Tmax = 84
Im-Pesaran-Shin W_tbar = -7,9225 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 139,298 [0,0000]
Inverse normal test = -8,47143 [0,0000]
Logit test: t(74) = -10,3149 [0,0000]

MSCI HP long deviation:

Augmented Dickey-Fuller test for MSCIhp_long
including 8 lags of (1-L)MSCIhp_long
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 33, lag order = 8
estimated value of (a - 1): -0,100142
test statistic = -0,816984 [0,8139]

Unit 2, T = 40, lag order = 8
estimated value of (a - 1): -0,180274
test statistic = -1,91704 [0,3247]

Unit 3, T = 56, lag order = 8
estimated value of (a - 1): -0,296664
test statistic = -3,17842 [0,0213]

Unit 4, T = 40, lag order = 8
estimated value of (a - 1): -0,171656
test statistic = -1,84327 [0,3598]

Unit 5, T = 83, lag order = 8
estimated value of (a - 1): -0,222305
test statistic = -2,94652 [0,0402]

Unit 6, T = 83, lag order = 8
estimated value of (a - 1): -0,111407
test statistic = -1,7695 [0,3962]

Unit 7, T = 83, lag order = 8
estimated value of (a - 1): -0,086521
test statistic = -2,65927 [0,0813]

Unit 8, T = 74, lag order = 8
estimated value of (a - 1): -0,00937346
test statistic = -0,375238 [0,9110]

Unit 9, T = 83, lag order = 8
estimated value of (a - 1): -0,132332
test statistic = -2,63231 [0,0864]

Unit 10, T = 83, lag order = 8
estimated value of (a - 1): -0,120947
test statistic = -2,3891 [0,1448]

Unit 11, T = 84, lag order = 8
estimated value of (a - 1): -0,113002
test statistic = -1,76164 [0,4001]

Unit 12, T = 83, lag order = 8
estimated value of (a - 1): 0,0051214
test statistic = 0,24196 [0,9752]

Unit 13, T = 83, lag order = 8
estimated value of (a - 1): -0,109535
test statistic = -2,23846 [0,1927]

Unit 14, T = 83, lag order = 8
estimated value of (a - 1): -0,0872952
test statistic = -2,06065 [0,2610]

H0: all groups have unit root

N = 14, Tmin = 33, Tmax = 84
Im-Pesaran-Shin W_tbar = -1,89754 [0,0289]

Choi meta-tests:
Inverse chi-square(28) = 42,5135 [0,0388]
Inverse normal test = -1,66494 [0,0480]
Logit test: t(74) = -1,5974 [0,0572]

Growth in reserves:

Augmented Dickey-Fuller test for g_in_reserves
including 8 lags of (1-L)g_in_reserves
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 80, lag order = 8
estimated value of (a - 1): -1,00787
test statistic = -2,72022 [0,0705]

Unit 2, T = 68, lag order = 8
estimated value of (a - 1): -0,757499
test statistic = -3,61785 [0,0055]

Unit 3, T = 46, lag order = 8
estimated value of (a - 1): -0,462298
test statistic = -1,28452 [0,6391]

Unit 4, T = 80, lag order = 8
estimated value of (a - 1): -1,1083
test statistic = -4,54956 [0,0001]

Unit 5, T = 80, lag order = 8
estimated value of (a - 1): -0,718759
test statistic = -3,12514 [0,0248]

Unit 6, T = 80, lag order = 8
estimated value of (a - 1): -0,968233
test statistic = -3,14963 [0,0231]

Unit 7, T = 80, lag order = 8
estimated value of (a - 1): -1,24813
test statistic = -3,58365 [0,0061]

Unit 8, T = 51, lag order = 8
estimated value of (a - 1): -1,86062
test statistic = -3,13565 [0,0241]

Unit 9, T = 80, lag order = 8
estimated value of (a - 1): -1,3224
test statistic = -3,49045 [0,0083]

Unit 10, T = 80, lag order = 8
estimated value of (a - 1): -0,282443
test statistic = -1,14435 [0,7003]

Unit 11, T = 68, lag order = 8
estimated value of (a - 1): -2,09084
test statistic = -4,18137 [0,0007]

Unit 12, T = 80, lag order = 8
estimated value of (a - 1): -1,10839
test statistic = -3,03908 [0,0314]

Unit 13, T = 80, lag order = 8
estimated value of (a - 1): -0,853894
test statistic = -2,51426 [0,1120]

Unit 14, T = 80, lag order = 8
estimated value of (a - 1): -0,775578
test statistic = -2,53346 [0,1075]

H0: all groups have unit root

N = 14, Tmin = 46, Tmax = 80
Im-Pesaran-Shin W_tbar = -6,37164 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 108,201 [0,0000]
Inverse normal test = -6,73498 [0,0000]
Logit test: t(74) = -7,68491 [0,0000]

Growth in trade balance:

Augmented Dickey-Fuller test for g_trade_balance
including 8 lags of (1-L)g_trade_balance
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 66, lag order = 8
estimated value of (a - 1): -0,848624
test statistic = -2,19166 [0,2095]

Unit 2, T = 76, lag order = 8
estimated value of (a - 1): -0,912887
test statistic = -2,68148 [0,0772]

Unit 3, T = 80, lag order = 8
estimated value of (a - 1): -1,03058
test statistic = -2,55346 [0,1029]

Unit 4, T = 76, lag order = 8
estimated value of (a - 1): -1,21115
test statistic = -2,97102 [0,0377]

Unit 5, T = 80, lag order = 8
estimated value of (a - 1): -1,33213
test statistic = -2,96716 [0,0381]

Unit 6, T = 80, lag order = 8
estimated value of (a - 1): -1,15842
test statistic = -2,89851 [0,0455]

Unit 7, T = 80, lag order = 8
estimated value of (a - 1): -1,30222
test statistic = -3,17456 [0,0215]

Unit 8, T = 74, lag order = 8
estimated value of (a - 1): -0,706115
test statistic = -3,88792 [0,0021]

Unit 9, T = 80, lag order = 8
estimated value of (a - 1): -1,06269
test statistic = -2,0999 [0,2449]

Unit 10, T = 74, lag order = 8
estimated value of (a - 1): -0,53155
test statistic = -1,8362 [0,3632]

Unit 11, T = 66, lag order = 8
estimated value of (a - 1): -2,2209
test statistic = -2,96088 [0,0387]

Unit 12, T = 80, lag order = 8
estimated value of (a - 1): -1,70392
test statistic = -3,75588 [0,0034]

Unit 13, T = 76, lag order = 8
estimated value of (a - 1): -2,10627
test statistic = -4,29028 [0,0005]

Unit 14, T = 80, lag order = 8
estimated value of (a - 1): -0,769091
test statistic = -2,96161 [0,0386]

H0: all groups have unit root

N = 14, Tmin = 66, Tmax = 80
Im-Pesaran-Shin W_tbar = -6,13943 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 96,6344 [0,0000]
Inverse normal test = -6,47129 [0,0000]
Logit test: t(74) = -7,01054 [0,0000]

Current account/GDP – nonstationary- 1st differences applied:

Augmented Dickey-Fuller test for d_current_accou
including 8 lags of (1-L)d_current_accou
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 65, lag order = 8
estimated value of (a - 1): -1,65323
test statistic = -3,54671 [0,0069]

Unit 2, T = 62, lag order = 8
estimated value of (a - 1): -2,76169
test statistic = -3,91495 [0,0019]

Unit 3, T = 53, lag order = 8
estimated value of (a - 1): -1,03082
test statistic = -2,38451 [0,1461]

Unit 4, T = 61, lag order = 8
estimated value of (a - 1): -1,17641
test statistic = -2,36446 [0,1520]

Unit 5, T = 66, lag order = 8
estimated value of (a - 1): -1,32805
test statistic = -3,03924 [0,0314]

Unit 6, T = 81, lag order = 8
estimated value of (a - 1): -1,69086
test statistic = -4,01899 [0,0013]

Unit 7, T = 82, lag order = 8
estimated value of (a - 1): -1,33085
test statistic = -3,60098 [0,0058]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -1,84512
test statistic = -1,87715 [0,3435]

Unit 9, T = 70, lag order = 8
estimated value of (a - 1): -1,88937
test statistic = -3,56644 [0,0065]

Unit 10, T = 81, lag order = 8
estimated value of (a - 1): -2,99626
test statistic = -5,90283 [0,0000]

Unit 11, T = 70, lag order = 8
estimated value of (a - 1): -0,327179
test statistic = -3,71598 [0,0039]

Unit 12, T = 81, lag order = 8
estimated value of (a - 1): -2,21183
test statistic = -4,28954 [0,0005]

Unit 13, T = 81, lag order = 8
estimated value of (a - 1): -2,36179
test statistic = -3,45035 [0,0094]

Unit 14, T = 82, lag order = 8
estimated value of (a - 1): -0,669228
test statistic = -2,19423 [0,2085]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 82
Im-Pesaran-Shin W_tbar = -7,99403 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 142,519 [0,0000]
Inverse normal test = -8,52973 [0,0000]
Logit test: t(74) = -10,4887 [0,0000]

Unemployment rate:

Augmented Dickey-Fuller test for U_rate
including 8 lags of (1-L)U_rate
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 31, lag order = 8
estimated value of (a - 1): -0,222418
test statistic = -1,90139 [0,3320]

Unit 2, T = 69, lag order = 8
estimated value of (a - 1): -0,0481142
test statistic = -2,27533 [0,1801]

Unit 3, T = 46, lag order = 8
estimated value of (a - 1): -0,00906689

test statistic = -0,187431 [0,9377]

Unit 4, T = 66, lag order = 8
estimated value of (a - 1): -0,0753511
test statistic = -1,40559 [0,5812]

Unit 5, T = 70, lag order = 8
estimated value of (a - 1): -0,0789103
test statistic = -2,34281 [0,1585]

Unit 6, T = 70, lag order = 8
estimated value of (a - 1): -0,181519
test statistic = -3,02363 [0,0328]

Unit 7, T = 68, lag order = 8
estimated value of (a - 1): -0,0203911
test statistic = -2,6083 [0,0912]

Unit 8, T = 66, lag order = 8
estimated value of (a - 1): -0,0706734
test statistic = -1,42774 [0,5703]

Unit 9, T = 78, lag order = 8
estimated value of (a - 1): -0,109168
test statistic = -2,03092 [0,2736]

Unit 10, T = 70, lag order = 8
estimated value of (a - 1): -0,0694819
test statistic = -2,44626 [0,1291]

Unit 11, T = 44, lag order = 8
estimated value of (a - 1): -0,0262054
test statistic = -3,88174 [0,0022]

Unit 12, T = 41, lag order = 8
estimated value of (a - 1): -0,267119
test statistic = -2,44434 [0,1296]

Unit 13, T = 73, lag order = 8
estimated value of (a - 1): -0,042843
test statistic = -2,26657 [0,1830]

Unit 14, T = 83, lag order = 8
estimated value of (a - 1): -0,0615139
test statistic = -2,50409 [0,1144]

H0: all groups have unit root

N = 14, Tmin = 31, Tmax = 83
Im-Pesaran-Shin W_tbar = -3,16352 [0,0008]

Choi meta-tests:
Inverse chi-square(28) = 54,0388 [0,0022]
Inverse normal test = -3,05354 [0,0011]
Logit test: t(74) = -3,09251 [0,0014]

Gross fixed capital formation g:

Augmented Dickey-Fuller test for g_I
including 8 lags of (1-L)g_I
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 69, lag order = 8
estimated value of (a - 1): -0,552053
test statistic = -2,30804 [0,1694]

Unit 2, T = 81, lag order = 8
estimated value of (a - 1): -0,342001
test statistic = -1,4795 [0,5443]

Unit 3, T = 48, lag order = 8
estimated value of (a - 1): -0,425871
test statistic = -2,46527 [0,1241]

Unit 4, T = 61, lag order = 8
estimated value of (a - 1): -0,17793
test statistic = -1,11639 [0,7117]

Unit 5, T = 81, lag order = 8
estimated value of (a - 1): -0,941548
test statistic = -3,62851 [0,0053]

Unit 6, T = 81, lag order = 8
estimated value of (a - 1): -1,02821
test statistic = -2,7626 [0,0638]

Unit 7, T = 80, lag order = 8
estimated value of (a - 1): -0,495592
test statistic = -2,21611 [0,2006]

Unit 8, T = 66, lag order = 8
estimated value of (a - 1): -1,37258
test statistic = -5,29862 [0,0000]

Unit 9, T = 81, lag order = 8
estimated value of (a - 1): -0,918437
test statistic = -3,27085 [0,0163]

Unit 10, T = 81, lag order = 8
estimated value of (a - 1): -0,859862
test statistic = -3,37829 [0,0118]

Unit 11, T = 69, lag order = 8
estimated value of (a - 1): -0,935956
test statistic = -2,75249 [0,0653]

Unit 12, T = 80, lag order = 8
estimated value of (a - 1): -0,134726
test statistic = -0,884 [0,7939]

Unit 13, T = 81, lag order = 8
estimated value of (a - 1): -1,08724
test statistic = -3,20082 [0,0200]

Unit 14, T = 81, lag order = 8
estimated value of (a - 1): -0,334218
test statistic = -2,69448 [0,0749]

H0: all groups have unit root

N = 14, Tmin = 48, Tmax = 81
Im-Pesaran-Shin W_tbar = -5,05134 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 89,3754 [0,0000]
Inverse normal test = -5,17882 [0,0000]
Logit test: t(74) = -6,01583 [0,0000]

Change in industrial production:

Augmented Dickey-Fuller test for change_IP
including 8 lags of (1-L)change_IP
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 67, lag order = 8
estimated value of (a - 1): -0,892015
test statistic = -2,642 [0,0845]

Unit 2, T = 81, lag order = 8
estimated value of (a - 1): -0,969957
test statistic = -3,66346 [0,0047]

Unit 3, T = 81, lag order = 8
estimated value of (a - 1): -0,79744
test statistic = -3,64451 [0,0050]

Unit 4, T = 81, lag order = 8
estimated value of (a - 1): -0,630023
test statistic = -3,2623 [0,0167]

Unit 5, T = 81, lag order = 8
estimated value of (a - 1): -1,27186
test statistic = -3,5558 [0,0067]

Unit 6, T = 81, lag order = 8
estimated value of (a - 1): -1,57464
test statistic = -4,47639 [0,0001]

Unit 7, T = 81, lag order = 8
estimated value of (a - 1): -0,706849
test statistic = -2,9459 [0,0403]

Unit 8, T = 69, lag order = 8
estimated value of (a - 1): -0,68484
test statistic = -2,92934 [0,0420]

Unit 9, T = 82, lag order = 8
estimated value of (a - 1): -1,04584
test statistic = -3,4005 [0,0110]

Unit 10, T = 78, lag order = 8
estimated value of (a - 1): -1,13549
test statistic = -3,50281 [0,0079]

Unit 11, T = 72, lag order = 8
estimated value of (a - 1): -1,22302
test statistic = -2,96519 [0,0383]

Unit 12, T = 81, lag order = 8
estimated value of (a - 1): -1,45556
test statistic = -3,4744 [0,0087]

Unit 13, T = 81, lag order = 8
estimated value of (a - 1): -0,563709
test statistic = -2,59894 [0,0931]

Unit 14, T = 81, lag order = 8
estimated value of (a - 1): -0,30218
test statistic = -2,44808 [0,1286]

H0: all groups have unit root

N = 14, Tmin = 67, Tmax = 82
Im-Pesaran-Shin W_tbar = -7,37665 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 119,212 [0,0000]
Inverse normal test = -7,92476 [0,0000]
Logit test: t(74) = -8,82813 [0,0000]

Market capitalization/GDP:

Augmented Dickey-Fuller test for market_cap_GDP
including 8 lags of (1-L)market_cap_GDP
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 76, lag order = 8
estimated value of (a - 1): -0,011639
test statistic = -1,85091 [0,3561]

Unit 2, T = 60, lag order = 8
estimated value of (a - 1): -0,017812
test statistic = -2,09979 [0,2449]

Unit 3, T = 76, lag order = 8
estimated value of (a - 1): -0,00974729
test statistic = -1,98255 [0,2948]

Unit 4, T = 72, lag order = 8
estimated value of (a - 1): -0,0142054
test statistic = -2,50144 [0,1151]

Unit 5, T = 76, lag order = 8
estimated value of (a - 1): -0,0208975
test statistic = -2,11563 [0,2386]

Unit 6, T = 76, lag order = 8
estimated value of (a - 1): -0,00427902
test statistic = -0,584995 [0,8716]

Unit 7, T = 76, lag order = 8
estimated value of (a - 1): -0,0148746
test statistic = -1,72403 [0,4191]

Unit 8, T = 72, lag order = 8
estimated value of (a - 1): -0,00835293
test statistic = -1,35045 [0,6081]

Unit 9, T = 76, lag order = 8
estimated value of (a - 1): -0,0161176
test statistic = -2,27803 [0,1792]

Unit 10, T = 76, lag order = 8
estimated value of (a - 1): -0,0086985
test statistic = -1,78441 [0,3887]

Unit 11, T = 76, lag order = 8
estimated value of (a - 1): -0,0204253
test statistic = -2,37139 [0,1500]

Unit 12, T = 76, lag order = 8
estimated value of (a - 1): -0,0194389
test statistic = -1,81913 [0,3716]

Unit 13, T = 76, lag order = 8
estimated value of (a - 1): -0,0153387
test statistic = -2,01631 [0,2799]

Unit 14, T = 76, lag order = 8
estimated value of (a - 1): -0,00958407
test statistic = -2,00442 [0,2851]

H0: all groups have unit root

N = 14, Tmin = 60, Tmax = 76
Im-Pesaran-Shin W_tbar = -1,89768 [0,0289]

Choi meta-tests:
Inverse chi-square(28) = 33,6807 [0,2116]
Inverse normal test = -1,6094 [0,0538]
Logit test: t(74) = -1,47317 [0,0725]

Private credit annual g x private credit/GDP – nonstationary – 1st differences applied:

Augmented Dickey-Fuller test for d_pcredit_gxpcr
including 8 lags of (1-L)d_pcredit_gxpcr
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 77, lag order = 8
estimated value of (a - 1): -0,863287
test statistic = -3,71855 [0,0039]

Unit 2, T = 56, lag order = 8
estimated value of (a - 1): -0,657144
test statistic = -2,40172 [0,1412]

Unit 3, T = 40, lag order = 8
estimated value of (a - 1): -0,499138
test statistic = -1,86205 [0,3507]

Unit 4, T = 60, lag order = 8
estimated value of (a - 1): -2,18722
test statistic = -3,5819 [0,0061]

Unit 5, T = 64, lag order = 8
estimated value of (a - 1): -2,5083
test statistic = -4,63232 [0,0001]

Unit 6, T = 76, lag order = 8
estimated value of (a - 1): -0,857393
test statistic = -3,3255 [0,0138]

Unit 7, T = 68, lag order = 8
estimated value of (a - 1): -0,786776
test statistic = -3,95916 [0,0016]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -1,15789
test statistic = -2,93562 [0,0414]

Unit 9, T = 68, lag order = 8
estimated value of (a - 1): -0,90279
test statistic = -2,4033 [0,1408]

Unit 10, T = 76, lag order = 8
estimated value of (a - 1): -1,4983
test statistic = -3,25908 [0,0168]

Unit 11, T = 69, lag order = 8
estimated value of (a - 1): -0,630206
test statistic = -2,34723 [0,1572]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): -1,14964
test statistic = -2,64406 [0,0841]

Unit 13, T = 76, lag order = 8
estimated value of (a - 1): -1,14414
test statistic = -1,6202 [0,4722]

Unit 14, T = 75, lag order = 8
estimated value of (a - 1): -0,571996
test statistic = -2,24748 [0,1896]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 77
Im-Pesaran-Shin W_tbar = -6,02186 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 98,8757 [0,0000]
Inverse normal test = -6,34288 [0,0000]
Logit test: t(74) = -7,09695 [0,0000]

Interaction Market capitalization/GDP:

Augmented Dickey-Fuller test for Inter_Market_ca

including 8 lags of (1-L)Inter_Market_ca
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 59, lag order = 8
estimated value of (a - 1): -0,0200048
test statistic = -1,78688 [0,3875]

Unit 2, T = 59, lag order = 8
estimated value of (a - 1): -0,0180059
test statistic = -1,94431 [0,3121]

Unit 3, T = 59, lag order = 8
estimated value of (a - 1): -0,0299159
test statistic = -2,52568 [0,1093]

Unit 4, T = 59, lag order = 8
estimated value of (a - 1): -0,0284289
test statistic = -2,35361 [0,1553]

Unit 5, T = 59, lag order = 8
estimated value of (a - 1): -0,0281208
test statistic = -2,24687 [0,1898]

Unit 6, T = 59, lag order = 8
estimated value of (a - 1): -0,0214329
test statistic = -1,73618 [0,4129]

Unit 7, T = 59, lag order = 8
estimated value of (a - 1): -0,0274889
test statistic = -1,7677 [0,3971]

Unit 8, T = 59, lag order = 8
estimated value of (a - 1): -0,0141264
test statistic = -1,43449 [0,5669]

Unit 9, T = 59, lag order = 8
estimated value of (a - 1): -0,0386311
test statistic = -2,50035 [0,1153]

Unit 10, T = 59, lag order = 8
estimated value of (a - 1): -0,0199187
test statistic = -1,94171 [0,3133]

Unit 11, T = 59, lag order = 8
estimated value of (a - 1): -0,0162219
test statistic = -1,43257 [0,5679]

Unit 12, T = 59, lag order = 8
estimated value of (a - 1): -0,0469008
test statistic = -2,19557 [0,2080]

Unit 13, T = 59, lag order = 8
estimated value of (a - 1): -0,0424076
test statistic = -2,49703 [0,1161]

Unit 14, T = 59, lag order = 8
estimated value of (a - 1): -0,0356456
test statistic = -2,54907 [0,1039]

H0: all groups have unit root

N = 14, Tmin = 59, Tmax = 59
Im-Pesaran-Shin W_tbar = -2,65832 [0,0039]

Choi meta-tests:
Inverse chi-square(28) = 40,2001 [0,0635]
Inverse normal test = -2,40347 [0,0081]
Logit test: t(74) = -2,24994 [0,0137]

Real MSCI index annual g:

Augmented Dickey-Fuller test for MSCI_p_a__g
including 8 lags of (1-L)MSCI_p_a__g
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 29, lag order = 8
estimated value of (a - 1): -0,173517
test statistic = -0,96363 [0,7681]

Unit 2, T = 36, lag order = 8
estimated value of (a - 1): -0,268213
test statistic = -1,58945 [0,4880]

Unit 3, T = 52, lag order = 8
estimated value of (a - 1): -0,319725
test statistic = -2,90532 [0,0447]

Unit 4, T = 36, lag order = 8
estimated value of (a - 1): -0,263327
test statistic = -1,60807 [0,4784]

Unit 5, T = 79, lag order = 8
estimated value of (a - 1): -0,324919
test statistic = -3,07567 [0,0284]

Unit 6, T = 79, lag order = 8
estimated value of (a - 1): -0,447319
test statistic = -3,17196 [0,0217]

Unit 7, T = 79, lag order = 8
estimated value of (a - 1): -0,0881232
test statistic = -1,8948 [0,3351]

Unit 8, T = 70, lag order = 8
estimated value of (a - 1): -0,282443
test statistic = -3,15229 [0,0229]

Unit 9, T = 79, lag order = 8
estimated value of (a - 1): -0,270219
test statistic = -2,91154 [0,0440]

Unit 10, T = 79, lag order = 8
estimated value of (a - 1): -0,215928
test statistic = -2,3239 [0,1644]

Unit 11, T = 80, lag order = 8
estimated value of (a - 1): -0,447079
test statistic = -3,14565 [0,0234]

Unit 12, T = 79, lag order = 8
estimated value of (a - 1): -0,219938
test statistic = -2,38606 [0,1457]

Unit 13, T = 79, lag order = 8
estimated value of (a - 1): -0,21087
test statistic = -2,27921 [0,1788]

Unit 14, T = 79, lag order = 8
estimated value of (a - 1): -0,186524
test statistic = -2,1823 [0,2129]

H0: all groups have unit root

N = 14, Tmin = 29, Tmax = 80
Im-Pesaran-Shin W_tbar = -3,9532 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 61,9271 [0,0002]
Inverse normal test = -3,96577 [0,0000]
Logit test: t(74) = -4,00516 [0,0001]

Property index annual g:

Augmented Dickey-Fuller test for property_ind_p_
including 2 lags of (1-L)property_ind_p_
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 85, lag order = 2
estimated value of (a - 1): -0,218453
test statistic = -5,51746 [0,0000]

Unit 2, T = 29, lag order = 2
estimated value of (a - 1): -0,0911965
test statistic = -1,92301 [0,3219]

Unit 3, T = 84, lag order = 2
estimated value of (a - 1): -0,0416344
test statistic = -1,98511 [0,2936]

Unit 4, T = 36, lag order = 2
estimated value of (a - 1): -0,0953785
test statistic = -0,92633 [0,7805]

Unit 5, T = 84, lag order = 2
estimated value of (a - 1): -0,0129378
test statistic = -2,03245 [0,2730]

Unit 6, T = 85, lag order = 2
estimated value of (a - 1): -0,157971
test statistic = -4,24847 [0,0005]

Unit 7, T = 24, lag order = 2
estimated value of (a - 1): -0,368698
test statistic = -1,77664 [0,3926]

Unit 8, T = 40, lag order = 2

estimated value of (a - 1): -0,164371
test statistic = -2,1843 [0,2122]

Unit 9, T = 84, lag order = 2
estimated value of (a - 1): -0,133279
test statistic = -3,31535 [0,0142]

Unit 10, T = 85, lag order = 2
estimated value of (a - 1): -0,0647214
test statistic = -1,4805 [0,5438]

Unit 11, T = 13, lag order = 2
estimated value of (a - 1): -1,00524
test statistic = -2,56472 [0,1004]

Unit 12, T = 5, lag order = 2
estimated value of (a - 1): -1,79562
test statistic = -2,07784 [0,2538]

Unit 13, T = 84, lag order = 2
estimated value of (a - 1): -0,135127
test statistic = -3,36006 [0,0124]

Unit 14, T = 84, lag order = 2
estimated value of (a - 1): -0,0486772
test statistic = -2,49339 [0,1170]

H0: all groups have unit root

Choi meta-tests:
Inverse chi-square(28) = 84,6624 [0,0000]
Inverse normal test = -4,621 [0,0000]
Logit test: t(74) = -5,62982 [0,0000]

Nonperforming loans:

Augmented Dickey-Fuller test for NPL
including 8 lags of (1-L)NPL
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 36, lag order = 8
estimated value of (a - 1): -0,0262629
test statistic = -6,46111 [0,0000]

Unit 2, T = 36, lag order = 8
estimated value of (a - 1): -0,0330654
test statistic = -3,3126 [0,0144]

Unit 3, T = 36, lag order = 8
estimated value of (a - 1): -0,0188861
test statistic = -1,10998 [0,7142]

Unit 4, T = 36, lag order = 8
estimated value of (a - 1): -0,0192943
test statistic = -0,516566 [0,8857]

Unit 5, T = 32, lag order = 8
estimated value of (a - 1): -0,0175595
test statistic = -1,3045 [0,6298]

Unit 6, T = 32, lag order = 8
estimated value of (a - 1): -0,0143733
test statistic = -1,08897 [0,7225]

Unit 7, T = 36, lag order = 8
estimated value of (a - 1): -0,016281
test statistic = -2,41166 [0,1385]

Unit 8, T = 36, lag order = 8
estimated value of (a - 1): -0,0291028
test statistic = -1,99232 [0,2904]

Unit 9, T = 28, lag order = 8
estimated value of (a - 1): -0,0419087
test statistic = -2,40344 [0,1407]

Unit 10, T = 28, lag order = 8
estimated value of (a - 1): -0,036422
test statistic = -3,64875 [0,0049]

Unit 11, T = 36, lag order = 8
estimated value of (a - 1): -0,014067
test statistic = -3,08433 [0,0278]

Unit 12, T = 36, lag order = 8
estimated value of (a - 1): -0,0237771
test statistic = -1,14198 [0,7013]

Unit 13, T = 32, lag order = 8
estimated value of (a - 1): -0,0577524
test statistic = -3,68956 [0,0043]

Unit 14, T = 36, lag order = 8
estimated value of (a - 1): 0,00422076
test statistic = 0,104123 [0,9661]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 36
Im-Pesaran-Shin W_tbar = -3,62695 [0,0001]

Choi meta-tests:
Inverse chi-square(28) = 87,9463 [0,0000]
Inverse normal test = -3,37283 [0,0004]
Logit test: t(74) = -4,92758 [0,0000]

Real MSCI annual g x market capitalization/GDP:

Augmented Dickey-Fuller test for MSCIxmarket_cap
including 8 lags of (1-L)MSCIxmarket_cap
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 26, lag order = 8
estimated value of (a - 1): -0,143776
test statistic = -0,830701 [0,8099]

Unit 2, T = 32, lag order = 8
estimated value of (a - 1): -0,276905
test statistic = -1,37135 [0,5980]

Unit 3, T = 48, lag order = 8
estimated value of (a - 1): -0,321535
test statistic = -2,82333 [0,0550]

Unit 4, T = 32, lag order = 8
estimated value of (a - 1): -0,295533
test statistic = -1,46893 [0,5496]

Unit 5, T = 75, lag order = 8
estimated value of (a - 1): -0,303995
test statistic = -3,02089 [0,0330]

Unit 6, T = 75, lag order = 8
estimated value of (a - 1): -0,56576
test statistic = -3,10271 [0,0264]

Unit 7, T = 75, lag order = 8
estimated value of (a - 1): -0,0952627
test statistic = -1,9948 [0,2893]

Unit 8, T = 67, lag order = 8
estimated value of (a - 1): -0,392205
test statistic = -2,22281 [0,1982]

Unit 9, T = 75, lag order = 8
estimated value of (a - 1): -0,267933
test statistic = -2,70305 [0,0734]

Unit 10, T = 75, lag order = 8
estimated value of (a - 1): -0,243592
test statistic = -2,38834 [0,1450]

Unit 11, T = 75, lag order = 8
estimated value of (a - 1): -0,467123
test statistic = -3,16236 [0,0223]

Unit 12, T = 75, lag order = 8
estimated value of (a - 1): -0,242954
test statistic = -1,99286 [0,2902]

Unit 13, T = 75, lag order = 8
estimated value of (a - 1): -0,219027
test statistic = -2,18317 [0,2126]

Unit 14, T = 75, lag order = 8
estimated value of (a - 1): -0,204078
test statistic = -2,26475 [0,1837]

H0: all groups have unit root

N = 14, Tmin = 26, Tmax = 75
Im-Pesaran-Shin W_tbar = -3,38514 [0,0004]

Choi meta-tests:
Inverse chi-square(28) = 53,9087 [0,0023]

Inverse normal test = -3,28603 [0,0005]
Logit test: t(74) = -3,26631 [0,0008]

Interaction real MSCI annual g:

Augmented Dickey-Fuller test for Inter_real_MSCI
including 8 lags of (1-L)Inter_real_MSCI
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 27, lag order = 8
estimated value of (a - 1): -0,883415
test statistic = -2,01412 [0,2809]

Unit 2, T = 33, lag order = 8
estimated value of (a - 1): -1,27823
test statistic = -2,95023 [0,0398]

Unit 3, T = 49, lag order = 8
estimated value of (a - 1): -0,860057
test statistic = -2,88714 [0,0468]

Unit 4, T = 33, lag order = 8
estimated value of (a - 1): -1,21691
test statistic = -2,92391 [0,0426]

Unit 5, T = 49, lag order = 8
estimated value of (a - 1): -1,07119
test statistic = -2,95533 [0,0393]

Unit 6, T = 49, lag order = 8
estimated value of (a - 1): -0,909982
test statistic = -3,12299 [0,0249]

Unit 7, T = 49, lag order = 8
estimated value of (a - 1): -1,01812
test statistic = -2,77211 [0,0623]

Unit 8, T = 49, lag order = 8
estimated value of (a - 1): -1,06118
test statistic = -3,11665 [0,0254]

Unit 9, T = 49, lag order = 8
estimated value of (a - 1): -1,00926
test statistic = -3,14383 [0,0235]

Unit 10, T = 49, lag order = 8
estimated value of (a - 1): -0,632977
test statistic = -2,39407 [0,1434]

Unit 11, T = 49, lag order = 8
estimated value of (a - 1): -0,852702
test statistic = -3,11672 [0,0254]

Unit 12, T = 49, lag order = 8
estimated value of (a - 1): -1,20204
test statistic = -3,31667 [0,0142]

Unit 13, T = 49, lag order = 8
estimated value of (a - 1): -0,632606
test statistic = -2,46367 [0,1245]

Unit 14, T = 49, lag order = 8
estimated value of (a - 1): -0,641555
test statistic = -2,48714 [0,1186]

H0: all groups have unit root

N = 14, Tmin = 27, Tmax = 49
Im-Pesaran-Shin W_tbar = -5,62927 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 83,8516 [0,0000]
Inverse normal test = -6,00584 [0,0000]
Logit test: t(74) = -6,09936 [0,0000]

Interaction real private credit annual g:

Augmented Dickey-Fuller test for Inter_real_g_pc including 8 lags of (1-L)Inter_real_g_pc test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 40, lag order = 8
estimated value of (a - 1): -0,279148
test statistic = -1,62507 [0,4697]

Unit 2, T = 40, lag order = 8
estimated value of (a - 1): -0,708028
test statistic = -3,29202 [0,0153]

Unit 3, T = 40, lag order = 8
estimated value of (a - 1): -0,262584
test statistic = -1,63661 [0,4638]

Unit 4, T = 40, lag order = 8
estimated value of (a - 1): -0,316515
test statistic = -1,96435 [0,3029]

Unit 5, T = 40, lag order = 8
estimated value of (a - 1): -0,256347
test statistic = -1,30159 [0,6312]

Unit 6, T = 40, lag order = 8
estimated value of (a - 1): -0,308103
test statistic = -1,84918 [0,3569]

Unit 7, T = 40, lag order = 8
estimated value of (a - 1): -0,619163
test statistic = -2,34025 [0,1593]

Unit 8, T = 40, lag order = 8
estimated value of (a - 1): -0,335546
test statistic = -1,97373 [0,2987]

Unit 9, T = 40, lag order = 8
estimated value of (a - 1): -0,347341
test statistic = -1,746 [0,4080]

Unit 10, T = 40, lag order = 8
estimated value of (a - 1): -0,570155
test statistic = -2,42777 [0,1340]

Unit 11, T = 40, lag order = 8
estimated value of (a - 1): -0,30472
test statistic = -1,39484 [0,5865]

Unit 12, T = 40, lag order = 8
estimated value of (a - 1): -0,671121
test statistic = -3,0354 [0,0317]

Unit 13, T = 40, lag order = 8
estimated value of (a - 1): -0,222496
test statistic = -1,47747 [0,5453]

Unit 14, T = 40, lag order = 8
estimated value of (a - 1): -0,306724
test statistic = -1,53883 [0,5140]

H0: all groups have unit root

N = 14, Tmin = 40, Tmax = 40
Im-Pesaran-Shin W_tbar = -2,4094 [0,0080]

Choi meta-tests:
Inverse chi-square(28) = 39,1948 [0,0778]
Inverse normal test = -1,93273 [0,0266]
Logit test: t(74) = -1,9275 [0,0289]

Interaction private credit/GDP – nonstationary, 1st differences of log applied:

Augmented Dickey-Fuller test for d_l_Inter_pcred
including 8 lags of (1-L)d_l_Inter_pcred
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 43, lag order = 8
estimated value of (a - 1): -0,208026
test statistic = -1,32182 [0,6217]

Unit 2, T = 43, lag order = 8
estimated value of (a - 1): -0,248795
test statistic = -1,39806 [0,5849]

Unit 3, T = 43, lag order = 8
estimated value of (a - 1): -0,749034
test statistic = -1,97913 [0,2963]

Unit 4, T = 43, lag order = 8
estimated value of (a - 1): -0,850217
test statistic = -1,58777 [0,4889]

Unit 5, T = 43, lag order = 8
estimated value of (a - 1): -0,708171
test statistic = -1,6029 [0,4811]

Unit 6, T = 43, lag order = 8
estimated value of (a - 1): -0,615506
test statistic = -2,15739 [0,2223]

Unit 7, T = 43, lag order = 8
estimated value of (a - 1): -0,346602
test statistic = -1,69329 [0,4347]

Unit 8, T = 27, lag order = 8
estimated value of (a - 1): -0,425801
test statistic = -1,21885 [0,6687]

Unit 9, T = 43, lag order = 8
estimated value of (a - 1): -0,594337
test statistic = -1,69426 [0,4342]

Unit 10, T = 43, lag order = 8
estimated value of (a - 1): -0,504534
test statistic = -1,37865 [0,5944]

Unit 11, T = 43, lag order = 8
estimated value of (a - 1): -0,891141
test statistic = -2,10517 [0,2427]

Unit 12, T = 43, lag order = 8
estimated value of (a - 1): -1,55021
test statistic = -3,55933 [0,0066]

Unit 13, T = 43, lag order = 8
estimated value of (a - 1): -1,13667
test statistic = -2,46083 [0,1253]

Unit 14, T = 43, lag order = 8
estimated value of (a - 1): -0,690504
test statistic = -1,90282 [0,3313]

H0: all groups have unit root

N = 14, Tmin = 27, Tmax = 43
Im-Pesaran-Shin W_tbar = -1,97769 [0,0240]

Choi meta-tests:
Inverse chi-square(28) = 34,7689 [0,1767]
Inverse normal test = -1,40721 [0,0797]
Logit test: t(74) = -1,43929 [0,0771]

Interaction real MSCI annual g x global market capitalization/GDP:

Augmented Dickey-Fuller test for Inter_MSCIxglob
including 8 lags of (1-L)Inter_MSCIxglob
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 26, lag order = 8
estimated value of (a - 1): -0,648856
test statistic = -1,21603 [0,6699]

Unit 2, T = 32, lag order = 8
estimated value of (a - 1): -1,14408
test statistic = -2,60835 [0,0912]

Unit 3, T = 48, lag order = 8
estimated value of (a - 1): -1,13378
test statistic = -3,14928 [0,0231]

Unit 4, T = 32, lag order = 8
estimated value of (a - 1): -0,910111
test statistic = -2,24903 [0,1890]

Unit 5, T = 48, lag order = 8
estimated value of (a - 1): -0,547299
test statistic = -2,3253 [0,1639]

Unit 6, T = 48, lag order = 8
estimated value of (a - 1): -0,805854
test statistic = -3,54773 [0,0069]

Unit 7, T = 48, lag order = 8
estimated value of (a - 1): -0,764502
test statistic = -2,53071 [0,1081]

Unit 8, T = 48, lag order = 8
estimated value of (a - 1): -0,586977
test statistic = -2,08022 [0,2529]

Unit 9, T = 48, lag order = 8
estimated value of (a - 1): -0,60032
test statistic = -2,97043 [0,0378]

Unit 10, T = 48, lag order = 8
estimated value of (a - 1): -0,592323
test statistic = -1,92453 [0,3212]

Unit 11, T = 48, lag order = 8
estimated value of (a - 1): -0,959982
test statistic = -3,11503 [0,0255]

Unit 12, T = 48, lag order = 8
estimated value of (a - 1): -0,94848
test statistic = -2,6701 [0,0793]

Unit 13, T = 48, lag order = 8
estimated value of (a - 1): -0,946701
test statistic = -2,34974 [0,1564]

Unit 14, T = 48, lag order = 8
estimated value of (a - 1): -1,05319
test statistic = -2,9041 [0,0449]

H0: all groups have unit root

N = 14, Tmin = 26, Tmax = 48
Im-Pesaran-Shin W_tbar = -4,53953 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 68,3819 [0,0000]
Inverse normal test = -4,65615 [0,0000]
Logit test: t(74) = -4,69233 [0,0000]

Interaction private credit annual g x global private credit/GDP:

Augmented Dickey-Fuller test for Inter_pcredit_g
including 8 lags of (1-L)Inter_pcredit_g
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 40, lag order = 8
estimated value of (a - 1): -0,333633
test statistic = -1,55587 [0,5053]

Unit 2, T = 40, lag order = 8
estimated value of (a - 1): -0,780771
test statistic = -3,12509 [0,0248]

Unit 3, T = 40, lag order = 8
estimated value of (a - 1): -0,281278
test statistic = -1,66107 [0,4512]

Unit 4, T = 40, lag order = 8
estimated value of (a - 1): -0,448608
test statistic = -2,23961 [0,1923]

Unit 5, T = 40, lag order = 8
estimated value of (a - 1): -0,232975
test statistic = -1,33442 [0,6157]

Unit 6, T = 40, lag order = 8
estimated value of (a - 1): -0,344273
test statistic = -1,85748 [0,3529]

Unit 7, T = 40, lag order = 8
estimated value of (a - 1): -0,659977
test statistic = -2,18658 [0,2113]

Unit 8, T = 28, lag order = 8
estimated value of (a - 1): -1,07445
test statistic = -2,63902 [0,0851]

Unit 9, T = 40, lag order = 8
estimated value of (a - 1): -0,37697
test statistic = -1,74473 [0,4086]

Unit 10, T = 40, lag order = 8
estimated value of (a - 1): -0,596963
test statistic = -2,44312 [0,1299]

Unit 11, T = 40, lag order = 8
estimated value of (a - 1): -0,317324
test statistic = -1,43428 [0,5670]

Unit 12, T = 40, lag order = 8
estimated value of (a - 1): -0,633809
test statistic = -2,02718 [0,2752]

Unit 13, T = 40, lag order = 8
estimated value of (a - 1): -0,248693
test statistic = -1,47378 [0,5472]

Unit 14, T = 40, lag order = 8
estimated value of (a - 1): -0,324225
test statistic = -1,53404 [0,5165]

H0: all groups have unit root

N = 14, Tmin = 28, Tmax = 40
Im-Pesaran-Shin W_tbar = -2,32638 [0,0100]

Choi meta-tests:
Inverse chi-square(28) = 36,8539 [0,1221]
Inverse normal test = -1,82426 [0,0341]
Logit test: t(74) = -1,76634 [0,0407]

CPI annual g:

Augmented Dickey-Fuller test for CPI_g_p_a_
including 8 lags of (1-L)CPI_g_p_a_
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 78, lag order = 8
estimated value of (a - 1): -0,143856
test statistic = -2,78868 [0,0599]

Unit 2, T = 75, lag order = 8
estimated value of (a - 1): -0,0795979
test statistic = -2,24077 [0,1919]

Unit 3, T = 55, lag order = 8
estimated value of (a - 1): -0,358569
test statistic = -2,72981 [0,0690]

Unit 4, T = 79, lag order = 8
estimated value of (a - 1): -0,0321705
test statistic = -1,68333 [0,4398]

Unit 5, T = 79, lag order = 8
estimated value of (a - 1): -0,196972
test statistic = -2,56577 [0,1002]

Unit 6, T = 79, lag order = 8
estimated value of (a - 1): -0,165712
test statistic = -2,189 [0,2105]

Unit 7, T = 79, lag order = 8
estimated value of (a - 1): -0,0409738
test statistic = -1,23509 [0,6615]

Unit 8, T = 71, lag order = 8
estimated value of (a - 1): -0,116012
test statistic = -3,88587 [0,0022]

Unit 9, T = 79, lag order = 8
estimated value of (a - 1): -0,216889
test statistic = -3,69675 [0,0042]

Unit 10, T = 79, lag order = 8
estimated value of (a - 1): -0,201672
test statistic = -3,57873 [0,0062]

Unit 11, T = 80, lag order = 8
estimated value of (a - 1): -0,111426
test statistic = -1,6268 [0,4688]

Unit 12, T = 79, lag order = 8
estimated value of (a - 1): -0,00899009
test statistic = -0,386613 [0,9092]

Unit 13, T = 79, lag order = 8
estimated value of (a - 1): -0,0918176
test statistic = -1,76062 [0,4006]

Unit 14, T = 79, lag order = 8
estimated value of (a - 1): -0,334132
test statistic = -2,83528 [0,0534]

H0: all groups have unit root

N = 14, Tmin = 55, Tmax = 80
Im-Pesaran-Shin W_tbar = -3,82553 [0,0001]

Choi meta-tests:
Inverse chi-square(28) = 67,2653 [0,0000]
Inverse normal test = -3,82983 [0,0001]
Logit test: t(74) = -4,13353 [0,0000]

Real effective exchange rate g:

Augmented Dickey-Fuller test for g_REER
including 8 lags of (1-L)g_REER
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 65, lag order = 8
estimated value of (a - 1): -1,04674
test statistic = -2,7785 [0,0614]

Unit 2, T = 65, lag order = 8
estimated value of (a - 1): -1,57063
test statistic = -3,19608 [0,0202]

Unit 3, T = 65, lag order = 8
estimated value of (a - 1): -0,789492
test statistic = -2,56789 [0,0997]

Unit 4, T = 65, lag order = 8
estimated value of (a - 1): -1,68125
test statistic = -3,65078 [0,0049]

Unit 5, T = 65, lag order = 8
estimated value of (a - 1): -1,20573
test statistic = -3,62719 [0,0053]

Unit 6, T = 65, lag order = 8
estimated value of (a - 1): -1,27658
test statistic = -3,30846 [0,0145]

Unit 7, T = 65, lag order = 8
estimated value of (a - 1): -1,05766
test statistic = -3,1008 [0,0265]

Unit 8, T = 65, lag order = 8
estimated value of (a - 1): -0,879733
test statistic = -3,22616 [0,0186]

Unit 9, T = 65, lag order = 8
estimated value of (a - 1): -1,44473
test statistic = -4,22975 [0,0006]

Unit 10, T = 65, lag order = 8
estimated value of (a - 1): -1,02041
test statistic = -2,77474 [0,0619]

Unit 11, T = 65, lag order = 8
estimated value of (a - 1): -1,71414
test statistic = -3,79601 [0,0030]

Unit 12, T = 65, lag order = 8
estimated value of (a - 1): -2,08659
test statistic = -3,17044 [0,0218]

Unit 13, T = 65, lag order = 8
estimated value of (a - 1): -0,646226
test statistic = -2,43822 [0,1312]

Unit 14, T = 65, lag order = 8
estimated value of (a - 1): -0,792234
test statistic = -2,56071 [0,1013]

H0: all groups have unit root

N = 14, Tmin = 65, Tmax = 65
Im-Pesaran-Shin W_tbar = -7,04294 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 111,211 [0,0000]
Inverse normal test = -7,5281 [0,0000]
Logit test: t(74) = -8,21731 [0,0000]

Private credit real annual g – nonstationary – 1st differences applied:

Augmented Dickey-Fuller test for d_pcredit_real_
including 8 lags of (1-L)d_pcredit_real_
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1, T = 77, lag order = 8
estimated value of (a - 1): -0,372108
test statistic = -2,86477 [0,0496]

Unit 2, T = 65, lag order = 8
estimated value of (a - 1): -0,82781

test statistic = -2,58511 [0,0960]

Unit 3, T = 41, lag order = 8
estimated value of (a - 1): -0,575614
test statistic = -2,2919 [0,1746]

Unit 4, T = 77, lag order = 8
estimated value of (a - 1): -1,77496
test statistic = -4,38947 [0,0001]

Unit 5, T = 77, lag order = 8
estimated value of (a - 1): -2,12219
test statistic = -4,8463 [0,0000]

Unit 6, T = 77, lag order = 8
estimated value of (a - 1): -0,908313
test statistic = -3,48918 [0,0083]

Unit 7, T = 77, lag order = 8
estimated value of (a - 1): -0,625332
test statistic = -2,52136 [0,1103]

Unit 8, T = 56, lag order = 8
estimated value of (a - 1): -1,54401
test statistic = -4,2957 [0,0004]

Unit 9, T = 77, lag order = 8
estimated value of (a - 1): -0,984153
test statistic = -3,03011 [0,0322]

Unit 10, T = 77, lag order = 8
estimated value of (a - 1): -1,42541
test statistic = -3,28564 [0,0156]

Unit 11, T = 77, lag order = 8
estimated value of (a - 1): -0,624887
test statistic = -2,461 [0,1252]

Unit 12, T = 77, lag order = 8
estimated value of (a - 1): -1,13502
test statistic = -3,82326 [0,0027]

Unit 13, T = 77, lag order = 8
estimated value of (a - 1): -1,15957
test statistic = -2,4274 [0,1341]

Unit 14, T = 77, lag order = 8
estimated value of (a - 1): -0,574731
test statistic = -2,15453 [0,2234]

H0: all groups have unit root

N = 14, Tmin = 41, Tmax = 77
Im-Pesaran-Shin W_tbar = -7,05552
[0,0000]

Choi meta-tests:
Inverse chi-square(28) = 120,399
[0,0000]
Inverse normal test = -7,56099 [0,0000]
Logit test: t(74) = -8,83563 [0,0000]

Global real MSCI annual g:

Augmented Dickey-Fuller test for
Glob_real_MSCI
including 8 lags of (1-L)Glob_real_MSCI
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1...14, T = 49, lag order = 8
estimated value of (a - 1): -0,273592
test statistic = -2,2788 [0,1789]

H0: all groups have unit root

N = 14, Tmin = 49, Tmax = 49
Im-Pesaran-Shin W_tbar = -3,50682
[0,0002]

Choi meta-tests:
Inverse chi-square(28) = 48,1783
[0,0103]
Inverse normal test = -3,44 [0,0003]
Logit test: t(74) = -3,18612 [0,0011]

Global real private credit annual g:

Augmented Dickey-Fuller test for
Glob_real_pcred
including 8 lags of (1-L)Glob_real_pcred
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 40, lag order = 8
estimated value of (a - 1): -0,255626
test statistic = -1,61281 [0,4760]

H0: all groups have unit root

N = 14, Tmin = 40, Tmax = 40
Im-Pesaran-Shin W_tbar = -1,06403
[0,1437]

Choi meta-tests:
Inverse chi-square(28) = 20,786
[0,8342]
Inverse normal test = -0,225319
[0,4109]
Logit test: t(74) = -0,201002 [0,4206]

Global market capitalization/GDP:

Augmented Dickey-Fuller test for
Glob_market_cap
including 8 lags of (1-
L)Glob_market_cap
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 59, lag order = 8
estimated value of (a - 1): -0,0246333
test statistic = -2,10175 [0,2441]

H0: all groups have unit root

N = 14, Tmin = 59, Tmax = 59
Im-Pesaran-Shin W_tbar = -2,80275
[0,0025]

Choi meta-tests:
Inverse chi-square(28) = 39,4836
[0,0735]
Inverse normal test = -2,59348 [0,0048]
Logit test: t(74) = -2,36377 [0,0104]

Global private credit/GDP:

Augmented Dickey-Fuller test for
Glob_pcredit_GD
including 8 lags of (1-L)Glob_pcredit_GD
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 44, lag order = 8
estimated value of (a - 1): -0,0981768
test statistic = -2,30352 [0,1709]

H0: all groups have unit root

N = 14, Tmin = 44, Tmax = 44
Im-Pesaran-Shin W_tbar = -3,63083
[0,0001]

Choi meta-tests:
Inverse chi-square(28) = 49,473
[0,0074]
Inverse normal test = -3,55742 [0,0002]
Logit test: t(74) = -3,30332 [0,0007]

Global private credit g x global private credit/GDP:

Augmented Dickey-Fuller test for
Glob_pcredit_gx
including 8 lags of (1-L)Globpcreditgx
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 40, lag order = 8
estimated value of (a - 1): -0,242366
test statistic = -1,59193 [0,4867]

H0: all groups have unit root

N = 14, Tmin = 40, Tmax = 40
Im-Pesaran-Shin W_tbar = -0,985767
[0,1621]

Choi meta-tests:
Inverse chi-square(28) = 20,1619
[0,8585]
Inverse normal test = -0,124588
[0,4504]
Logit test: t(74) = -0,111129 [0,4559]

Global MSCI real annual g x global market capitalization/GDP:

Augmented Dickey-Fuller test for Glob_MSCIxglob
including 8 lags of (1-L)Glob_MSCIxglob
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 48, lag order = 8
estimated value of (a - 1): -0,272363
test statistic = -2,30827 [0,1693]

H0: all groups have unit root

N = 14, Tmin = 48, Tmax = 48
Im-Pesaran-Shin W_tbar = -3,6264 [0,0001]

Choi meta-tests:
Inverse chi-square(28) = 49,724 [0,0069]
Inverse normal test = -3,57995 [0,0002]
Logit test: t(74) = -3,3259 [0,0007]

Global real GDP annual g:

Augmented Dickey-Fuller test for Glob_real_GDP_g
including 8 lags of (1-L)Glob_real_GDP_g
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 52, lag order = 8
estimated value of (a - 1): -0,263023
test statistic = -1,82326 [0,3695]

H0: all groups have unit root

N = 14, Tmin = 52, Tmax = 52
Im-Pesaran-Shin W_tbar = -1,7261 [0,0422]

Choi meta-tests:
Inverse chi-square(28) = 27,8739 [0,4711]
Inverse normal test = -1,24624 [0,1063]
Logit test: t(74) = -1,11718 [0,1338]

Global CPI annual g:

Augmented Dickey-Fuller test for Glob_CPI_g_p_a_
including 8 lags of (1-L)Glob_CPI_g_p_a_
test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

Unit 1,...,14, T = 52, lag order = 8
estimated value of (a - 1): -0,33383
test statistic = -2,431 [0,1332]

H0: all groups have unit root

N = 14, Tmin = 52, Tmax = 52
Im-Pesaran-Shin W_tbar = -4,09377 [0,0000]

Choi meta-tests:
Inverse chi-square(28) = 56,4552 [0,0011]
Inverse normal test = -4,15926 [0,0000]
Logit test: t(74) = -3,91784 [0,0001]

2. Correlations between FSI and selected variables in chapter 6

H0: no correlation with FSI rejected for variables in **bold**

Correlation coefficients, using the observations 1:01 - 14:93
(missing values were skipped)
5% critical value (two-tailed) = 0,0543 for n = 1302

	MSCIhp short	**Real MSCI hp long deviation**	**Real MSCI annual g**	**Property index g**	
	-0,0414	-0,0744	-0,3592	-0,1820	FSI
Real MSCI annual g x market capitalization/GDP	**Interaction real MSCI annual g**	Interaction real MSCI annual g x global market capitalization/GDP	REER g	**Global real MSCI annual g**	
-0,3350	0,2435	0,0227	-0,0460	-0,3702	FSI
				Global real MSCI annual g x global market capitalization/GDP	
				-0,3358	FSI

3. Lags Identification for the Short model in section 6.2

Real GDP annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,47563	0,0930409	-15,8600	<0,00001	***
real_GDP_p_a__g	-15,151	4,81191	-3,1486	0,00164	***
real_GDP_p__1	16,4208	5,33031	3,0806	0,00207	***
real_GDP_p__4	-6,19876	2,01609	-3,0746	0,00211	***

Mean dependent var	0,197062	S.D. dependent var	0,398024
McFadden R-squared	0,018249	Adjusted R-squared	0,008384
Log-likelihood	-398,0799	Akaike criterion	804,1598
Schwarz criterion	822,9823	Hannan-Quinn	811,3834

Likelihood ratio test: Chi-square(3) = 14,7994 [0,0020]

Real M2 annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,32795	0,102584	-12,9450	<0,00001	***
real_M2_p_a_4	-2,87608	1,29806	-2,2157	0,02671	**
real_M2_p_a_6	2,03411	1,09436	1,8587	0,06307	*

Mean dependent var	0,202830	S.D. dependent var	0,402344
McFadden R-squared	0,006703	Adjusted R-squared	-0,000312
Log-likelihood	-424,7806	Akaike criterion	855,5611
Schwarz criterion	869,7897	Hannan-Quinn	861,0120

Likelihood ratio test: Chi-square(2) = 5,73332 [0,0569]

Real Money annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,96829	0,102703	-9,4280	<0,00001	***
real_money_p_a_	-4,54847	0,998407	-4,5557	<0,00001	***
real_money__4	-2,84839	0,932085	-3,0559	0,00224	***

Mean dependent var	0,204465	S.D. dependent var	0,403548
McFadden R-squared	0,045248	Adjusted R-squared	0,038288
Log-likelihood	-411,5532	Akaike criterion	829,1064
Schwarz criterion	843,3456	Hannan-Quinn	834,5604

Likelihood ratio test: Chi-square(2) = 39,0089 [0,0000]

M2/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,47596	0,0958247	-15,4027	<0,00001	***
M2_GDP	0,996373	0,506036	1,9690	0,04896	**
M2_GDP_8	0,351129	0,360303	0,9745	0,32979	

Mean dependent var	0,198483	S.D. dependent var	0,399110
McFadden R-squared	0,008783	Adjusted R-squared	0,001172
Log-likelihood	-390,6872	Akaike criterion	787,3745
Schwarz criterion	801,3944	Hannan-Quinn	792,7632

Likelihood ratio test: Chi-square(2) = 6,92363 [0,0314]

Money/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,34124	0,0948804	-14,1361	<0,00001	***
money_GDP_4	-6,57486	2,75984	-2,3823	0,01720	**
money_GDP_5	-4,5441	2,38877	-1,9023	0,05714	*
money_GDP_8	2,93029	1,59043	1,8425	0,06541	*

Mean dependent var	0,197236	S.D. dependent var	0,398162
McFadden R-squared	0,020218	Adjusted R-squared	0,010098
Log-likelihood	-387,2602	Akaike criterion	782,5204
Schwarz criterion	801,2388	Hannan-Quinn	789,7128

Likelihood ratio test: Chi-square(3) = 15,9825 [0,0011]

Real domestic credit annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,4064	0,1016	-13,8425	<0,00001	***
real_domest_1	1,00118	0,773155	1,2949	0,19535	
real_domest_8	-0,691617	0,829678	-0,8336	0,40451	

Mean dependent var	0,200000	S.D. dependent var	0,400231
McFadden R-squared	0,002552	Adjusted R-squared	-0,004379
Log-likelihood	-431,7435	Akaike criterion	869,4869
Schwarz criterion	883,7751	Hannan-Quinn	874,9555

Likelihood ratio test: Chi-square(2) = 2,20926 [0,3313]

Government deficit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,42627	0,101567	-14,0426	<0,00001	***
gov_deficit_2	4,1075	2,4898	1,6497	0,09900	*
gov_deficit_3	5,59307	2,89184	1,9341	0,05310	*
gov_deficit_4	8,79056	3,30918	2,6564	0,00790	***
gov_deficit_5	12,7663	3,76256	3,3930	0,00069	***
gov_deficit_6	10,4584	3,66223	2,8558	0,00429	***

gov_deficit_7	7,09582	3,45052	2,0565	0,03974	**
gov_deficit_8	5,58421	3,08295	1,8113	0,07009	*

Mean dependent var	0,200000	S.D. dependent var	0,400308
McFadden R-squared	0,023823	Adjusted R-squared	-0,000773
Log-likelihood	-317,5129	Akaike criterion	651,0258
Schwarz criterion	686,8415	Hannan-Quinn	664,9178

Likelihood ratio test: Chi-square(7) = 15,4974 [0,0301]

Government debt/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,36493	0,0934281	-14,6094	<0,00001	***
gov_debt_GD_4	-4,09839	1,90202	-2,1548	0,03118	**
gov_debt_GD_6	-2,8026	1,73755	-1,6130	0,10675	

Mean dependent var	0,199450	S.D. dependent var	0,399862
McFadden R-squared	0,011417	Adjusted R-squared	0,003158
Log-likelihood	-359,0902	Akaike criterion	724,1805
Schwarz criterion	737,9472	Hannan-Quinn	729,4928

Likelihood ratio test: Chi-square(2) = 8,29425 [0,0158]

Private credit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,52912	0,0971735	-15,7360	<0,00001	***
private_cre_5	0,676987	0,523596	1,2930	0,19603	
private_cre_8	1,07172	0,567017	1,8901	0,05875	*

Mean dependent var	0,191250	S.D. dependent var	0,393531
McFadden R-squared	0,010484	Adjusted R-squared	0,002800
Log-likelihood	-386,3312	Akaike criterion	778,6625
Schwarz criterion	792,7163	Hannan-Quinn	784,0613

Likelihood ratio test: Chi-square(2) = 8,18616 [0,0167]

Real MSCI_HP_short deviation:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,40499	0,0907966	-15,4741	<0,00001	***
MSCIhp_short	-1,57925	0,689562	-2,2902	0,02201	**
MSCIhp_shor_1	2,12926	0,782091	2,7225	0,00648	***
MSCIhp_shor_5	1,09033	0,451041	2,4174	0,01563	**
MSCIhp_shor_8	-0,849345	0,313986	-2,7050	0,00683	***

Mean dependent var	0,209102	S.D. dependent var	0,406918
McFadden R-squared	0,046056	Adjusted R-squared	0,034062
Log-likelihood	-397,6779	Akaike criterion	805,3557
Schwarz criterion	828,8594	Hannan-Quinn	814,3779

Likelihood ratio test: Chi-square(4) = 38,3995 [0,0000]

Reserves g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,3729	0,092547	-14,8346	<0,00001	***
g_in_reserves	-1,22136	0,824622	-1,4811	0,13857	
g_in_reserv_6	1,14187	0,727812	1,5689	0,11667	

Mean dependent var	0,203791	S.D. dependent var	0,403055
McFadden R-squared	0,005099	Adjusted R-squared	-0,001931
Log-likelihood	-424,5621	Akaike criterion	855,1243
Schwarz criterion	869,3387	Hannan-Quinn	860,5710

Likelihood ratio test: Chi-square(2) = 4,35184 [0,1135]

Trade balance g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,37949	0,0854862	-16,1370	<0,00001	***
g_trade_balance	-0,00613312	0,00572856	-1,0706	0,28434	
g_trade_bal_1	-0,00683825	0,00681404	-1,0036	0,31559	

Mean dependent var	0,202576	S.D. dependent var	0,402155
McFadden R-squared	0,005710	Adjusted R-squared	-0,001260
Log-likelihood	-427,9182	Akaike criterion	861,8364
Schwarz criterion	876,0862	Hannan-Quinn	867,2936

Likelihood ratio test: Chi-square(2) = 4,91532 [0,0856]

Current account/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,41298	0,0893981	-15,8055	<0,00001	***
current_acc_2	-11,2815	6,41207	-1,7594	0,07851	*
current_acc_8	16,2379	6,38252	2,5441	0,01096	**

Mean dependent var	0,199507	S.D. dependent var	0,399876
McFadden R-squared	0,011140	Adjusted R-squared	0,003746
Log-likelihood	-401,2515	Akaike criterion	808,5030
Schwarz criterion	822,6015	Hannan-Quinn	813,9152

Likelihood ratio test: Chi-square(2) = 9,04024 [0,0109]

Unemployment rate:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,02955	0,200766	-5,1281	<0,00001	***
U_rate_2	-14,7826	8,79355	-1,6811	0,09275	*
U_rate_6	8,87013	8,25204	1,0749	0,28242	

Mean dependent var	0,202381	S.D. dependent var	0,402014
McFadden R-squared	0,005847	Adjusted R-squared	-0,001244

Log-likelihood	-420,6221	Akaike criterion	847,2442
Schwarz criterion	861,4444	Hannan-Quinn	852,6867

Likelihood ratio test: Chi-square(2) = 4,94739 [0,0843]

Gross fixed capital formation g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,2284	0,101272	-12,1297	<0,00001	***
g_I	-3,30922	1,16603	-2,8380	0,00454	***
g_I_1	-1,61233	0,701286	-2,2991	0,02150	**
g_I_2	-1,28068	0,710599	-1,8022	0,07151	*
g_I_3	-1,50024	0,68715	-2,1833	0,02902	**
g_I_8	2,17101	1,00851	2,1527	0,03134	**

Mean dependent var	0,202326	S.D. dependent var	0,401967
McFadden R-squared	0,017476	Adjusted R-squared	0,003622
Log-likelihood	-425,5353	Akaike criterion	863,0707
Schwarz criterion	891,6122	Hannan-Quinn	873,9975

Likelihood ratio test: Chi-square(5) = 15,1377 [0,0098]

Industrial production change:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,40108	0,0876048	-15,9932	<0,00001	***
change_IP	-6,2561	2,39428	-2,6129	0,00898	***
change_IP_4	5,59518	2,44644	2,2871	0,02219	**

Mean dependent var	0,200226	S.D. dependent var	0,400396
McFadden R-squared	0,008928	Adjusted R-squared	0,002150
Log-likelihood	-438,6810	Akaike criterion	883,3620
Schwarz criterion	897,7154	Hannan-Quinn	888,8498

Likelihood ratio test: Chi-square(2) = 7,90369 [0,0192]

Marketcap/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,51015	0,149481	-10,1026	<0,00001	***
market_cap_GDP	-22,5477	4,08776	-5,5159	<0,00001	***
market_cap__1	33,6955	7,1103	4,7390	<0,00001	***
market_cap__3	-18,3953	5,7499	-3,1992	0,00138	***
market_cap__5	11,0808	4,00019	2,7701	0,00560	***
market_cap__7	-3,85133	1,52309	-2,5286	0,01145	**

Mean dependent var	0,202326	S.D. dependent var	0,401967
McFadden R-squared	0,091710	Adjusted R-squared	0,077857
Log-likelihood	-393,3841	Akaike criterion	798,7682
Schwarz criterion	827,3098	Hannan-Quinn	809,6950

Likelihood ratio test: Chi-square(5) = 79,4402 [0,0000]

Private credit annual g x private credit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,45886	0,0911506	-16,0049	<0,00001	***
pcredit_gxpcred	-1,80095	0,68029	-2,6473	0,00811	***
pcredit_gxp_4	-2,22137	0,766188	-2,8992	0,00374	***
pcredit_gxp_6	-1,0876	0,657352	-1,6545	0,09802	*

Mean dependent var	0,191832	S.D. dependent var	0,393985
McFadden R-squared	0,018385	Adjusted R-squared	0,008258
Log-likelihood	-387,7434	Akaike criterion	783,4868
Schwarz criterion	802,2650	Hannan-Quinn	790,6971

Likelihood ratio test: Chi-square(3) = 14,524 [0,0023]

Interaction market capitalization/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,57085	0,150023	-10,4707	<0,00001	***
Inter_Market_ca	-19,2396	4,00949	-4,7985	<0,00001	***
Inter_Marke_1	37,6	9,49531	3,9599	0,00007	***
Inter_Marke_2	-21,5851	6,94911	-3,1062	0,00190	***
Inter_Marke_5	7,17089	3,55323	2,0181	0,04358	**
Inter_Marke_6	-3,80298	2,31189	-1,6450	0,09998	*

Mean dependent var	0,207026	S.D. dependent var	0,405429
McFadden R-squared	0,092174	Adjusted R-squared	0,077412
Log-likelihood	-368,9970	Akaike criterion	749,9939
Schwarz criterion	778,0790	Hannan-Quinn	760,7849

Likelihood ratio test: Chi-square(5) = 74,9303 [0,0000]

Nonperforming loans:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,911665	0,18897	-4,8244	<0,00001	***
NPL_6	118,685	36,1287	3,2851	0,00102	***
NPL_7	-137,976	37,9168	-3,6389	0,00027	***

Mean dependent var	0,179245	S.D. dependent var	0,383920
McFadden R-squared	0,059611	Adjusted R-squared	0,047574
Log-likelihood	-234,3740	Akaike criterion	474,7481
Schwarz criterion	487,5667	Hannan-Quinn	479,7655

Likelihood ratio test: Chi-square(2) = 29,7139 [0,0000]

Interaction real private credit annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,68748	0,122205	-13,8087	<0,00001	***

Inter_real__4	119,051	48,9083	2,4342	0,01493	**
Inter_real__6	108,493	51,4165	2,1101	0,03485	**
Inter_real__8	100,264	43,0233	2,3305	0,01978	**

Mean dependent var	0,182948	S.D. dependent var	0,386968
McFadden R-squared	0,075241	Adjusted R-squared	0,060309
Log-likelihood	-247,7385	Akaike criterion	503,4771
Schwarz criterion	520,8102	Hannan-Quinn	510,2436

Likelihood ratio test: Chi-square(3) = 40,3132 [0,0000]

Interaction private credit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,46714	0,111652	-13,1402	<0,00001	***
Inter_pcred_4	-5,1642	2,68126	-1,9260	0,05410	*
Inter_pcred_8	6,26427	2,54644	2,4600	0,01389	**

Mean dependent var	0,190395	S.D. dependent var	0,392949
McFadden R-squared	0,011940	Adjusted R-squared	0,001369
Log-likelihood	-280,4125	Akaike criterion	566,8251
Schwarz criterion	579,9296	Hannan-Quinn	571,9330

Likelihood ratio test: Chi-square(2) = 6,77732 [0,0338]

Interaction real MSCI annual g x global market capitalization/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,60542	0,155304	-10,3373	<0,00001	***
Inter_MSCIx_1	-5,19673	2,97966	-1,7441	0,08115	*
Inter_MSCIx_5	3,85206	1,78095	2,1629	0,03055	**
Inter_MSCIx_8	5,84136	1,85571	3,1478	0,00165	***

Mean dependent var	0,194175	S.D. dependent var	0,395884
McFadden R-squared	0,030321	Adjusted R-squared	0,017172
Log-likelihood	-294,9685	Akaike criterion	597,9371
Schwarz criterion	615,6430	Hannan-Quinn	604,8205

Likelihood ratio test: Chi-square(3) = 18,4469 [0,0004]

Interaction private credit annual g x global private credit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,93201	0,146619	-13,1771	<0,00001	***
Inter_pcredit_4	15,873	6,39092	2,4837	0,01300	**
Inter_pcredit_5	19,0179	8,30344	2,2904	0,02200	**
Inter_pcredit_7	36,3715	10,0257	3,6278	0,00029	***
Inter_pcredit_8	32,424	9,70727	3,3402	0,00084	***

Mean dependent var	0,186933	S.D. dependent var	0,390212
McFadden R-squared	0,213326	Adjusted R-squared	0,194489
Log-likelihood	-208,8159	Akaike criterion	427,6317
Schwarz criterion	449,1904	Hannan-Quinn	436,0558

Likelihood ratio test: Chi-square(4) = 113,251 [0,0000]

CPI annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,27847	0,106661	-11,9863	<0,00001	***
CPI_g_p_a_	7,42976	3,79235	1,9591	0,05010	*
CPI_g_p_a__1	-11,63	4,62024	-2,5172	0,01183	**
CPI_g_p_a__7	1,50106	0,557451	2,6927	0,00709	***

Mean dependent var	0,203872	S.D. dependent var	0,403105
McFadden R-squared	0,012894	Adjusted R-squared	0,003885
Log-likelihood	-438,3007	Akaike criterion	884,6014
Schwarz criterion	903,7120	Hannan-Quinn	891,9104

Likelihood ratio test: Chi-square(3) = 11,4502 [0,0095]

REER annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,42657	0,087783	-16,2511	<0,00001	***
g_REER_3	5,86113	2,43263	2,4094	0,01598	**
g_REER_5	4,41218	2,18616	2,0182	0,04357	**

Mean dependent var	0,200000	S.D. dependent var	0,400231
McFadden R-squared	0,010949	Adjusted R-squared	0,004018
Log-likelihood	-428,1089	Akaike criterion	862,2177
Schwarz criterion	876,5059	Hannan-Quinn	867,6863

Likelihood ratio test: Chi-square(2) = 9,47846 [0,0087]

Global real private credit annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,68674	0,141896	-11,8872	<0,00001	***
Glob_real_p_4	35,007	10,071	3,4760	0,00051	***
Glob_real_p_5	18,0383	10,5077	1,7167	0,08604	*
Glob_real_p_7	26,7987	10,3305	2,5941	0,00948	***
Glob_real_p_8	31,5059	9,51604	3,3108	0,00093	***

Mean dependent var	0,182948	S.D. dependent var	0,386968
McFadden R-squared	0,229771	Adjusted R-squared	0,211107
Log-likelihood	-206,3407	Akaike criterion	422,6814
Schwarz criterion	444,3478	Hannan-Quinn	431,1396

Likelihood ratio test: Chi-square(4) = 123,109 [0,0000]

Global market capitalization/GDP:

Dependent variable: Transf_FSI

Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-3,37164	0,566475	-5,9520	<0,00001	***
Glob_market_cap	-17,7698	4,17281	-4,2585	0,00002	***
Glob_market_1	24,6089	6,22866	3,9509	0,00008	***
Glob_market_3	-8,23681	3,13887	-2,6241	0,00869	***
Glob_market_6	3,72922	1,06147	3,5132	0,00044	***

Mean dependent var	0,207026	S.D. dependent var	0,405429
McFadden R-squared	0,080568	Adjusted R-squared	0,068267
Log-likelihood	-373,7143	Akaike criterion	757,4287
Schwarz criterion	780,8329	Hannan-Quinn	766,4211

Likelihood ratio test: Chi-square(4) = 65,4955 [0,0000]

Global private credit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	0,156992	1,36196	0,1153	0,90823	
Glob_pcredit_GD	3,55011	1,48316	2,3936	0,01668	**
Glob_pcredi_1	-3,95425	1,42563	-2,7737	0,00554	***

Mean dependent var	0,188235	S.D. dependent var	0,391188
McFadden R-squared	0,014319	Adjusted R-squared	0,005197
Log-likelihood	-324,1756	Akaike criterion	654,3511
Schwarz criterion	667,9174	Hannan-Quinn	659,6023

Likelihood ratio test: Chi-square(2) = 9,41829 [0,0090]

Global private credit annual g x global private credit/GDP:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-1,67188	0,141492	-11,8161	<0,00001	***
Glob_pcredit__4	9,10232	2,66034	3,4215	0,00062	***
Glob_pcredit__5	4,68902	2,79469	1,6778	0,09338	*
Glob_pcredit__7	7,06014	2,7576	2,5603	0,01046	**
Glob_pcredit__8	8,42231	2,53783	3,3187	0,00090	***

Mean dependent var	0,182948	S.D. dependent var	0,386968
McFadden R-squared	0,226295	Adjusted R-squared	0,207631
Log-likelihood	-207,2718	Akaike criterion	424,5437
Schwarz criterion	446,2101	Hannan-Quinn	433,0018

Likelihood ratio test: Chi-square(4) = 121,247 [0,0000]

Global real GDP annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-1,38262	0,0944805	-14,6339	<0,00001	***
Glob_real_GDP_g	-27,1331	6,16144	-4,4037	0,00001	***
Glob_real_G_1	23,1356	6,46377	3,5793	0,00034	***

Mean dependent var	0,204897	S.D. dependent var	0,403887
McFadden R-squared	0,025702	Adjusted R-squared	0,018079
Log-likelihood	-383,4081	Akaike criterion	772,8162
Schwarz criterion	786,7786	Hannan-Quinn	778,1876

Likelihood ratio test: Chi-square(2) = 20,2286 [0,0000]

Global CPI annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-1,62511	0,110174	-14,7505	<0,00001	***
Glob_CPI_g_p_a_	103,453	17,6533	5,8603	<0,00001	***
Glob_CPI_g__2	-43,8444	21,3328	-2,0553	0,03985	**
Glob_CPI_g__4	61,0124	21,3857	2,8529	0,00433	***
Glob_CPI_g__7	-54,6939	23,754	-2,3025	0,02131	**
Glob_CPI_g__8	61,6197	22,8106	2,7014	0,00691	***

Mean dependent var	0,187861	S.D. dependent var	0,390884
McFadden R-squared	0,073766	Adjusted R-squared	0,055819
Log-likelihood	-309,6493	Akaike criterion	631,2985
Schwarz criterion	658,5360	Hannan-Quinn	641,8330

Likelihood ratio test: Chi-square(5) = 49,3214 [0,0000]

Real private credit annual g:

Dependent variable: Transf_FSI
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-1,44819	0,0881346	-16,4316	<0,00001	***
pcredit_rea_4	-6,36764	2,50165	-2,5454	0,01092	**
pcredit_rea_8	-5,21059	2,47958	-2,1014	0,03561	**

Mean dependent var	0,192714	S.D. dependent var	0,394663
McFadden R-squared	0,010481	Adjusted R-squared	0,003288
Log-likelihood	-412,7334	Akaike criterion	831,4669
Schwarz criterion	845,7061	Hannan-Quinn	836,9209

Likelihood ratio test: Chi-square(2) = 8,74306 [0,0126]

4. Lags Identification for the Long model in section 6.2

Real GDP annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,856039	0,0802078	-10,6728	<0,00001	***
real_GDP_p_a__g	-11,8535	4,64494	-2,5519	0,01071	**
real_GDP_p__1	14,0515	5,67189	2,4774	0,01323	**
real_GDP_p__3	-5,20539	2,82167	-1,8448	0,06507	*
real_GDP_p__8	2,80151	1,5932	1,7584	0,07868	*

Mean dependent var	0,297845	S.D. dependent var	0,457601
McFadden R-squared	0,009286	Adjusted R-squared	-0,001119
Log-likelihood	-476,0607	Akaike criterion	962,1215
Schwarz criterion	985,4753	Hannan-Quinn	971,0988

Likelihood ratio test: Chi-square(4) = 8,92412 [0,0630]

M2 annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,842214	0,0899678	-9,3613	<0,00001	***
real_M2_p_a_	-1,8666	1,79821	-1,0380	0,29925	
real_M2_p_a_1	2,36842	1,66526	1,4223	0,15495	

Mean dependent var	0,308585	S.D. dependent var	0,462177
McFadden R-squared	0,002206	Adjusted R-squared	-0,003425
Log-likelihood	-531,5092	Akaike criterion	1069,018
Schwarz criterion	1083,296	Hannan-Quinn	1074,484

Likelihood ratio test: Chi-square(2) = 2,3507 [0,3087]

Real Money annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,711687	0,103776	-6,8579	<0,00001	***
real_money_p_a_	-5,05219	1,16292	-4,3444	0,00001	***
real_money__2	3,21991	1,25872	2,5581	0,01052	**
real_money__4	-1,71789	0,968322	-1,7741	0,07605	*
real_money__8	1,32297	0,629171	2,1027	0,03549	**

Mean dependent var	0,306587	S.D. dependent var	0,461353
McFadden R-squared	0,024978	Adjusted R-squared	0,015262
Log-likelihood	-501,7912	Akaike criterion	1013,582
Schwarz criterion	1037,219	Hannan-Quinn	1022,644

Likelihood ratio test: Chi-square(4) = 25,7095 [0,0000]

M2/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,914003	0,0816707	-11,1913	<0,00001	***
M2_GDP	0,883993	0,461756	1,9144	0,05557	*
M2_GDP_3	0,37264	0,334195	1,1150	0,26483	

Mean dependent var	0,300122	S.D. dependent var	0,458589
McFadden R-squared	0,006148	Adjusted R-squared	0,000182
Log-likelihood	-499,7345	Akaike criterion	1005,469
Schwarz criterion	1019,608	Hannan-Quinn	1010,893

Likelihood ratio test: Chi-square(2) = 6,18304 [0,0454]

Money/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,82749	0,081369	-10,1696	<0,00001	***
money_GDP	-1,85113	1,58514	-1,1678	0,24289	
money_GDP_8	1,37807	1,23949	1,1118	0,26622	

Mean dependent var	0,303526	S.D. dependent var	0,460070
McFadden R-squared	0,002750	Adjusted R-squared	-0,003405
Log-likelihood	-486,0350	Akaike criterion	978,0700
Schwarz criterion	992,1012	Hannan-Quinn	983,4621

Likelihood ratio test: Chi-square(2) = 2,68049 [0,2618]

Real domestic credit annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,991877	0,0908633	-10,9161	<0,00001	***
real_domest_1	1,30795	0,719163	1,8187	0,06896	*
real_domest_7	1,07962	0,658615	1,6392	0,10117	

Mean dependent var	0,296083	S.D. dependent var	0,456791
McFadden R-squared	0,006108	Adjusted R-squared	0,000419
Log-likelihood	-524,0968	Akaike criterion	1054,194
Schwarz criterion	1068,492	Hannan-Quinn	1059,665

Likelihood ratio test: Chi-square(2) = 6,44155 [0,0399]

Government deficit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,867562	0,0870775	-9,9631	<0,00001	***
gov_deficit_2	4,02755	2,32145	1,7349	0,08275	*
gov_deficit_3	5,10648	2,59339	1,9690	0,04895	**

gov_deficit_4	6,47952	2,89049	2,2417	0,02498	**
gov_deficit_5	9,02056	3,23917	2,7848	0,00536	***
gov_deficit_6	7,61279	3,14347	2,4218	0,01544	**
gov_deficit_7	5,43554	2,99227	1,8165	0,06929	*
gov_deficit_8	5,03145	2,73846	1,8373	0,06616	*

Mean dependent var	0,298462	S.D. dependent var	0,457935
McFadden R-squared	0,016234	Adjusted R-squared	-0,003958
Log-likelihood	-389,7789	Akaike criterion	795,5577
Schwarz criterion	831,3735	Hannan-Quinn	809,4498

Likelihood ratio test: Chi-square(7) = 12,8639 [0,0755]

Government debt/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,837051	0,0826062	-10,1330	<0,00001	***
gov_debt_GD_3	-3,4263	1,79765	-1,9060	0,05665	*
gov_debt_GD_4	-3,68792	1,77799	-2,0742	0,03806	**
gov_debt_GD_6	-3,33381	1,6808	-1,9835	0,04731	**

Mean dependent var	0,292985	S.D. dependent var	0,455445
McFadden R-squared	0,015693	Adjusted R-squared	0,006596
Log-likelihood	-432,7913	Akaike criterion	873,5826
Schwarz criterion	891,9383	Hannan-Quinn	880,6657

Likelihood ratio test: Chi-square(3) = 13,8005 [0,0032]

Private credit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,982181	0,0830227	-11,8303	<0,00001	***
private_cre_5	1,03028	0,457902	2,2500	0,02445	**
private_cre_7	0,608491	0,475589	1,2794	0,20074	

Mean dependent var	0,287485	S.D. dependent var	0,452870
McFadden R-squared	0,009094	Adjusted R-squared	0,002897
Log-likelihood	-479,7039	Akaike criterion	965,4077
Schwarz criterion	979,4877	Hannan-Quinn	970,8144

Likelihood ratio test: Chi-square(2) = 8,80501 [0,0122]

Real MSCI hp short deviation:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,846674	0,078892	-10,7321	<0,00001	***
MSCIhp_shor_1	1,79603	0,327406	5,4856	<0,00001	***
MSCIhp_shor_8	-0,880654	0,252855	-3,4828	0,00050	***

Mean dependent var	0,309963	S.D. dependent var	0,462763
McFadden R-squared	0,050845	Adjusted R-squared	0,044884
Log-likelihood	-477,7143	Akaike criterion	961,4285
Schwarz criterion	975,5307	Hannan-Quinn	966,8418

Likelihood ratio test: Chi-square(2) = 51,1811 [0,0000]

Reserves g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,915065	0,0822326	-11,1278	<0,00001	***
g_in_reserv_7	0,601832	0,60721	0,9911	0,32162	
g_in_reserv_8	1,10208	0,60338	1,8265	0,06777	*

Mean dependent var	0,299883	S.D. dependent var	0,458474
McFadden R-squared	0,004272	Adjusted R-squared	-0,001459
Log-likelihood	-521,1897	Akaike criterion	1048,379
Schwarz criterion	1062,640	Hannan-Quinn	1053,840

Likelihood ratio test: Chi-square(2) = 4,47241 [0,1069]

Trade balance g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,805313	0,0743245	-10,8351	<0,00001	***
g_trade_balance	-0,00545477	0,00611948	-0,8914	0,37273	
g_trade_bal_6	0,0382495	0,033521	1,1411	0,25384	

Mean dependent var	0,310304	S.D. dependent var	0,462889
McFadden R-squared	0,003550	Adjusted R-squared	-0,002122
Log-likelihood	-527,0421	Akaike criterion	1060,084
Schwarz criterion	1074,334	Hannan-Quinn	1065,541

Likelihood ratio test: Chi-square(2) = 3,75542 [0,1529]

Current account/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,858904	0,0761924	-11,2728	<0,00001	***
current_acc_5	-6,37834	5,51448	-1,1567	0,24741	
current_acc_6	-2,18846	5,59743	-0,3910	0,69581	

Mean dependent var	0,297821	S.D. dependent var	0,457577
McFadden R-squared	0,001392	Adjusted R-squared	-0,004572
Log-likelihood	-502,3392	Akaike criterion	1010,678
Schwarz criterion	1024,828	Hannan-Quinn	1016,106

Likelihood ratio test: Chi-square(2) = 1,4004 [0,4965]

Unemployment rate:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0,104979	0,179871	0,5836	0,55947	
U_rate_1	-30,4126	8,33653	-3,6481	0,00026	***
U_rate_5	13,7853	7,76687	1,7749	0,07592	*

Mean dependent var	0,300475	S.D. dependent var	0,458737
McFadden R-squared	0,037449	Adjusted R-squared	0,031620
Log-likelihood	-495,4120	Akaike criterion	996,8239
Schwarz criterion	1011,031	Hannan-Quinn	1002,269

Likelihood ratio test: Chi-square(2) = 38,5485 [0,0000]

Gross fixed capital formation g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,847571	0,0813797	-10,4150	<0,00001	***
g_I	-3,12391	1,01223	-3,0862	0,00203	***
g_I_3	-3,78485	1,25473	-3,0165	0,00256	***
g_I_7	3,31099	1,1912	2,7796	0,00544	***
g_I_8	2,69692	0,933332	2,8896	0,00386	***

Mean dependent var	0,302326	S.D. dependent var	0,459533
McFadden R-squared	0,018590	Adjusted R-squared	0,009103
Log-likelihood	-517,2295	Akaike criterion	1044,459
Schwarz criterion	1068,244	Hannan-Quinn	1053,565

Likelihood ratio test: Chi-square(4) = 19,5947 [0,0006]

Industrial production change:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,844078	0,0757341	-11,1453	<0,00001	***
change_IP	-3,58553	2,07438	-1,7285	0,08390	*
change_IP_4	4,49146	2,08443	2,1548	0,03118	**

Mean dependent var	0,304299	S.D. dependent var	0,460370
McFadden R-squared	0,004694	Adjusted R-squared	-0,000829
Log-likelihood	-540,6354	Akaike criterion	1087,271
Schwarz criterion	1101,624	Hannan-Quinn	1092,759

Likelihood ratio test: Chi-square(2) = 5,09926 [0,0781]

Market capitalization/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,22944	0,124299	-9,8909	<0,00001	***
market_cap_GDP	-2,80875	1,05205	-2,6698	0,00759	***
market_cap__1	3,34546	1,05431	3,1731	0,00151	***

Mean dependent var	0,310624	S.D. dependent var	0,463016
McFadden R-squared	0,027029	Adjusted R-squared	0,021438
Log-likelihood	-522,0696	Akaike criterion	1050,139
Schwarz criterion	1064,431	Hannan-Quinn	1055,609

Likelihood ratio test: Chi-square(2) = 29,0056 [0,0000]

Real private credit annual g x private credit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,892192	0,0785416	-11,3595	<0,00001	***
pcredit_gxpcred	-1,12612	0,555872	-2,0259	0,04278	**
pcredit_gxp_4	-1,30447	0,661603	-1,9717	0,04865	**
pcredit_gxp_8	-0,732781	0,613702	-1,1940	0,23246	

Mean dependent var	0,290932	S.D. dependent var	0,454478
McFadden R-squared	0,006109	Adjusted R-squared	-0,002245
Log-likelihood	-475,8444	Akaike criterion	959,6887
Schwarz criterion	978,3971	Hannan-Quinn	966,8782

Likelihood ratio test: Chi-square(3) = 5,84998 [0,1191]

Interaction market capitalization/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,62788	0,138069	-11,7903	<0,00001	***
Inter_Marke_3	2,57085	0,605917	4,2429	0,00002	***
Inter_Marke_6	-8,86142	4,00155	-2,2145	0,02679	**
Inter_Marke_7	13,9851	6,28082	2,2266	0,02597	**
Inter_Marke_8	-6,63329	2,88228	-2,3014	0,02137	**

Mean dependent var	0,293898	S.D. dependent var	0,455830
McFadden R-squared	0,081767	Adjusted R-squared	0,071485
Log-likelihood	-446,5374	Akaike criterion	903,0748
Schwarz criterion	926,5166	Hannan-Quinn	912,0785

Likelihood ratio test: Chi-square(4) = 79,5268 [0,0000]

Nonperforming loans:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0,521542	0,214483	2,4316	0,01503	**
NPL	-67,7091	16,2658	-4,1627	0,00003	***
NPL_6	376,491	151,459	2,4858	0,01293	**
NPL_7	-631,864	254,881	-2,4791	0,01317	**
NPL_8	269,042	113,638	2,3675	0,01791	**

Mean dependent var	0,284501	S.D. dependent var	0,451656
McFadden R-squared	0,135990	Adjusted R-squared	0,118212
Log-likelihood	-243,0113	Akaike criterion	496,0226
Schwarz criterion	516,7969	Hannan-Quinn	504,1950

Likelihood ratio test: Chi-square(4) = 76,4968 [0,0000]

Interaction real private credit annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,19573	0,105492	-11,3348	<0,00001	***
Inter_real_g_pc	148,52	52,7104	2,8177	0,00484	***

Inter_real__2	107,263	55,8883	1,9192	0,05495	*
Inter_real__4	119,764	54,745	2,1877	0,02869	**
Inter_real__6	81,1179	42,9005	1,8908	0,05865	*

Mean dependent var	0,262238	S.D. dependent var	0,440236
McFadden R-squared	0,081826	Adjusted R-squared	0,066634
Log-likelihood	-302,1895	Akaike criterion	614,3790
Schwarz criterion	636,1247	Hannan-Quinn	622,8622

Likelihood ratio test: Chi-square(4) = 53,8609 [0,0000]

Interaction private credit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,1009	0,105879	-10,3977	<0,00001	***
Inter_pcredit_G	5,22915	2,52423	2,0716	0,03830	**
Inter_pcred_1	3,12239	2,32925	1,3405	0,18008	
Inter_pcred_8	-2,91917	2,28239	-1,2790	0,20090	

Mean dependent var	0,267606	S.D. dependent var	0,443101
McFadden R-squared	0,012701	Adjusted R-squared	0,000577
Log-likelihood	-325,7396	Akaike criterion	659,4791
Schwarz criterion	676,8476	Hannan-Quinn	666,2568

Likelihood ratio test: Chi-square(3) = 8,38099 [0,0388]

Interaction real MSCI annual g x global market capitalization/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,32325	0,135553	-9,7619	<0,00001	***
Inter_MSCIxglob	4,78342	1,81004	2,6427	0,00822	***
Inter_MSCIx_5	4,02318	1,76118	2,2844	0,02235	**
Inter_MSCIx_8	3,69254	1,71355	2,1549	0,03117	**

Mean dependent var	0,280992	S.D. dependent var	0,449855
McFadden R-squared	0,023378	Adjusted R-squared	0,012246
Log-likelihood	-350,9020	Akaike criterion	709,8041
Schwarz criterion	727,4250	Hannan-Quinn	716,6610

Likelihood ratio test: Chi-square(3) = 16,7998 [0,0008]

Interaction private credit annual g x global private credit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-1,44712	0,136038	-10,6377	<0,00001	***
Inter_pcredit_g	36,2331	8,40349	4,3117	0,00002	***
Inter_pcred_1	24,6728	8,90229	2,7715	0,00558	***
Inter_pcred_4	44,9345	10,2972	4,3638	0,00001	***
Inter_pcred_5	28,1032	10,12	2,7770	0,00549	***
Inter_pcred_8	27,1628	7,87088	3,4511	0,00056	***

Mean dependent var	0,272388	S.D. dependent var	0,445604
McFadden R-squared	0,251150	Adjusted R-squared	0,232035
Log-likelihood	-235,0582	Akaike criterion	482,1164
Schwarz criterion	507,8213	Hannan-Quinn	492,1728

Likelihood ratio test: Chi-square(5) = 157,668 [0,0000]

CPI annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,794338	0,0955815	-8,3106	<0,00001	***
CPI_g_p_a__1	-3,82451	1,76509	-2,1667	0,03025	**
CPI_g_p_a__8	1,89797	0,615731	3,0825	0,00205	***

Mean dependent var	0,302166	S.D. dependent var	0,459459
McFadden R-squared	0,015036	Adjusted R-squared	0,009453
Log-likelihood	-529,2489	Akaike criterion	1064,498
Schwarz criterion	1078,827	Hannan-Quinn	1069,979

Likelihood ratio test: Chi-square(2) = 16,1584 [0,0003]

REER g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,86096	0,0748104	-11,5086	<0,00001	***
g_REER_3	2,73565	2,09841	1,3037	0,19234	
g_REER_4	4,08345	2,01974	2,0218	0,04320	**

Mean dependent var	0,301714	S.D. dependent var	0,459264
McFadden R-squared	0,007220	Adjusted R-squared	0,001621
Log-likelihood	-531,9026	Akaike criterion	1069,805
Schwarz criterion	1084,128	Hannan-Quinn	1075,284

Likelihood ratio test: Chi-square(2) = 7,73696 [0,0209]

Real private credit annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-0,909996	0,0761363	-11,9522	<0,00001	***
pcredit_real_g	-3,86677	2,23847	-1,7274	0,08409	*
pcredit_rea_4	-3,77065	2,31944	-1,6257	0,10402	
pcredit_rea_8	-4,26655	2,21748	-1,9240	0,05435	*

Mean dependent var	0,287897	S.D. dependent var	0,453049
McFadden R-squared	0,005520	Adjusted R-squared	-0,002311
Log-likelihood	-507,9995	Akaike criterion	1023,999
Schwarz criterion	1042,985	Hannan-Quinn	1031,271

Likelihood ratio test: Chi-square(3) = 5,63944 [0,1305]

Global private credit annual g:

Dependent variable: Transf_FSI_long

Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,974365	0,114606	-8,5019	<0,00001	***
Glob_real_pcred	37,0788	8,78699	4,2197	0,00002	***
Glob_real_p_1	24,5912	8,65243	2,8421	0,00448	***
Glob_real_p_4	40,3641	6,99058	5,7741	<0,00001	***
Glob_real_p_7	13,0861	6,22779	2,1012	0,03562	**

Mean dependent var	0,264286	S.D. dependent var	0,441346
McFadden R-squared	0,228088	Adjusted R-squared	0,212628
Log-likelihood	-249,6328	Akaike criterion	509,2655
Schwarz criterion	530,9052	Hannan-Quinn	517,7153

Likelihood ratio test: Chi-square(4) = 147,526 [0,0000]

Global market capitalization/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-5,2126	0,548777	-9,4986	<0,00001	***
Glob_market_cap	2,32891	0,700138	3,3264	0,00088	***
Glob_market_3	1,98312	0,812806	2,4398	0,01469	**
Glob_market_7	1,03089	0,602918	1,7098	0,08730	*

Mean dependent var	0,304071	S.D. dependent var	0,460306
McFadden R-squared	0,100629	Adjusted R-squared	0,092344
Log-likelihood	-434,2342	Akaike criterion	876,4683
Schwarz criterion	895,1361	Hannan-Quinn	883,6456

Likelihood ratio test: Chi-square(3) = 97,1712 [0,0000]

Global private credit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	10,5172	1,98033	5,3108	<0,00001	***
Glob_pcredi_3	-2,04846	0,879236	-2,3298	0,01982	**
Glob_pcredi_7	-0,964673	0,688583	-1,4010	0,16123	

Mean dependent var	0,255217	S.D. dependent var	0,436333
McFadden R-squared	0,070481	Adjusted R-squared	0,062003
Log-likelihood	-328,9199	Akaike criterion	663,8398
Schwarz criterion	677,1435	Hannan-Quinn	669,0099

Likelihood ratio test: Chi-square(2) = 49,8807 [0,0000]

Global private credit annual g x global private credit/GDP:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-0,958894	0,114176	-8,3984	<0,00001	***
Glob_pcredit_gx	9,57762	2,33185	4,1073	0,00004	***
Glob_pcredi_1	6,44444	2,31005	2,7897	0,00528	***
Glob_pcredi_4	10,5348	1,8602	5,6632	<0,00001	***
Glob_pcredi_7	3,3419	1,64695	2,0291	0,04244	**

Mean dependent var	0,264286	S.D. dependent var	0,441346
McFadden R-squared	0,224763	Adjusted R-squared	0,209302
Log-likelihood	-250,7084	Akaike criterion	511,4167
Schwarz criterion	533,0564	Hannan-Quinn	519,8665

Likelihood ratio test: Chi-square(4) = 145,374 [0,0000]

Global real GDP annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-1,16016	0,103104	-11,2523	<0,00001	***
Glob_real_GDP_g	-15,064	6,22884	-2,4184	0,01559	**
Glob_real_G_1	21,6132	6,83107	3,1640	0,00156	***
Glob_real_G_8	16,9169	4,18375	4,0435	0,00005	***

Mean dependent var	0,268786	S.D. dependent var	0,443649
McFadden R-squared	0,028074	Adjusted R-squared	0,018143
Log-likelihood	-391,4694	Akaike criterion	790,9387
Schwarz criterion	809,0971	Hannan-Quinn	797,9617

Likelihood ratio test: Chi-square(3) = 22,6154 [0,0000]

Global CPI annual g:

Dependent variable: Transf_FSI_long
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	-1,21057	0,100344	-12,0642	<0,00001	***
Glob_CPI_g_p_a_	92,1181	12,565	7,3313	<0,00001	***
Glob_CPI_g__4	63,2136	12,4605	5,0731	<0,00001	***
Glob_CPI_g__8	39,1791	10,7183	3,6553	0,00026	***

Mean dependent var	0,268786	S.D. dependent var	0,443649
McFadden R-squared	0,115232	Adjusted R-squared	0,105301
Log-likelihood	-356,3643	Akaike criterion	720,7287
Schwarz criterion	738,8870	Hannan-Quinn	727,7517

Likelihood ratio test: Chi-square(3) = 92,8254 [0,0000]

5. BMA analytical likelihood results for the Short model in section 6.3

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
realmoneyg_4	1.000000000	-1.139185e+00	1.976151e-01	0.00000000	6
MSCIhpshort_5	1.000000000	5.820925e-01	1.226538e-01	1.00000000	18
U_rate_2	1.000000000	3.733823e+00	6.070599e-01	1.00000000	23
Globpcredg_7	0.999813712	8.029007e+01	1.801876e+01	1.00000000	61
GlobpcgxglobpcGDP_7	0.997918244	-1.994653e+01	4.673590e+00	0.00018668	70
MSCIhpshort_8	0.997306100	3.619222e-01	9.129707e-02	1.00000000	19
real.money.g	0.977509806	-6.606420e-01	2.202692e-01	0.00000000	5
Int_pcgxglopcGDP_5	0.976425232	1.882128e+00	6.577962e-01	1.00000000	50
Int_pcgxglopcGDP_4	0.925260741	1.555067e+00	6.775796e-01	1.00000000	49
GlobGDPg_1	0.698369685	2.156001e+00	1.650829e+00	1.00000000	73
realGDPg__1	0.626334918	1.373795e+00	1.177983e+00	1.00000000	2
GlobCPIg	0.559195681	4.392098e+00	4.469233e+00	1.00000000	74
CPIg_1	0.363387867	-8.361212e-01	1.197417e+00	0.00000000	54
mcapGDP_1	0.352441899	6.006833e-01	1.057151e+00	0.99615981	31
mcapGDP	0.302799161	-3.954766e-01	7.160775e-01	0.13431582	30
mcapGDP_3	0.275434407	-1.667599e-01	3.383781e-01	0.13446511	32
Int_mcapGDP_2	0.248255073	2.453969e-02	7.038223e-02	0.99259582	39
Int_realpcredg_8	0.234311769	-5.755347e+00	1.147095e+01	0.00000000	45
Int_pcgxglopcGDP_8	0.220700510	3.642365e-01	7.498051e-01	1.00000000	52
Int_mcapGDP_1	0.179414652	3.485392e-02	1.467721e-01	0.97929082	38
rdomcred	0.169483217	9.406493e-02	2.336646e-01	1.00000000	9
M2.GDP	0.120606756	1.706651e-02	5.244882e-02	1.00000000	7
Int_realpcredg_6	0.105216121	-1.573451e+00	5.217299e+00	0.00000000	44
Int_mcapGDP	0.087053609	-1.687312e-02	1.079203e-01	0.44139678	37
GlobGDPg	0.071835672	1.740964e-01	6.991092e-01	0.98428683	72
Int_MSCIgxglomcapGDP_5	0.070544488	7.257455e-02	2.961541e-01	1.00000000	47
mcapGDP_5	0.048653277	-9.658566e-03	7.184204e-02	0.16489600	33
GlobCPIg_2	0.047314166	-2.985332e-01	1.522822e+00	0.00000000	75
Int_mcapGDP_5	0.045474564	3.143196e-03	2.289649e-02	0.89835661	40
pcredg_8	0.039455753	-2.979239e-02	1.742492e-01	0.00000000	59
Globpcredg_4	0.030638951	1.703091e-01	2.794264e+00	1.00000000	60
govdefGDP_6	0.030529750	1.550548e-02	1.057303e-01	1.00000000	12
CPIg	0.028712295	-4.071310e-02	3.274816e-01	0.08662143	53
MSCIhpshort_1	0.026040760	4.194225e-03	3.138564e-02	1.00000000	17
GlobpcgxglobpcGDP_4	0.025728552	-1.894560e-02	7.188083e-01	0.91681380	69
I_g	0.021609842	2.795297e-03	2.347737e-02	1.00000000	24
curaccGDP_8	0.021509139	3.267022e-02	2.745640e-01	1.00000000	22
pcredGDP_8	0.019918701	2.652237e-03	2.337895e-02	1.00000000	15

mcapGDP_7	0.019611687	1.132656e-03	2.975057e-02	0.50496483	34
real.GDP.g	0.019258965	2.495873e-02	2.269922e-01	0.89184399	1
tradebalg	0.018903481	-1.208663e-05	1.100437e-04	0.00000000	21
realGDPg__4	0.017597649	-1.498877e-02	1.419061e-01	0.00000000	3
I_g_3	0.014560653	-1.570006e-03	1.687748e-02	0.00000000	26
Int_MSCIgxglomcapGDP_8	0.013308307	-7.659953e-03	8.940597e-02	0.01562399	48
govdefGDP_4	0.010760738	3.788828e-03	5.017761e-02	1.00000000	10
reservesg	0.010587744	-1.593255e-03	2.145700e-02	0.00000000	20
Globpcredg_8	0.010445385	3.077190e-01	5.079072e+00	0.94624022	62
GlobpcredGDP_1	0.010424438	2.100718e-03	3.035973e-02	0.96979838	68
GlobpcredGDP	0.009698288	1.703119e-03	2.582425e-02	0.94669153	67
GlobpcgxglobpcGDP_8	0.009564414	-7.670729e-02	1.313319e+00	0.51777405	71
CPIg_7	0.009273273	7.571649e-03	1.204170e-01	0.87716287	55
MSCIhpshort	0.008963031	-8.802234e-04	1.460447e-02	0.11526325	16
I_g_8	0.008883794	7.657291e-04	1.188933e-02	1.00000000	27
govdebtGDP_4	0.008794266	-1.365118e-03	2.147444e-02	0.00000000	14
IP_change_4	0.008725068	2.863869e-03	4.563411e-02	1.00000000	29
GlobmcapGDP_6	0.008630912	1.403082e-03	2.643716e-02	0.80761654	66
NPL_6	0.008305080	4.462509e-03	8.039529e-02	0.78270128	41
Int_realpcredg_4	0.007867840	-6.034120e-02	1.155281e+00	0.02853188	43
GlobCPIg_4	0.007251572	3.304832e-03	3.038708e-01	0.56817967	76
NPL_7	0.007128736	2.417529e-03	6.355401e-02	0.66233873	42
pcredgxpcredGDP_4	0.006774275	4.121474e-04	8.168829e-03	1.00000000	36
GlobCPIg_7	0.006534361	1.235212e-02	2.594667e-01	1.00000000	77
IP_change	0.006503505	1.672789e-03	3.583319e-02	1.00000000	28
realM2g_4	0.006484128	-1.123425e-03	2.434410e-02	0.06231110	4
REERg_3	0.006096463	2.047469e-03	4.371193e-02	1.00000000	56
GlobmcapGDP	0.005820379	-4.146425e-04	1.101558e-02	0.03096834	63
I_g_1	0.005576738	-2.997230e-04	8.123352e-03	0.00000000	25
Int_pcgxglopcGDP_7	0.005571767	1.807101e-03	4.718347e-02	0.97621910	51
moneyGDP_4	0.005426970	7.199434e-04	1.804313e-02	1.00000000	8
GlobmcapGDP_1	0.005369736	-3.302421e-04	1.243707e-02	0.12424780	64
GlobmcapGDP_3	0.005256404	1.848727e-04	1.294972e-02	0.75877349	65
govdefGDP_7	0.005195792	-9.975713e-04	2.829164e-02	0.00000000	13
govdefGDP_5	0.005171050	-9.613888e-04	2.757202e-02	0.00000000	11
pcredg_4	0.004734763	-1.006828e-03	3.732644e-02	0.00000000	58
GlobCPIg_8	0.004699359	-5.515346e-03	1.802672e-01	0.00000000	78
REERg_5	0.003847857	-3.956921e-04	2.846248e-02	0.08195883	57
pcredgxpcredGDP	0.003787045	3.627818e-05	4.048587e-03	0.88736636	35
Int_pcredGDP_8	0.003604163	-1.571063e-04	2.289527e-02	0.25070717	46

6. BMA analytical likelihood results for the Long model in section 6.3

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
rdomcred_1	9.995154e-01	9.811599e-01	2.671749e-01	1.00000000	9
Int_pcgxglopcGDP_4	9.895954e-01	2.689677e+00	7.348940e-01	1.00000000	50
U_rate_5	9.576251e-01	3.069003e+00	1.135001e+00	1.00000000	23
CPIg_8	9.438266e-01	-2.725278e+00	1.199204e+00	0.00000000	54
Int_realpcredg_4	9.255204e-01	-3.248957e+01	1.425561e+01	0.00000000	43
CPIg_1	8.930508e-01	-3.563054e+00	1.751088e+00	0.00000000	53
real.GDP.g	7.844488e-01	-1.991839e+00	1.280924e+00	0.00000000	1
GlobmcapGDP	7.566969e-01	8.154992e-01	5.524922e-01	1.00000000	62
MSCIhpshort_8	6.843711e-01	2.171372e-01	1.688311e-01	1.00000000	18
Globpcredg_1	6.719890e-01	8.765984e+01	7.198865e+01	1.00000000	59
GlobpcgxglobpcGDP_1	6.719890e-01	-2.340703e+01	1.925486e+01	0.00000000	66
GlobmcapGDP_3	6.706778e-01	8.718768e-01	6.985540e-01	1.00000000	63
M2GDP	5.579485e-01	1.131140e-01	1.159424e-01	1.00000000	7
Int_realpcredg	4.153446e-01	-1.417712e+01	1.881471e+01	0.00000000	42
Int_MSCIgxglomcapGDP	3.818233e-01	5.166374e-01	7.267101e-01	1.00000000	45
Globpcredg	3.592674e-01	2.996798e+01	5.155987e+01	1.00000000	58
GlobCPIg	3.531431e-01	4.669363e+00	6.568650e+00	1.00000000	72
GlobpcgxglobpcGDP	3.403311e-01	-7.419209e+00	1.320932e+01	0.23949030	65
Int_mcapGDP_3	3.217733e-01	2.177535e-01	3.724519e-01	1.00000000	34
NPL_7	3.179057e-01	-5.589945e-01	8.976171e-01	0.00000000	40
GlobCPIg_8	3.144037e-01	3.729839e+00	5.996646e+00	1.00000000	74
Int_mcapGDP_6	3.095463e-01	-1.490858e+00	2.640508e+00	0.18915358	35
NPL_8	3.060829e-01	-5.109280e-01	8.403234e-01	0.00000000	41
Int_mcapGDP_7	3.037364e-01	2.312393e+00	4.079498e+00	1.00000000	36
Int_mcapGDP_8	2.842169e-01	-1.004649e+00	1.788500e+00	0.11689103	37
MSCIhpshort_1	2.610512e-01	7.473622e-02	1.402511e-01	1.00000000	17
NPL_6	1.997081e-01	-3.418965e-01	7.491328e-01	0.00000000	39
pcredg_8	1.979538e-01	-2.263022e-01	5.098853e-01	0.00000000	57
Globpcredg_7	1.964200e-01	-4.341102e+00	1.518784e+01	0.00770520	61
GlobpcgxglobpcGDP_7	1.786001e-01	9.411644e-01	4.092221e+00	0.39769316	68
GlobpcredGDP_3	1.132073e-01	-9.831859e-02	2.993156e-01	0.00000000	64
real.money.g	9.619713e-02	-4.073835e-02	1.376691e-01	0.00000000	4
pcredGDP_5	8.765365e-02	1.675079e-02	6.091640e-02	1.00000000	16
Int_pcgxglopcGDP_8	8.194862e-02	6.902094e-02	2.607309e-01	1.00000000	52
Int_pcgxglopcGDP_5	6.814028e-02	6.930167e-02	2.888426e-01	1.00000000	51
U_rate_1	6.615911e-02	1.403831e-02	8.990065e-01	0.64050034	22
IP_change_4	6.277775e-02	4.277292e-02	1.890487e-01	1.00000000	29
tradebalg	3.754525e-02	-3.183032e-05	1.867949e-04	0.00000000	20
Globpcredg_4	2.398046e-02	1.340734e+00	1.099271e+01	0.99552960	60

GlobpcgxglobpcGDP_4	2.180095e-02	-3.465669e-01	2.915748e+00	0.30360686	67
pcredg	1.985538e-02	1.637177e-02	1.361347e-01	1.00000000	56
mcapGDP	1.863335e-02	1.617810e-03	2.768614e-02	0.98883325	30
GlobGDPg_8	1.495890e-02	3.499092e-02	3.138507e-01	1.00000000	71
govdefGDP_6	1.346976e-02	6.392833e-03	6.525874e-02	1.00000000	13
Int_MSCIgxglomcapGDP_5	1.316139e-02	-1.093932e-02	1.109603e-01	0.00000000	46
mcapGDP_1	1.274409e-02	-5.911161e-05	3.235153e-02	0.94089256	31
real.money.g_8	1.146237e-02	2.769723e-03	3.022978e-02	1.00000000	6
curaccGDP	1.142843e-02	1.611511e-02	1.792630e-01	1.00000000	21
NPL	1.054081e-02	2.317728e-03	1.523853e-01	0.50205475	38
GlobGDPg	8.577226e-03	1.619230e-02	2.433606e-01	0.82877722	69
real.money.g_2	5.073160e-03	-1.110078e-03	1.939949e-02	0.00000000	5
Int_pcgxglopcGDP	4.458360e-03	4.330709e-03	7.354817e-02	1.00000000	48
Int_pcredGDP	4.234662e-03	-2.929899e-03	5.468156e-02	0.00000000	44
GlobGDPg_1	3.837110e-03	-5.930916e-03	1.310138e-01	0.07879694	70
realGDPg__1	2.990007e-03	-1.760431e-03	6.636572e-02	0.17756253	2
moneyGDP	1.977531e-03	-6.171505e-04	1.836989e-02	0.00000000	8
realM2g	1.489053e-03	-8.205016e-05	1.237368e-02	0.43393324	3
GlobCPIg_4	1.455944e-03	-5.398025e-03	1.795786e-01	0.00000000	73
govdebtGDP_4	1.270496e-03	-2.094458e-04	7.935453e-03	0.00000000	14
pcredgxpcredGDP_4	7.417547e-04	4.531747e-05	2.718644e-03	1.00000000	33
Int_MSCIgxglomcapGDP_8	6.317804e-04	2.084271e-04	1.367787e-02	1.00000000	47
Int_pcgxglopcGDP_1	4.784762e-04	1.861897e-04	1.292598e-02	1.00000000	49
I_g	4.410104e-04	2.735320e-05	2.293209e-03	1.00000000	24
IP_change	4.260523e-04	1.308006e-04	1.015249e-02	1.00000000	28
pcredgxpcredGDP	3.438188e-04	-4.284273e-05	2.954492e-03	0.00000000	32
I_g_7	3.165892e-04	-1.662513e-05	1.817727e-03	0.00000000	26
REERg_4	2.343823e-04	7.635008e-05	8.190047e-03	1.00000000	55
govdefGDP_5	2.106974e-04	-3.922487e-05	5.164521e-03	0.00000000	12
govdefGDP_3	2.046729e-04	2.903169e-05	4.367881e-03	1.00000000	10
I_g_3	9.976839e-05	-4.583547e-06	9.954017e-04	0.00000000	25
govdefGDP_4	0.000000e+00	0.000000e+00	0.000000e+00	NA	11
govdebtGDP_6	0.000000e+00	0.000000e+00	0.000000e+00	NA	15
reservesg_8	0.000000e+00	0.000000e+00	0.000000e+00	NA	19
I_g_8	0.000000e+00	0.000000e+00	0.000000e+00	NA	27

7. Collinearity testing for the Short and the Long model in sections 7.2 and 7.3

Short model collinearity:

Variance Inflation Factors

Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

realmoneygl4	1,304
MSCIhpshortl5	2,230
Uratel2	1,235
Globpcredgl7	422,098
GlobpcgxglobpcG	423,536
MSCIhpshortl8	1,383
realmoneyg	1,198
Int_pcgxglopcGD	1,626
Int_pcga	1,923
GlobGDPgl1	2,057
realGDPgl1	1,469
GlobCPIg	1,297

VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient between variable j and the other independent variables

Short model after exclusion of globpcgxglobpcGDPl7:

Variance Inflation Factors

Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

realmoneygl4	1,288
MSCIhpshortl5	2,216
Uratel2	1,218
Globpcredgl7	1,531
MSCIhpshortl8	1,383
realmoneyg	1,198
Int_pcgxglopcGD	1,613
Int_pcga	1,922
GlobGDPgl1	2,047
realGDPgl1	1,466
GlobCPIg	1,275

VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient between variable j and the other independent variables

Long model collinearity:

Variance Inflation Factors

Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

rdomcredl1	1,055
Int_pcgxglopcGD	2,273
Uratel5	1,234
CPIgl8	3,469
Int_realpcredgl	2,441
CPIgl1	5,661
realGDPg	3,857
GlobmcapGDP	3,959
MSCIhpshortl8	1,503
Globpcredgl1	512,362
GlobpcgxglobpcG	513,448
GlobmcapGDPl3	3,304
M2GDP	1,091

VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient
between variable j and the other independent variables

Long model after exclusion of globpcgxglobpcGDPl1:

Variance Inflation Factors

Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

rdomcredl1	1,054
Int_pcgxglopcGD	2,271
Uratel5	1,217
CPIgl8	3,449
Int_realpcredgl	2,407
CPIgl1	5,432
realGDPg	3,695
GlobmcapGDP	3,835
MSCIhpshortl8	1,338
Globpcredgl1	1,816
GlobmcapGDPl3	3,113
M2GDP	1,091

VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient
between variable j and the other independent variables