Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

RIGOROUS THESIS

Financial Stress in the Czech and Slovak Republic: Measurement and Effects on the Real Economy

Author: **Mgr. Ján Malega**

Supervisor: **doc. Roman Horváth, Ph.D.**

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Declaration of Authorship

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

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Prague, September 7, 2016

Signature

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Abstract

In the scope of this thesis, we estimate a financial stress index particularly for the Czech Republic with application for Slovakia, and examine its development during the period 2002-2014. The advantage of the index is primarily its ability to measure the current level of stress in the financial system incorporating information from various sectors of the economy and expressing it in a single-value statistic. We find a marked increase in financial stress at the beginning of the global financial crisis and European sovereign debt crisis with a decrease to nearly pre-crisis levels by the end of our study period. Next, we estimate vector autoregression models and find out that financial stress has systematic effects on unemployment, prices and interest rates, with the maximum response occurring approximately one to two years after the shock in the Czech Republic, and with a half-year delay in Slovakia. Specifically, an increase in financial stress is associated with higher unemployment, lower prices and lower interest rates, indicating its detrimental effects on the real economy.

JEL Classification	G17, G32
Keywords	financial stress index, vector autoregression, impulse responses

Abstrakt

Táto štúdia sa zaoberá odhadnutím indexu finančného stresu so zameraním hlavne na prípad Českej Republiky s aplikáciou na Slovensko a na preskúmanie vývoja počas obdobia 2002-2014. Výhodou indexu je hlavne jeho schopnosť zmerať aktuálnu výšku stresu vo finančnom systéme, pričom zahrňuje informácie z rôznych ekonomických sektorov a vyjadruje ich v tvare jednočíselného ukazovateľa. Na začiatku globálnej finančnej krízy a podobne počas dlhovej krízy v eurozóne sme zistili výrazné zvýšenie finančného stresu s poklesom na takmer predkrízovú úroveň na konci nášho pozorovaného obdobia. V ďalšom kroku odhadujeme modely vektorovej autoregresie a prichádzame k zisteniu, že finančný stres má systematické dopady na nezamestnanosť, hladinu cien a úrokové sadzby, pričom maximálna odozva sa vyskytuje približne jeden až dva roky po šoku v Českej republike a s oneskorením o pol roka v prípade Slovenska. Zvýšenie finančného stresu je spojené konkrétne s vyššou nezamestnanosťou, nižšou hladinou cien a nižšími úrokovými sadzbami, čo naznačuje jeho škodlivé účinky na reálnu ekonomiku.

JEL Klasifikácia	G17, G32
Kľúčové slová	index finančného stresu, vektorová autoregresia, impulzne odozvy

E-mail autora/author	malega.jan@gmail.com
E-mail školiteľ/supervisor	roman.horvath@fsv.cuni.cz

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Acronyms

ACF – Autocorrelation function

AR – Autoregressive (model)

ARCH – Autoregressive Conditional Heteroskedasticity (model)

BRIBOR – Bratislava Interbank Offered Rate

CDF – Cumulative Density Function

CISS –Composite Indicator of Systemic Stress

CNB – Czech National Bank

CZEONIA - Czech Overnight Index Average

EONIA – Euro Overnight Index Average

EURIBOR – Euro Interbank Offered Rate

EV – Equal Variance (aggregation method)

FSI – Financial Stress Index

FSR – Financial Stability Report

GARCH – Generalized Autoregressive Conditional Heteroskedasticity (model)

GDP – Gross Domestic Product

HP – Hodrick-Prescott (filter)

IMF – International Monetary Fund

INF – Inflation

IR – Interest Rates

KMO – Kaiser-Meyer-Olkin (statistic)

NBS – National Bank of Slovakia

OLS – Ordinary Least Squares (regression)

PACF – Partial Autocorrelation Function

PCA – Principal Component Analysis

PRIBOR - Prague Interbank Offered Rate

PX – Prague Exchange (index)

ROA – Return On Assets

ROE – Return On Equity

SAX – Slovak Auction Index

SKONIA – Slovak Overnight Index Average

UNEM – Unemployment

VAR – Vector Autoregression

Rigorous Thesis Proposal

Předpokládaný název rigorózní práce v češtině:

Modelování indexu finančního stresu pomocí vektorové autoregrese

Předpokládaný název rigorózní práce v angličtině:

Modelling of Financial Stress Index using Vector Autoregression Analysis

Předpokládaný termín předložení práce:	marec 2016

Charakteristika tématu a jeho dosavadní zpracování žadatelem (rozsah do 1000 znaků):

Nedávna finančná kríza poukázala na silný vzťah medzi finančným stresom a ekonomickou aktivitou, pričom zároveň odkryla závažné nedostatky v súčasnej metodológii testovania finančného stresu. To zdôrazňuje fakt, že nové nástroje sú potrebné a hoci súčasná literatúra je nimi zahltená, len málo autorov sa zameriava na krajiny strednej a východnej Európy akou je Česká republika.

V tejto práci vytvoríme index, ktorý bude slúžiť ako indikátor zvýšeného finančného stresu a pomocou tohto indexu vyhodnotíme dopad hospodárskeho spomalenia trhu na celkovú ekonomiku. V snahe dosiahnuť tento cieľ, rôzne medzinárodné metodológie tvorenia indexov budú analyzované a vyhodnotené vzhľadom na české ekonomické prostredie pričom budú následne použité na vytvorenie špeciálneho indexu pre prípad Českej republiky. Podstatnou výhodou tohto prístupu je, že sa nám podarí zachytiť obdobia začiatku turbulencií na finančných trhoch, čo môže byť následne použité na zníženie dopadov krízy.

Předpokládaný cíl rigorózní práce, původní přínos autora ke zpracování tématu, případně formulace problému, výzkumné otázky nebo hypotézy (rozsah do 1200 znaků):

Cieľom tejto práce je vytvoriť index finančného stresu a to konkrétne pre prípad Českej republiky a identifikovať všetky kľúčové makroekonomické ukazovatele potrebné na jeho konštrukciu. Predpokladáme, že nami vytvorený index bude správne reflektovať skutočný stav a zmeny v ekonomike a zároveň bude slúžiť ako konzervatívny ukazovateľ, ktorý včas identifikuje potencionálne rizikové úrovne finančného stresu. Významnou výhodou tohto prístupu je jeho jednoduchá interpretácia, schopnosť indexu zmerať aktuálnu výšku stresu vo finančnom systéme, pričom ho vyjadrí v tvare jednočíselného ukazovateľa čím sa uľahčí aj jeho porovnateľnosť s inými indexami. Predpokladáme, že náš index úspešne zaznamená a vyhodnotí kritické obdobia zvýšeného finančného stresu a to hlavne počas nedávnej finančnej krízy. Navyše, v tejto práci budeme skúmať dopad finančného stresu na reálnu ekonomiku.

Předpokládaná struktura práce (rozdělení do jednotlivých kapitol a podkapitol se stručnou charakteristikou jejich obsahu)**:**

1. Úvod
2. Prehľad literatúry
   2.1. Popis dopadov finančného stresu
   2.2. Prehľad českého finančného sektoru
   2.3. Analýza zahraničných indexov finančného stresu
3. Metodológia
   3.1. Dáta
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   3.3. Vektorová autoregresia a metóda impulzných odoziev
4. Vytvorenie indexu finančného stresu
   4.1. Výber jednotlivých premenných
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5. Empirické výsledky
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   5.2. Historické vyhodnotenie indexu
   5.3. Analýza dopadov finančného stresu
6. Záver

Vymezení podkladového materiálu (např. analyzované tituly a období, za které budou analyzovány) **a metody (techniky) jeho zpracování:**

Hlavným zdrojom našich dát je verejná databáza ČNB ARAD, potom finančná databáza ECB, a Pražská burza cenných papierov. Všetky dáta budú štandardizované, pričom pokrývajú obdobie od februára 2002 do februára 2015 a sa založené na mesačnej frekvencii. Vzhľadom na problém s dostupnosťou niektorých časových rád dlhšie obdobie nezahrňujeme. Časové rady ako napr. hrubý domáci produkt, ktoré sú merané len kvartálne budú transformované na mesačné dáta pomocou kubickej interpolácie.

Ukazovateľ finančného stresu bude skonštruovaný ako vážený priemer rozptylov finančných indexov pozostávajúcich z kľúčových ekonomických sektorov (bankový, devízový, dlhopisový a akciový) zahrňujúci všetky dostupné informácie v danom čase. Jednotlivé váhy budú stanovené metódou hlavných komponentov. Systematické interakcie medzi finančným stresom a makro-ekonomikou budú analyzované vektorovou autoregresiou spolu s metódou impulzných odoziev.

Základní literatura (nejméně 10 nejdůležitějších titulů k tématu a metodě jeho zpracování; u všech titulů je nutné uvést stručnou anotaci na 2-5 řádků)**:**

[1] **Cardarelli, R., Elekdag, S., Lall, S. (2011):** *Financial stress and economic contractions*. Journal of Financial Stability 7, pp. 78–97.

- Článok popisuje prístup merania finančného stresu pre 17 pokročilých ekonomík, pričom porovnaní s ostatnými prístupmi v tomto koncepte boli zahrnuté aj binárne premenné.

[2] **Cevik, I. E., Dibooglu, S., Kutan, M. A. (2013):** *Measuring financial stress in transition*

economies. Journal of Financial Stability 9, pp. 597 – 611.

- Cevik et al. ako sú jedni z mála autorov, ktorí sa zaoberajú vytvorením indexu finančného stresu pre tranzitívne ekonomiky. Je dôležité spomenúť, že v svojej práci použili metódu hlavných komponentov ako spôsob na určenie jednotlivých váh pri agregácii indexu. Navyše inšpiratívne bolo aj použitie kubickej interpolácie na transformáciu dát z kvartálnych na mesačné.

[3] **Geršl, A., Heřmánek, J. (2006):** *Financial stability indicators: advantages and disadvantages of their use in the assessment of the financial system stability*. CNB - Financial Stability Review, pp. 69-79.

- Geršl a Heřmánek hodnotia výhody a nevýhody indikátorov finančného stresu používaných v Českej republike zároveň vytvorili Bankový index stability, ktorý používa ČNB.

[4] **Grimaldi, M. (2010):** *Detecting and interpreting financial stress in the euro area*. The European Central Bank Working Paper Series, No. 1214.

- V porovnaní s väčšinou postupov pri vytváraní hraničnej hodnoty indexu, Grimaldi použil odlišný prístup a to taký, že hraničnú hodnotu určil na základe zoznamu historických udalostí finančného stresu. Na vytvorenie finálneho indexu použil logit model.

[5] **Hakkio, S. C., Keeton, W. R. (2009):** *Financial Stress: What Is It, How Can It Be Measured, and What Does It Matter?* Federal Reserve Bank of Kansas City Economic Review, Second Quarter 2009.

- Táto empirická štúdia vytvorila index finančného stresu pre Federálnu banku v Kansase, pričom sa sústredila na zachytenie vzťahov a dopadov finančného stresu na reálnu ekonomiku.

[6] **Holló, D., Kremer, M., Duca, M. (2012):** *CISS – A Composite indicator of Systemic Stress in the financial sector*. ECB Working Paper Series, No. 1426, March 2012.

- Holló et al. vytvorili kombinovaný ukazovateľ systémového finančného stresu zložený z premenných pokrývajúcich 3 hlavné sektory a to: trhy, sprostredkovateľov a infraštruktúru, pričom delenie pokračovalo aj na menšie jednotky ako akciové trhy, banky atď.

[7] **Illing, M., Liu, Y. (2006):** *Measuring Financial Stress in a Developed Country: an Application to Canada.* Journal of Financial Stability, Vol. 2, No. 4.

- Index finančného stresu vytvorený Illing a Liu bol jedným z prvých kombinovaných indexov pričom boli využité rôzne makroekonomické a finančné ukazovatele.

[8] **Jakubík, P., Teplý, P. (2011):** *The JT Index as an Indicator of Financial Stability of Corporate Sector*. Prague Economic Papers, 2 , 2011.

- Jakubík a Teplý vytvorili ich JT index na meranie finančnej stability v štatutárnom sektore v Českej republike. Index je založený na skórovacom modeli, ktorý používa dáta z bilancie a to konkrétne 4 druhy indikátorov merajúcich: likviditu, solventnosť, rentabilitu a aktivitu v danom sektore.

[9] **Krzak, M., Poniatowski, G., Wasik, K. (2014):** *Measuring financial stress index and economic sensitivity in CEE countries*. CASE network research project, No. 117/2014.

- Podobne ako Cevik et al. aj Krzak a spoluautori sa venovali meraniu finančného stresu a to konkrétne pre prípade CEE krajín, kde ich výber premenných môže slúžiť ako inšpirácia pri vytváraní indexu pre Českú republiku.

[10] **Oet, V. M., Eiben, R., Bianco, T., Gramlich, D., Ong, J. S. (2011):** *The Financial Stress Index: Identification of Systemic Risk Conditions*. Federal Reserve Bank of Cleveland, Working Paper, November 2011.

- Článok od Oet. et al pokračoval a rozšíril prácu Illing a Liu v oblasti kombinovaného indexu finančného stresu pričom použil odlišnú metódu váženia jednotlivých indexov a to na základe ich zastúpenia v celkových pohľadávkach danej krajiny.

1 Introduction

In response to the global financial crisis, national and international policy institutions started more intensive monitoring of the soundness of the financial system, analyzing the potential impacts of financial stress on the economy, and implementing a number of policy measures. Due to the depth and consequences of the crisis, many supervisory authorities have begun to consider a new set of techniques designed to measure the potential vulnerability of financial institutions. In particular, a strong emphasis was placed on research regarding the development of tools measuring risk and uncertainty as well as their ability to serve as early warning indicators (Vermeulen et al., 2014).

The financial crisis uncovered significant deficiencies in the current stress testing framework calibration (Blaschke et al., 2001). According to Borio et al. (2010), many of these stress testing scenarios were not sufficiently adverse therefore providing a false sense of security. Although stress tests are currently a standard tool for many institutions, they are not designed to serve as early warning indicators. Many deficiencies are connected with construction of feasible scenarios which hold particularly for the Central and Eastern European countries such as the Czech Republic or Slovakia. The issue of these countries is relatively short time series and possible events of structural breaks (Geršl et al., 2012).

In the thesis[1], we aim to calculate a measure of financial instability in the form of a financial stress indicator for the Czech Republic. It measures the level of financial stress by incorporating all the available information in a given period and aggregating them into a single index value. Advantages of this approach include simplicity, easy interpretation and ability to tailor it to the specific conditions of a given economy (Grimaldi, 2010). Illing and Liu (2006) developed a financial stress index for Canada, Sinenko et. al (2013) created a FSI particularly for Latvia, whereas Cardarelli et al. (2011) developed a FSI to analyze periods of financial stress in 17 advanced economies. Currently, several private institutions also use FSIs to measure stress, for example, Bloomberg and the OECD, which publishes a composite indicator of economic activities for its members.

[1] According to the current rigorous procedure effective from 01.10.2015 this is the extended thesis (with additional analysis of the Slovak Republic) based on the thesis of *Malega, J. (2015): Modelling of Financial Stress Index in the Czech Republic using Vector Autoregression Analysis*, and the article of *Horváth, R., Malega, J. (2016): Financial Stress in the Czech Republic: Measurement and Effects on the Real Economy* with forthcoming publication in Prague Economic Papers.

Therefore, the focus of this thesis is to analyze the economic environment along with various internationally applied methodologies, to select potential variables based on current research, including those unexplored in previous research, and to aggregate them into a financial stress index. The motivation is to extend and improve current methodologies of measuring financial stress and create an indicator that is particularly suited to the environment of the Czech Republic and, with its help, to identify periods of financial distress. Despite the fact that the financial stress index is tailored particularly for the Czech Republic, we test its robustness by implementing it in Slovakia setting assuming that economic conditions are similar. Furthermore, we estimate vector autoregression models, in both countries, to examine the systematic relations between financial stress and the real economy to understand the speed and magnitude of the effects caused by financial stress.

Our results for both countries show, that financial stress increased rapidly at the beginning of the global financial crisis (in 2008) and European sovereign debt crisis (in 2011) with a relatively rapid return to pre-crisis levels afterwards. Vector autoregression estimates suggest that financial stress has systematic effects on the real economy. We find that higher financial stress increases unemployment and decreases both prices and interest rates. Our results suggest that the maximum impact of financial stress on the real economy occurs approximately from one to two years after the shock in the Czech Republic and with a half-year delay in case of Slovakia.

The thesis is organized as follows: Section 2 - literature review, provides an introduction to the concept of financial stress followed by a brief overview of the Czech and Slovak financial sector. Next, it describes historical development of financial stress indices, review of current methodologies and finally the concept of a single composite financial stress index. Section 3 – methodology, describes the source of data used in the paper and three aggregation methods. The end of the section introduces vector autoregression and impulse responses. The following section 4 describes underlying variables, construction of the financial stress index and technique to compute threshold for identification of excessive periods of financial stress. Finally, section 5 presents our main findings and the financial stress indices for the Czech and Slovak Republic, along with the analysis of identified historical events during the crisis. The section ends with commentary on effects of financial stress on the real economy, followed by conclusion.

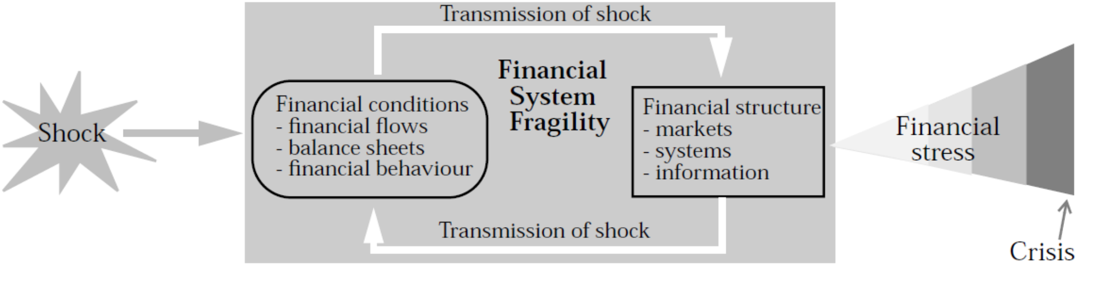
2 Literature review

The recent financial crisis led to the creation of macroprudential policies designed to safeguard financial stability with a focus on reducing the risk of instability in the system as a whole. Financial stress measures have been developed to assess the current degree of financial imbalance.

2.1 Financial stress and its impact

There are many definitions of financial instability. According to Illing and Liu (2006), financial stress is characterized as a disruption of normal market functioning. The level of the financial stress is based on the strength of a shock and vulnerability of the financial market.

Figure 2.1: Schematic of financial stress



Source: Illing and Liu (2006)

Holló et al. (2012) describe financial stress as: *"Systemic stress is interpreted as that amount of systemic risk which has already materialized. Systemic risk, in turn, can be defined as the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially."* (Holló et al., 2012, pp. 8, accessed on 10.4.2014). Hendricks et al. (2007) refer to systemic risk as a movement from a stable positive equilibrium to an unstable negative equilibrium.

The Czech National Bank defines financial stability as a state where financial system performs without any severe or unwanted impacts on the current or future development of the economy. Emphasis is put especially on the system soundness and resilience against potential shocks. Disruption of the financial stability is related not only to shocks that may arise externally from domestic developments of economic policies or institutional changes, but also due to weak spots inside the economy. Possible interactions between external shocks and weakened spots may arise into collapse of crucial financial institutions and therefore to failure of the whole financial system (CNB-FSR, 2013).

According to Hakkio and Keeton (2009), the main source of financial stress is an increase in financial risk. Financial risk has more symptoms with uncertainty being among the most important ones. Overreaction of investors on new information arrivals causes the rise of uncertainty in terms of prices, directly affecting a volatility level of fundamental market prices. There is also another type of uncertainty that concerns behaviour of all other investors. Another characteristic of financial risk is information asymmetry which leads to moral hazard or adverse selection problems causing decrease of asset market prices.

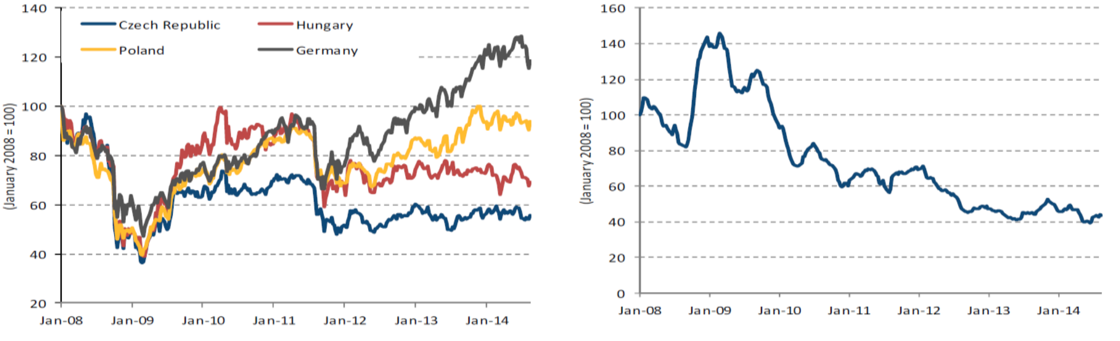
Hakkio and Keeton (2009) also describe some behavioural reactions of investors connected to increase in financial risk. In particular, they mention flight to quality and flight to liquidity. Flight to quality can be understood as a rapid change in state to being adverse to the risk and therefore lowered willingness to hold risky assets. The rising demand for safer assets (e.g. government bonds) causes expected return to fall and contrary returns on risky assets to rise. It results in wider spreadings of expected revenues. Flight to liquidity arises during the period of financial distress when investors are unwilling to hold illiquid assets. Impact is similar as before and so the spread between liquid and illiquid assets is enlarged.

It is also necessary to distinguish between financial stress and fragility of financial system. According to Illing and Liu (2006), the fragility is described by sensitivity to change in financial conditions of the economy. It means that intense change in market conditions can make institutions more vulnerable to financial stress. However, Bell and Pain (2000) emphasize that fragility of the financial system itself does not have to necessarily create financial stress. It is mostly result of interaction between exogenous shocks and fragility.

2.2 Brief overview of the financial sector and its potential risks

Banking sector in the Czech Republic is typical for its conservative structure of balance sheet. The majority of resident deposits are denominated in the local currency (approximately 80%), while in other Eastern and Central European countries these ratios reach 50%. In 2011, only 16.5% of total assets were owned by non-bank financial institutions, what emphasizes the fact that Czech financial system is mostly bank based (Moghadam and Viñals, 2012). On the other hand, equity market has been playing a relatively negligible role in the Czech economy. Good example is shown in the Figure 2.2, where you can see a comparison with other European countries.

Figure 2.2: Comparison of equity (left) and trade volumes (right)



Source: Rusnok (2014)

Another peculiarity of the Czech financial system is that bank business activities are funded especially by domestic deposits which are demonstrated by stable 75% loan-to-deposit ratio. The key profits from financial activities originate mainly from interest income and fees, which makes Czech banks less vulnerable to financial stress. As regards ownership in 1995, 24% of banks were foreign-controlled, while nowadays it is more than 80% of all banks in the Czech Republic. Lending may be more prudent in the Czech Republic compared to other CEE countries and despite the financial crisis in 2008, the ratio of non-performing loans to total loans is gradually decreasing as of the end of 2010 (Rusnok, 2014).

Development of the external debt in the Czech Republic was quite solid, although it followed an upward trend in the past three consecuting years. At present, the increase is comparable to other European countries; however, in the future, external debt financing for the government can pose a risk to financial stability. The main threat for the banking sector lies in slowing down of the economy, resulting in rising credit losses and visible decline in profitability (CNB-FSR, 2015).

An important intervention in the banking sector can be caused by serious aggravation in credit portfolio resulting from adverse development in the global economy. The source of credit risk stems from restrained domestic demand and disinflationary pressures. Insufficient demand is stimulated also by the fact that some sectors are generating high surpluses which are not spent and therefore CNB is using exchange rate as a monetary policy to fight this significant fall in demand. Financial cycle in the Czech Republic is now experiencing phase of modest credit recovery and slowed domestic activity which discourages lending activity and risk-taking (Tomšík, 2014).

Credit risks in banks can be represented by non-performing loans ratio to total loans to residents. This ratio remained stable for the past two years; however, currently we face a modest increase. (CNB-FSR, 2015).

In case of Slovakia, the quality of the loan portfolio of the banking sector improved since 2015 with non-performing loans ratio coming down to 3.9%. In contrast, low interest rates have been increasing indebtedness of the public and private sectors, which may pose a significant risk for future economic growth. In absolute numbers, the year-on-year rise in the outstanding bank loans lended to households came to its maximum levels in the history of retail lending in Slovakia at the end of 2015 (ASFS, 2015). The low interest rates also threaten financial stability by reducing bank's profits as loans are affected more than deposits. This trend has a greater influence on banking sector in countries like Slovakia, which follow rather traditional business models (NBS-FSR, 2015). Lending to non-financial corporations, as within houshehold sector, was at its peak compared to any level in the post-crisis period (ASFS, 2015).

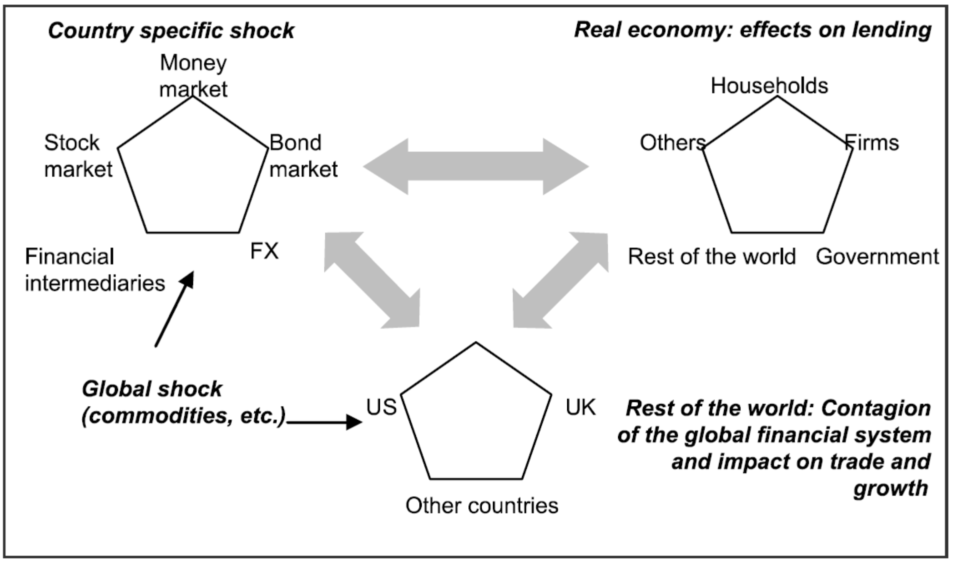
Slovak banking sector is typical with its relatively high exposure to concentration risk – banking sector is heavily dependent on group of clients with relatively hight degree of ownership that are economically interlinked. If one of them would fail, the sector would be greatly impacted; however, this exposure decreased during 2015. Equity market in Slovakia is very tiny, even when compared to the Czech Republic, and therefore it has no great impact on financial stability (ASFS, 2015).

Another potential risk to financial stability is related to the high degree of uncertainty in European and global macroeconomic state of economy. The Czech Republic is highly dependent on its main trading partner Germany, which makes them closely linked to their growth performance, therefore it is likely to be negatively impacted because of increased concerns of recession in the euro area (Moghadam and Viñals, 2012). Similarly, as Slovakia is a small open economy, there is a space for systemic risk resulting from sensitivity to global economy events and country's main trading partners (NBS-FSR, 2015).

Contagion effects and spillovers of financial stress may pose a significant risk for financially open countries, such as the Czech Republic and Slovakia, which are strongly linked to the euro area. These links facilitate not only functioning of the markets but also transmissions of financial stress between countries. Contagion is defined as a transfer of financial stress that can occur across borders and is typical for countries with a high level of financial openness. Volatility spillover has gained lot of attention recently (see Adam and Benecká, 2013).

Soriano and Climent (2006) wrote a review on transmission of volatility using the *GARCH* models. However, in general, literature for the CEE countries is still limited. Geršl and Komárková (2009) were examining evidence of the Global financial crisis and they found out that during the crisis, a spiral effect emerged even in the countries which were not directly affected a negative liquidity. Moreover, Geršl (2007) in his studies about Cross-Border contagion claims, that the integration of the CEE countries on international financial markets increases mainly because of the entry of foreign banks into local markets and significant abroad borrowings. He admits that the risk of cross-border contagion might increase as well.

Figure 2.3: Transmission of financial stress between countries



Source: Adam and Benecká (2013)

2.3 Financial stress indices

Economists have always tried to discover an appropriate approach that would be able to identify potentially dangerous episodes of financial stress in advance. In the beginning, academic literature relied on detailed description of historical events (financial crises etc.) in order to determine the following stressful period. Current methodology measuring financial stress and its impacts on economy has significantly evolved.

This section provides a brief overview of financial stress indices proposed by different countries. Considering that there are many different approaches applied internationally, we present a selection of several well-known indicators. Subsections are divided into FSIs used in developed and developing countries to compare different set of underlying variables stemming from limited data availability in developing countries.[2]

2.3.1 Financial stress indices in developed countries

One of the first known financial stress indices was created by Illing and Liu (2006) for Canadian financial system. Their study proved that the approach is capable of identifying most of stressful events. They compared nine different indicators consisting of most appropriate variables which were weighted according to given sector's share in the economy. This period also revealed that systemic risk is behaving differently in banking sector or in securities and FX market. There is obviously some subjectivity presented in identification of banking crisis (Oet et al., 2011). Misina and Tkacz (2009) continued research and examined impact of credit and price movements and their influence on Canadian stability.

In 2009, the Cleveland Financial Stress Index was constructed. It was an extension of the approach of Illing and Liu (2006) with added weightings methods (Oet et al., 2011). A different approach was employed by Hakkio and Keeton (2009) based on signs of different types of financial stress. Their financial stress index is still actively used in the the Federal Reserve Bank of Kansas City.

Grimaldi (2010) used quite a different approach in constructing FSI. The whole procedure was divided into three steps. Firstly, a list of stressful events was created as a benchmark for setting the threshold level. Since there is no generally agreed list of stressful events in the euro area, recent literature inspired by many qualitative studies was used to confirm the judgement in identification of such events. Second step consisted of selection of individual indicators for measurement of stress. To some extent, the choice of variables reproduced current studies (trying to cover banking, equity, money and debt markets and volatility). Variables were aggregated together into two summary indices capturing level and rate of change in variables. Finally, logit model was used to extract information incorporated in both indices effectively. Although methodology used by Grimaldi (2010) has an exceptional feedback, once again it was designed broadly for the whole euro area, and therefore its predictive power for such a single economy could be limited.

Cardarelli et al. (2011) implemented and applied their approach on 17 advanced economies. Their concept was extended and binary variables were included expressing states: crisis/no crisis. States were selected when one of the indicators

[2] It is not a general rule but there is often a data availability issue in transition economies that went through periods of structural breaks etc., so we decided to divide these approaches accordingly.

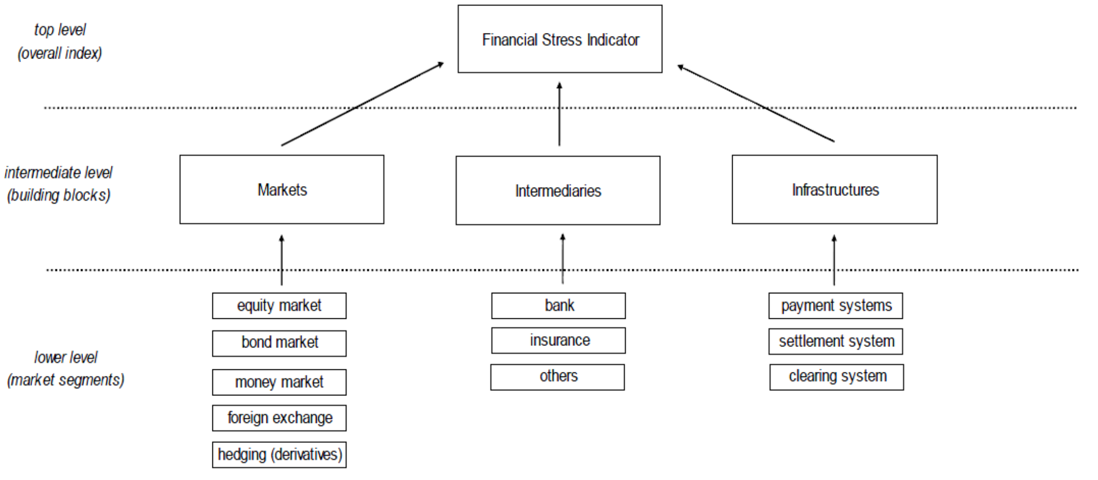
reached extreme values. This approach was monitoring financial stress in individual sectors of an economy. Moreover, in their empirical paper they discovered that banking distress is much more likely to create a period of financial downturn, when compared to uncertainty caused by dynamics in foreign exchange market. The binary approach has its drawbacks, though, as it excludes situations, which were successfully maintained, and therefore have not materialized into serious crises, into which they might otherwise become (Oet et al., 2011). Furthermore, it only enables to identify the start and the end of the stress episode, but does not measure changes in the financial stress during the period, making it difficult to compare individual episodes and to determine, how much worse is one episode in comparison with another (Sinenko et al., 2013).

By contrast, Illing and Liu (2006) use binary variables to determine financial strains periods and subsequently treat them as banking, debt or currency crises. Holló et al. (2012) claim that focusing in crisis event itself does not tell us anything about stress levels throughout different stages of a particular crisis, and they promote an alternative approach of creating Financial Stress Index.

The Composite Indicator of Systemic Stress (CISS) created by Holló et al. (2012) is specific, as it is designed to put more weight on situations where financial stress spreads are higher across the whole financial system at the same time. CISS is based on five subindices, representing five market segments, which are created from fifteen individual variables measuring financial stress. These individual stress variables are standardized by their means and then aggregated together as an arithmetic average of three transformed individual stress variables. The following five subindices are aggregated into the one composite financial stress index using method based on quantile transformation and cumulative distribution function.

According to Holló et al. (2012) the financial system can be divided into three key divisions: markets, intermediaries and infrastructures and each of these divisions can be further divided into additional segments (e.g. banks, insurance companies, etc.). In the following Figure 2.4 we can see detailed structure of the creation of FSI based on the procedure of Holló et al., (2012).

Figure 2.4: Construction structure of the CISS financial stress index



Source: Holló et al. (2012)

Although the financial stress index constructed by Holló et al. (2012) can be a good predictive tool for the whole euro area, for which it was designed, in case of small open economies, such as the Czech Republic or Slovakia, it may be inaccurate or even misleading. The potential issue can be that the CISS systemic stress indicator, which was designed to represent market-wide development and therefore prefers broader set of standard indicators, which are available for a group of countries (Holló et al, 2012). At the same time, however, it ignores market-specific anomalies which are typical for every single economy.

One of the globally and recently used conventional single indicator measuring uncertainty is an implied volatility based on stock market dynamics. However, contemporary contribution of the stock market volatility to the real economy is becoming insignificant. The main reason is the source of implied volatility that is derived from stock market and its movements, which does not necessarily have anything in common with the real state of economy. Moreover, the casual direction is usually supposed to run from macroeconomy to stock market and its volatility, rather than the opposite way (Islami and Kurz-Kim, 2013).

2.3.2 Financial stress indices in developing countries

As we are aiming to assess financial stress in the Czech Republic, we are particularly interested in literature that focuses on the developing Central and Eastern European transition economies.

Brüggeman and Linne (2002) analysed the vulnerability of the CEE countries to a financial crisis. They used extended signals approach and developed composite indicator measuring evolution of the risk of given countries. Schardax (2002) developed an early warning model for currency crises for twelve CEE countries. Kittelmann et al., (2006) in their paper examine the CEE countries (the Czech Republic, Hungary, Slovakia), particularly their vulnerability and determinants of financial crises.

Regarding financial stress indices, Sinenko et al. (2013) created Latvian financial stress index, dividing the whole financial system into three sectors in the same way as Holló et al. (2012), and assigned a set of indicators for each to assess financial stress. All of them were aggregated by various aggregation methods and compared afterwards. Krzak et al. (2014) choose a different set of underlying variables, focusing particularly on uncertainty about current and future value of assets on bond, FX and stock markets using Principal Component Analysis. Šimáček (2012) used a similar approach for the Czech Republic and Hungary, where he divided the financial system into five sectors: banking, money, monetary, bond and stock market, and assigned representative indicators. To differentiate this thesis from Šimáček (2012), we use somewhat different underlying variables based on our research – especially those recommended by current literature – to create our financial stress index. In addition, we estimate vector autoregression models, as we particularly aim to examine the effects of financial stress on the real economy.

Another approach was proposed by Jakubík and Teplý (2011) to assess the financial stability of the Czech corporate sector. The index was based on a financial scoring model using corporate accounting data of Czech companies. Scoring models are mostly used by risk management in order to evaluate creditworthiness of lenders and therefore estimate their probability of default. They used logistic regression as one of the many possible methods in evaluating the scoring model. There were 22 indicators chosen from four key sectors such as liquidity, solvency, profitability and activity indicators. However, just seven of them were identified as significant financial indicators capable of describing the financial downturn periods with a one-year prediction. Among the most important ratios were interest coverage, financial leverage and cash ratio. This technique helps to broaden the existing methodology used by the Czech National Bank.

2.4 Current methodology for assessing financial stress

There are several tools and methodologies used by the Czech National Bank to evaluate system's stability. One of the internationally employed tools to monitor systemic health is financial soundness indicators.

Financial soundness indicators

In order to strengthen resilience of individual economies and avoid potential failure of the whole financial system, the International Monetary Fund (IMF) created financial soundness indicators to support macroprudential analyses of the financial market and to enhance financial stability. Financial soundness indicators are measuring the current financial health and soundness of financial institutions in a given country. They are based on conceptual framework developed by the IMF and designed to foster an international comparison among participating countries (IMF, 2006).

The financial soundness indicators consist of two parts: The core set, which is compulsory for participating countries and contains basic indicator mainly for banking sector (e.g. regulatory capital to risk weighted assets, ROA, ROE, non-interest expenses to gross income, trading income etc.) and encouraged set, which includes supplementary variables characterizing market liquidity, real estate market, etc. The Czech National Bank and the National Bank of Slovakia (NBS) are both involved in this project, publishing all data (both core and encouraged datasets). These data provide aggregate information on the financial sector, being evaluated by the CNB or NBS authorities along with other financial supervisory indicators (CNB, 2013).

Banking Stability Index

Banking stability index is another supervisory tool used to assess potential financial risk, which was presented by Geršl and Heřmánek (2006) in the Financial Stability Report. Since financial market data in the Czech Republic are fairly limited because of relatively small number of listed debt securities and shares, the index is based mainly on balance sheet data. The index comprises nine variables in total. The selection of individual variables was inspired by international practice. Majority of them serves in the same way as the financial soundness indicators proposed by the International Monetary Fund.

As an asset quality indicator, the ratio of non-performing loans to total loans was used to determine the level of exposure to credit risk. Capital adequacy and profitability ratios (ROA and ROE) express a buffer that has to be at disposal by a bank against potential risks. Liquidity ratios (quick assets to total assets and non-bank deposits) measure reserves necessary to be held in order to mitigate potential liquidity issues. Cumulative net balance sheet position to total assets stands as an interest rate risk measure and reflects the time mismatch between assets and liabilities. Moreover, it indirectly determines potential losses caused by possible rise in interest rates. The last two indicators (absolute value of open balance sheet and total position in foreign exchange to Tier 1 capital) indicate exposure to foreign exchange risk, including movements of exchange rates in both directions. This index is currently used by the Czech National Bank as one of the leading indicators to determine financial stress.

2.4.1 Review of the current stress assessing methodologies

According to Geršl and Heřmánek (2006), financial soundness indicators set by the International Monetary Fund pose some methodological discrepancies due to national limitations (for example, data collection). Following studies confirmed that banks in the Czech Republic demonstrated very low net open position in foreign exchange involvement in comparison with other CEE nations, such as Hungary. Moreover, banks in the Czech Republic (in 2005) recorded lowest numbers in the interest margin and non-interest expenses to gross income ratio among five CEE countries included. This implies that Czech banks relied more on the non-interest profit than banks from the other countries. Due to distinct results of indicators for various countries, we cannot simply compare financial states of banking sector among different countries. One of the possible methods could be a comparison of the financial soundness of the banking sector among individual countries based on the ranking acquired by an aggregation of several indicators.

Working paper of Geršl et al. (2012) states that the current methodology used by the CNB for stress-testing is accepted as a reliable and robust framework, which is in accordance with the recent literature. However, in case of rapidly evolving risk in banking sector, they propose to test difference scenarios as ad-hoc shocks, concentrated risk in portfolios, possible risk of excessive dividend pay-outs and international interbank exposures.

According to Moghadam and Viñals IMF report about Czech financial stability (2012), there is always a room for refinement of the analysis of risks identifications concerning financial stability. For instance, in case of contagion type risks, better stress tests can facilitate to access information whether current capital and liquidity buffers are sufficient or any other intervention is needed. Moreover, CNB should also improve potential risks identification of real estate price bubbles and credit booms in case they emerge again. This tools were mentioned in Basel III as counter-cyclical capital buffers.

2.5 A single composite financial stress index

As we have previously listed, there is a variety of data approaches to create a financial stress index. It can be based on high-frequency (daily or weekly) financial market data with market-based indicators such as: FSI of the Bank of Canada (Illing and Liu, 2006), International Monetary Fund FSI (Cardarelli et al., 2009) or Composite indicator of systemic stress used by the European Central Bank (Holló et al., 2012). Or an alternative approach is to use data from financial institutions, balance sheets and macroeconomic variables such as: FSI of the Central Bank of Luxembourg (Rouabah, 2007), Financial Stability Conditions Index of the De Nederlandsche Bank (Van den End, 2006) or Banking stability index of the Czech National Bank published by Geršl and Heřmánek (2006).

Although both approaches have become very popular in practice, we decided to use mainly macroeconomic variables due to the fact, that the Czech Republic has relatively few listed share and debt securities of domestic banks, and also because there is not enough available high frequency data with sufficiently long history.

Many of the previously mentioned papers were based on principle of a single composite financial stress index. Practically it means that several subindices, each representing an important part of the economy, are aggregated into one single composite indicator describing financial system as a whole. It enables monitoring the financial stress not only in particular sectors, but also in the whole financial system during the entire exposure of the stress, and thus measuring its intensity. This is also confirmed by Sinenko et al. (2013), who claim that monitoring a financial stress becomes substantially easier through the use of a single composite indicator. Another significant advantage is that financial stress index is capable of capturing periods of distress that have not materialized into a fully-fledged crisis, which allows to study effects and effectiveness of macroeconomic policies in order to prevent such an issue in the future (Šimáček, 2012).

According to Holló et al. (2012), FSI is a powerful tool in measuring the effectiveness of government interventions toward mitigating systemic stress. Moreover, FSI is highly appropriate for application as an early warning indicator (Illing and Liu, 2006). It enables to identify the sources and causes of the financial stress thought the possible so-called index decomposition, i.e. throughout analysis of individual parts of an index (Gadanecz and Jayram, 2009).

The proper financial stress index is supposed to maintain continuality and thus to have ability to capture the current level of financial stress and identify it even after new observations have been added. Continuality is achieved by proper selection of variables with sufficiently long high frequency time series data and proper aggregation methodology. Extreme values in financial stress indices reflex moderate stress of financial system and therefore potential crisis. In order to avoid financial distress, it is crucial to properly identify the level when the financial index starts to reach critical values and capture that period in advance.

There are FSIs designed for different countries, however, we aim particularly to create FSI tailored for the Czech Republic. We believe that overall index may be more biased and bring unwanted noise to our results. Our claim is supported by Slingenberg and Haan (2011) who constructed a multi-country FSI and their results showed that only credit growth has a predictive power for most of countries, but other indicators work only in some cases.

There are also different techniques to financial stress indices in terms of aggregation methods. Simple approach is to use equal variance weighting method, in other words assigning the same weights for all variables. This approach often meets with substantial criticism; however, it may serve as useful benchmark. It was used by Cardarelli et al. (2011) or Sandhal et al. (2011). To address the question of how important each of the variables is, Oet et al. (2011) implemented credit weighting scheme. All the indicators were identified as belonging to one of four sectors in the economy (banking, foreign exchange, debt and equity) and weighted in terms of their share of total credit in the given sectors. Brave and Butters (2011) capture the systemic nature of financial stress by taking cross-correlations of a huge number of variables and the past development of the index in order to assign weights for every sub-index. Different technique is factor analysis using principal components. It was applied in work by Illing and Liu (2006) or Hakkio and Keeton (2009) among others. As for the advantage of this method, weights of individual variables are based on their historical importance, including effect of fluctuations in the economy. More detailed description of the aggregation methods will be found in the following chapters under the section Methodology.

3 Methodology

3.1 Data

The main source of our Czech macroeconomic and financial data is ARAD, the public database of the Czech National Bank. The data on 10Y German bonds yield are obtained from the European Central Bank Financial Data Warehouse. Additionally, data for the PX index are acquired from the Prague Stock Exchange. Macroeconomic data for Slovakia are obtained mostly from the public database of the National Bank of Slovakia. The EONIA rate was acquired from the European Central Bank and SAX index from the Bratislava Stock Exchange.

To prevent any information loss, the data were not seasonally adjusted. Our underlying data are covering at monthly frequency[3] the period between February 2002 and the start of 2015[4]. Although we wanted to include earlier historical time series, we face problem of data availability for some of our indicators. Nevertheless, our intention was to construct the FSI based on period containing the most recent crisis and previous episodes of financial stress, which are covered.

3.2 Standardization of data

To be able to compare and aggregate all variables into a single composite financial stress index, raw data has to be standardized. The key point of data standardization is to make every variable equally weighted in the index. Otherwise, highly volatile variables as well as variables with relatively high nominal value would contribute more. Standard approach for standardization is achieved by subtraction of the mean value from individual variables and when done, the mean deducted value is divided by its standard deviation. Basically, for each observation it computes its distance from long-term average measured in standard deviations.[5]

$$Y_{i,j} = \frac{X_{i,j} - \overline{X}_j}{\sigma_j} \tag{3.1}$$

[3] External debt and GDP growth were exceptionally used with quarterly frequency because they are not available in monthly frequencies. Both variables were transformed by cubic spline interpolation to monthly data (for further details see section *Choice of financial variables*)
[4] Time span between series slightly differs, e.g. time series used in VAR analysis are shorter than those in FSI due to limited data availability for interest rates etc.
[5] See Illing and Liu (2006) or Cardarelli et al. (2011)

where $Y_{i,j}$ is a standardized value of variable j in time i , X is a non-standardized value, $\overline{X}_J$ stands for sample mean and σ_j is a sample standard deviation.

We are aware of the fact that excessive interventions to data can affect the results and make them more difficult to interpret; therefore, we did not further modify our data (e.g. by normalization or rescaling)[6].

This approach was used on inputs by two aggregation methods: equal variance weights and principal component analysis. Aggregation method based on quantile transformation is standardizing data by computing their cumulative density functions. However, unlike in equal variance or principal component analysis, standardization is applied after using data adjustment in order to acquire comparable index.

3.3 Aggregation methods

Illing and Liu (2006, pp. 18, accessed on 21.4.2014) stated that *"choice of how to combine the variables is probably the hardest part in construction of financial stress index."* Although there are numerous methods used worldwide, we decided to follow Sinenko et al. (2013) and compare three of them, which are used mostly:

1. variance equal weighting method
2. method based on quantile transformation and cumulative distribution function
3. principal components analysis

When building our financial stress index, all the three approaches were tested. We will briefly discuss methodology of each of them in the following chapter.

3.3.1 Method of equal variance weights

Method of equal variance is a standard approach and can be interpreted as equal variance or risk weighting which ensures that every variable included in the index is equally important. In the first step, all data are standardized, as we have already described it in the previous chapter. Then, all underlying variables are aggregated into one index by arithmetic mean for a given period:

$$FSI_t = \sum_{j=1}^{n} \frac{(X_{j,t} - \overline{X}_J)}{\sigma\,(X_j)} \tag{3.2}$$

[6] See Islami and Kurz-Kim (2013) and their rescalling minimum – maximum method.

where $X_{j,t}$ is a non-standardized value of indicator j in time t, $\overline{X_j}$ is a sample mean, $\sigma\ (X_j)$ is a sample standard deviation. FSI_t is an aggregated value of the financial stress index in period *t*.

We are aware of the fact that there is a disadvantage and so that the mean and standard deviation are, by construction, calculated for the whole sample, which makes this approach sensitive to the inclusion of new information. However, it can serve as a useful benchmark for the other two methods. For a reference, similar approach was used in discussion paper of Islami and Kurz-Kim (2013).

3.3.2 Method based on cumulative distribution function

The second method is based on quantile transformation and the cumulative distribution function, which is relatively more robust compared to the previous method. The method removes the sensitivity of the sample mean and sample variance to outliers and the assumption of their fixed value based on computation of the entire sample. The methodology involves creating a cumulative density function $CDF\ (X_{i,j})$ for each indicator j. The variable values are sorted in ascending order with the values ranging from 0 to 1. Once all the indicators have ranks assigned, the CDFs are computed by dividing the rank of each variable by its number of observations in a given sample, transforming them into percentiles. This value reflects the probability that given variable reaches a value less than or equal to the current value. The higher the percentile, the more severe the stress event it represents (Sinenko et al., 2013). The final index is then re-produced by arithmetic mean of the transformed variables and then standardized.

$$CDF(X) = \frac{1}{m}\sum_{j=1}^{n} I(X_{i,j} \leq X) \text{ where } I\big(X_{i,j} \leq X\big) = \begin{cases} 1, if\ X_{i,j} \leq X \\ 0, if\ X_{i,j} > X \end{cases} \qquad (3.3)$$

The main disadvantage of this method is that it does not take into account the absolute difference in values among the variables, just their order. Another issue concerns newly added observations, which can adjust the order of the data, even though nature of events remain the same (Šimáček, 2012). We also observe that this methodology is not appropriate for data series with increased rate of the same values (e.g. zeros). The reason is that ranking among the observations with the same value is distributed randomly, which would induce noise in the final index. It was used by Holló et al. (2012) and Sinenko (2013).

3.3.3 Principal Component Analysis

Principal component analysis is a statistical technique that is transforming likely correlated variables into a smaller number of components. In other words, this approach reveals structural relationships in data identifying eigenvectors and thus reducing the dimensionality for the data space. Each eigenvector is defined by its eigenvalue and represents a linear combination of the data accounting for most of the variance in the original data. It follows the rule that the higher eigenvalue is, the more data is described by the given eigenvector (Cevik et al. 2013). Under the assumption that each variable is sensitive to financial stress, and if financial stress is one of the main factors responsible for the observed correlations among variables, then it can be identified as a principal component. [7]

There are several approaches when computing weights in PCA. Rouabah (2007) applied arithmetical average of the first few components that stands for the most of variance and using final value as the weighted coefficient.[8] However, in line with Cevik et al. (2013), we use only the first principal component, as we believe that including multiple components, which are averaged later on, introduces unwanted noise into our data. The first principal component from the FSI represents 41.50% of the total variance in Czech data.

A prerequisite for applying principal component analysis is a strong correlation among variables in a dataset. It helps to ensure that cutting of variables will not significantly reduce the information provided. Therefore, if the condition of a correlation between variables is not valid, the first component will not present sufficient information about the examined phenomenon. In order to ensure that data has sufficient correlation, we undertook a Kaiser-Meyer-Olkin (KMO) test statistics. KMO statistics is a sum of correlation coefficients and therefore a large value of the KMO statistics means that correlation of two variables can be also explained by the others.[9] The overall value of the KMO statistic is 0.6637, which is more than sufficient to undertake principal component analysis.[10]

The advantage of this method is that it helps to separate variables with regard to minimal loss of information, which does not affect financial stress and therefore has no value for us. Before we apply the method of principal components, data should be standardized like in the method of equal variance weights.

[7] Similar methodology was applied by Illing and Liu (2006) or Stock and Watson (2001).

[8] Number of components taken into account are selected according to eigenvalue level that is commonly higher than one.

[9] KMO statistics takes values between 0 and 1, all the values around and higher than 0.5 are sufficient for further computation (Stata manual, 2014).

[10] The first principal component in case of FSI for Slovakia represents 29.98% of the total variance and value of KMO statistic is 0.4708 that is on the edge but admissible.

Pitfall of this approach is the opacity of the whole method. Some economists believe that setting weights is subjected to peculiarity of the data, and not to author's reasonable consideration. Another issue is the assumption based on weighting coefficient that expects all relationships in the data to be valid, even though it is not probable (Oet et al., 2011). It is also being criticised due to the fact, that cases with short time series, which do not cover serious stress periods, may lead to considerable index revisions (Oet et al., 2011). We partially solved this issue by including longer period covering the period of the global financial crisis.

Alternative approach could be based on credit weights used by Oet et al. (2011). Weights are assigned according to a total share of credit for each of the four sectors in the economy. The advantage is that the method answers questions of how much each indicator matters in the whole economy, although if there are multiple indicators for a single sector, the weight is divided equally among them, which might be an issue. We do not include credit weighting methodology due to very complicated and insufficient data collection. However, it can be used for further research.[11]

3.4 Introduction to Vector Autoregression and Impulse Responses

Vector Autoregression model (VAR) is commonly used for analysis of multiple time series and system forecasting. VAR model is an upgrade of the univariate autoregressive (AR) model, adjusted for multivariate dynamic time series (Wang and Zivot, 2006).

In general, VAR model is an p-equation, p-variable linear model, where each of its variables are explained by lagged values of their own and other variables. This simple framework makes VAR easy to use, capture and interpret dynamics in multivariate time series data (Stock and Watson, 2001). Our general specification, assuming that the economy is described by a structural VAR(p) model, that is of a linear stochastic dynamic form (omitting the constant), is the following (Lütkepohl, 2005):

$$Y_t = AY_{t-1} + U_t \tag{3.4}$$

where

[11] Another idea worth of consideration would be to use regression to determine the comovements of all variables.

$$Y_t := \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, A := \begin{bmatrix} A_1 & \dots & A_{p-1} & A_p \\ I_k & \dots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & I_k & 0 \end{bmatrix}, U_t := \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{3.5}$$
$$(Kp \times 1) \qquad (Kp \times Kp) \qquad (Kp \times 1)$$

Errors U_t are usually correlated, therefore errors are orthogonalized by Cholesky decomposition[12], making the covariance matrix of resulting innovations diagonal.

Note that each equation would have exactly the same regressors, thus the $Var(p)$ model is only a Seemingly Unrelated Regression (SUR) model with merely lagged variables. Since there are only lagged values of the endogenous variables on the right side of the equation, we have no problem with simultaneity and we can simply use OLS estimation (Wang and Zivot, 2006).

To interpret VAR model and examine the effects of financial stress on the macroeconomic environment in the Czech Republic, we use the method of impulse responses. The impulse responses function traces out the responsiveness to shocks of a one standard deviation (by default) to error terms of dependent variables in the VAR model. The shock directly affects the given variable and is transmitted to all other dependent variables in the model through the dynamic structure of the VAR. We can examine the intensity and length of shock on all variables in the system (Baxa, 2012).

[12] Commonly used in literature, see Holló et al. (2012).

4 Construction of the Financial Stress Index

The construction of a financial stress indicator is a complex task and there is no universal consensus, which methodology would be most suitable for identifying financial stress. A well-created index is supposed to reflect the current state of economy; however, a noisy indicator is utterly useless in monitoring the systemic risk. Adam and Benecká (2013) emphasize, that single composite financial stress indices prove important in understanding financial crises, as they allow analysing financial stress coming from different sources. Although our indicator is slightly restrictive and lacks complete information, we try to reflect vulnerabilities in the four main parts of the financial sector (banking, foreign exchange, debt and equity). We realize that underlying variables incorporated in the index may be subjected to various effects, nevertheless, we assume that the influence of financial stress is the most severe one.

The index itself is a snapshot of the present state of a financial sector, defined in the way that rising levels reflect increasing financial stress. Not all cases with elevated level of index must be accompanied by a serious financial stress period (verified on historical data). Therefore, a crucial objective is also to identify the proper threshold when FSI reaches levels that should be a concern for policymakers, and on the other hand to avoid false stress periods.

Eventhough the FSI does not predict future development of the economy, if we expect one of our indicators to change, we can make a forecast by keeping ceteris paribus condition for all other indicators and observe the evolution of the index.

To sum up, while creating the financial stress index, there are three major issues to be considered. The first problem lies in the choice of the proper underlying variables, which reflect the current state with high economic relevance. The next step describes, how these variables are supposed to be aggregated to set proper weights for each of them. Finally, to identify the period of financial stress, we have to properly determine the threshold level that serves as an early warning indicator. Answers to these questions will be provided in the following chapters.

4.1 Choice of the financial stress variables

Our selection of the underlying variables follows, to some extent, traditional indicators used in papers internationally, such as Illing and Liu (2006), Grimaldi (2010), Oet et al. (2011), Islami and Kurz-Kim (2013). However, we perform significant adjustments based on independent recommendations discussed in previous sections. Clearly, the variables are also chosen based on data availability as in the case of CEE countries, hence there is often an issue with insufficiently short time series and missing or limited data due to transformation period. Our goal was to find highly relevant data covering period of the financial crisis, and to maintain monthly frequency.

Another problem is a possibility of the contagion effect, when an abnormal event in one market affects another one substantially and causes significant deviations. This makes the whole identification of stress very difficult and has to be taken into account. Moreover, some indicators tend to reflect movements of a business cycle, therefore we have to be also wary about proper selection of underlying variables, which are not affected regularly by business cycle fluctuations (Oet et al., 2011).

We focus especially on banking sector, as this sector is the most important part of the financial system stability, as we have already mentioned. This claim is also confirmed by Cardarelli et al. (2011), who proved that financial crises accompanied by increased banking sector stress, particularly in the credit institution sector, are followed by more extensive recessions and protracted downturns than crises, which materialized from currency or debt markets. This is especially true for the countries where the credit sector dominates in the national financial system, as in the case of the Czech Republic.

Despite all the possible literature and current methodologies or criteria for selecting variables for financial stress index, the choice of the variables remains mostly arbitrary, as we are not able to capture all the linkages in the real economy (pointed out by Geršl and Heřmánek, 2006). This fact was admitted also by Hanschel and Monin (2005) and Illing and Liu (2006). Although selection may be partially limited and some information might be lost, chosen variables from various sectors together cover relatively a large part of the financial system.

Inspired by Illing and Liu (2006), we divided financial system into four sectors and chose 7 individual indicators in total from the following sectors[13]:

[13] Plots of all indicators used in our financial stress index are included in the Appendix A

Banking sector

In the majority of the current literature concerning banking stress, there is no difference between economy wide shocks and idiosyncratic shocks in banking sector. Changing credit portfolio is a good signal of elevated stress, emphasized by the fact that credit institutions are much more prudent in granting loans during the downturn period, when risk aversion and uncertainty is significantly higher. Broadly used variables are bank profits, changes in credit, bank share prices and loan losses (Illing and Liu, 2006).[14]Based on previous research, we decided to cover these[15]:

Credit gap: The deviation of credit from its trend values (a credit gap) is a convenient measure of periods of distress in the financial sector.[16] As a proxy for credit, we use total loans and receivables provided to clients. In order to determine how credit growth in the economy is positioned, we apply the Hodrick-Prescott (HP) filter[17] to capture its trend. An important feature of this indicator is that it tends to increase quickly before stress events take place; therefore, it performs very well in determining downturn periods (Borio et al., 2010). The trend is obtained by the HP filter method using a smoothing parameter lambda. We use $\lambda = 14400$, which is a commonly used value in literature. To acquire the risk component from the data, we examine the difference between the credit level and its HP trend.

Liquidity indicator: Following Islami and Kurz-Kim (2013), we use the spread between the 3M PRIBOR and the interest rate set by the Czech National Bank – CZEONIA – as our liquidity indicator.[18] The PRIBOR quoted for 3 months expresses the short-term costs of bank lending on the interbank market, whereas CZEONIA is a weighted average of the interest rates of all unsecured overnight deposits by other banks (CNB, 2001). This indicator is a reasonable measure of liquidity stress in the interbank market because the spread between the two rates increases during a downturn period when market liquidity is endangered (Oet et al., 2011). This can be

[14] We also wanted to include ratio of non-performing loans to total loans as an asset quality indicator, however it provides lagged results compared to other indicators because the ratio is updated with monthly delays. It may serve well as a backward looking indicator.

[15] An additional underlying variable capturing risk in the banking sector may be the ratio of non-performing loans to total loans. However, this asset quality indicator is backward looking and does not typically capture future risk well. An alternative in the form of loan loss provisions is not used because of data availability.

[16] Hanschel and Monnin (2005) confirm that gaps may be more suitable measures of imbalances than simple growth rates. Hilbers et al. (2005) add that the application of solely credit ratio might, in our case (as a part of CEE countries) be misleading due to the fact that rapid excessive credit growth can be also the reason of the convergence to advanced economies.

[17] For further information about the methodology, see Hodrick and Prescott (1997).

[18] For Slovakia, we use 3M BRIBOR (after 2008 EURIBOR) and SKONIA (after 2008 EONIA) instead.

explained as flight to quality, thus lowered willingness of investors to keep risky assets. Credit risk concerns tend to rise, and therefore have a crucial negative impact on the economy.

Volatility of short and long term interest rates: We use the difference between the 10Y Treasury bond yield and the short-term 3M PRIBOR rate.[19] We assume that during a non-stress period, the spread is relatively stable, while during financial stress it tends to change, increasing the volatility. This indicator expresses uncertainty in the development of interest rates, and therefore represents a threat to the profitability of financial institutions. As a measure, we use simple historical volatility.[20]

Foreign exchange sector

Foreign exchange sector represents stress based on exchange rates, depreciation of currencies or their volatility. Another important fact concerning foreign markets are spillovers, in other words transmission of financial stress among countries. As we have already stated, the Czech Republic is a financially open country and is strongly linked with the euro area, which exposes its economy to a transmission of financial volatility (Adam and Benecká, 2013).

Exchange rate volatility: Geršl et al. (2012) express doubts about the international measures, claiming that risk of contagion is about to increase, especially in the case of CEE countries, which are strongly linked with the euro area. This is also supported by the study of Adam and Benecká (2013), who discovered that transmission of financial stress from the euro area to the Czech Republic has evolved over time, and that the degree of contagion depends significantly on the level of stress in economies. In order to capture contagion effects via the exchange rate, we use the weighted historical volatility of the EUR/CZK and USD/CZK exchange rates.[21] The weights for EUR and USD exchange rates are identical, based on the average volume of total foreign exchange market turnover with these currencies in past years. Adam and Benecká (2013) use weights of 0.6 and 0.4 respectively, but changing the weights in this direction did not significantly affect the results.

[19] For Slovakia, we apply the difference of 10Y treasury bonds and 3M BRIBOR (after 2008 EURIBOR).
[20] For further information on how the historical volatility was computed see the Volatility forecast section at the end of this chapter.
[21] In case of Slovakia, we use solely the USD/EUR exchange rate.

Debt sector

Stress in debt sector is often represented by a spread in yields between risky and risk-free assets. Widening spreads indicate expectation of increasing future losses, greater uncertainty and related lower confidence, mutual lack of trust and higher dispersion of probable loss. To determine uncertainty in domestic market, representative government bonds or treasury bills are usually used as proxies, while on the corporate level we can use corporate bond spreads (Illing and Liu, 2006).

10-year Czech Government Bond and German Bund spread: High interest rates on government debt may crowd out the effects of fiscal policy on the economy and subsequently increase financial stress (Louzis and Vouldis, 2013). The German Bund, or the long-term German bond, is commonly used as a benchmark for its low credit risk premium and liquidity; moreover, the Czech economy is closely linked to Germany. Specifically, the spread between the 10-year Czech Government Bond and German Bund rates expresses market uncertainty, liquidity and the country's creditworthiness.[22] In general, boom periods are accompanied by lower spreads, while periods of financial stress are characterized by quickly widening spreads. Therefore, spreads are convenient tools for measuring the current state of the economy (Borio et al., 2010).

External debt: In emerging market economies, net external debt is important to maintain sustainable growth. However, excessive debt is perceived to have devastating effects on future economic growth. In the recent literature, external debt is often considered a potential leading indicator of financial stress, especially in developing countries (Aizenman and Pasricha, 2010). Cevik et al. (2013) use growth rate of external debt as the stress component. There is also an opinion that similarly as GDP, external debt experiences inverted U-shape relation – at first it helps the economy to recover but in higher amounts after reaching a given threshold it may pose a risk.[23] We assume that fast growth in external debt is perceived as risky and to extract the stress component, similar methodology was used as in the above mentioned credit gap indicator. However, there is only quarterly data for external debt publicly available so we interpolate them to acquire data with monthly frequency. Similarly as Cevik et al. (2013), we apply cubic spline interpolation as it is straightforward and offers stable results.[24]

[22] In terms of Slovakia we refined this indicator as the spread between 10Y Slovak Government bonds and 10Y European Area bonds.
[23] See Kuznets curve and relation of change GDP to inequality.
[24] For further information about methodology, see McKinley and Levine (1998).

Equity sector

Equity sector is often represented by diversity on stock market. Convenient measures of stress are turnover ratios, trading volume or volatility of stock prices.

Volatility of the PX Stock Exchange Index: The PX index is the official price index of the Prague Stock Exchange, and it represents a sound measure of the profitability of the share market in the Czech Republic. Therefore, we decided to include the volatility of the PX index as one of our underlying variables.[25] Index calculation is based on the International Finance Corporation methodology which is recommended for construction of indices in emerging economies. The index was launched in April 1994 and the value was fixed at 1000 points. It consists of the most influential companies which are quoted on the Czech market, dividend yields are not included. We assume that higher volatility represents higher risk and we estimate the conditional volatility using a *GARCH (1,1)* model. The main reason is that it suitably accounts for volatility clustering, which is typical of stock markets.

4.1.1 Volatility forecast

To estimate volatility of the PX Stock Exchange index, we apply two approaches and compare them. In the first approach, we compute historical volatility, common and straightforward measure of volatility. We estimate variance as squared difference of two adjacent rolling log-prices (mean corrected values). Merton (1980) showed that accuracy of estimated volatility with the use of historical volatility is rising with sampling frequency. In our case we deal only with monthly data, and to confirm our results, we decided to compute conditional volatility as well.

The second approach is more robust. First we obtain stationary time series out of non-stationary price levels where data are first-log-differenced. Stationarity is tested by Augumented Dickey-Fuller test and we reject H_0 hypothesis of unit root with p-value close to zero, therefore no form of non-stationarity is present. Then we test for autocorrelation in residuals where in both ACF and PACF plot residuals are significant. Additionally, we test *ARCH effects* where we reject the null hypothesis of *no arch effect presented*.[26] Due to heteroscedasticity in our data, we compare several different *ARCH* and *GARCH* models while *GARCH (1,1)* fits best for both Czech and

[25] In the case of Slovakia, we use SAX index computed by the Bratislava Stock Exchange.
[26] We obtain the same results in case of Slovakia.

Slovak case. [27] The *GARCH (1,1)* model is generally considered the most common for financial applications. [28]

Its form is as follows:

$$a_t = \sigma_t \epsilon_t \tag{4.1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4.2}$$

where a_t is a mean corrected return($a_t = r_t - \mu_t$), ϵ_t is a random variable with a strong white noise process and it holds that $\alpha_1 + \beta_1 < 1$. Clearly, large previous shocks in return and volatility in period $t-1$ are also affecting volatility in period t, therefore volatility clustering is well captured. After estimation of the model and its residuals comes the last step to predict conditional volatility recursively by 1-step ahead forecast:

$$\sigma_t^2(1) = \alpha_0 + \alpha_1 a_t^2(0) + \beta_1 \sigma_t^2(0) \tag{4.3}$$

$$\sigma_t^2(2) = \alpha_0 + \alpha_1 a_t^2(1) + \beta_1 \sigma_t^2(1) \tag{4.4}$$

$$\sigma_t^2(n) = \alpha_0 + \alpha_1 a_t^2(n-1) + \beta_1 \sigma_t^2(n-1) \tag{4.5}$$

where n is number of observations, $\alpha_0, \alpha_1, \beta_1$ are estimated parameters, a_t^2 are residuals and as $\sigma_t^2(1)$ we took the historical volatility computed in the first approach.

Results obtained by both approaches are much the same and therefore, for further computation, we use those estimated by *GARCH (1,1)* as it accounts well for volatility clustering that is typical for price development in that case.

4.2 Threshold identification

It is important to note that not all cases with elevated index values must be accompanied by a period of serious financial stress (as verified ex post based on historical data). We set a certain threshold to visually distinguish a level, above which financial stress should represent a concern.[29] It is noteworthy that a critical level of

[27] Ad. *GARCH (1,1)* model selection, although *GARCH (2,1)* and *GARCH (2,2)* have slightly higher log likelihood statistic, we opted for *GARCH (1,1)* due to the fact that all coefficients were significant whereas in *GARCH (2,1)* and *GARCH (2,2)* were not.

[28] All tests and plots are included in the Appendix B.

[29] Computed threshold level is created solely for data visualisation purpose, we do not use it later on in our models.

financial stress does not necessarily mean that economy is experiencing a financial crisis, yet ideally it may serve as an early warning indicator.

Following Cardarelli et al. (2011), we set the threshold in two steps. In the first step, we estimate the long-term trend using the HP filter (with lambda 14400 for monthly data). In the second step, we add a constant to the long-term trend. The constant is calculated as a half of the standard deviation of the financial stress series. Contrary to Cardarelli et al. (2011), who use one standard deviation, we prefer rather conservative approach to avoid underestimating of a potential risk, since estimations can significantly worsen during periods of emerging risks.

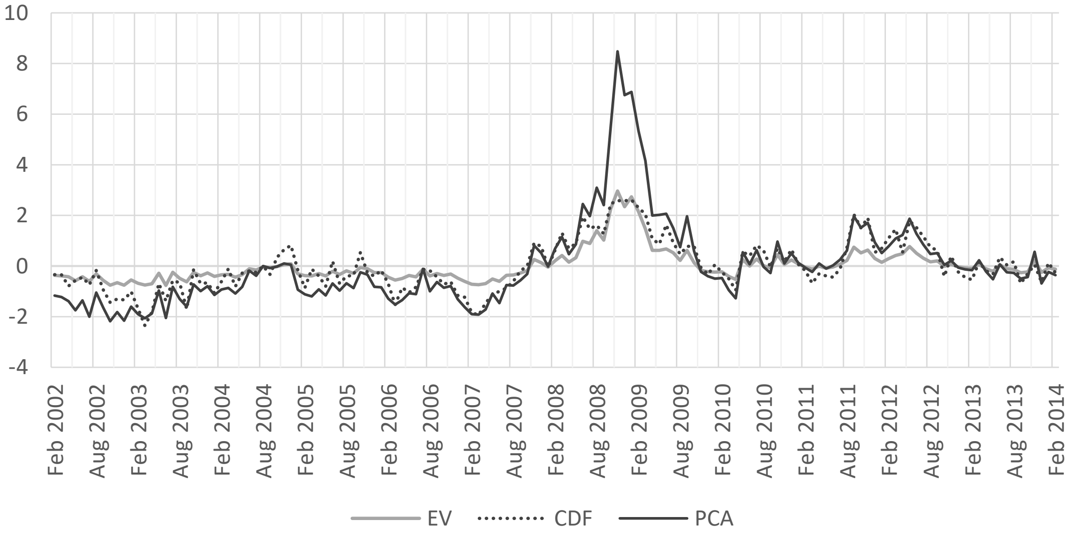
However, the approach is sensitive to extreme observations (e.g., the global financial crisis in 2008), which can neglect previous significant periods of financial stress. According to Krzak et al. (2014), this issue may be partially solved by using percentile measures instead of deviation from the mean. A stressful period can be defined as an event wherein the FSI reaches a value above a specific percentile for the whole sample, and therefore, extreme observations will affect the threshold selection to a lesser degree. In addition, the threshold should be always revised with respect to specific historical events of financial stress.

5 Empirical results

In the following section we present our financial stress index for the Czech Republic followed by Slovakia. Then we estimate vector autoregression models for both countries and examine the effects of financial stress on the real economy.

5.1 Financial Stress Index

Figure 5.1: Czech Republic: Comparison of different aggregation methods



Source: author's calculation

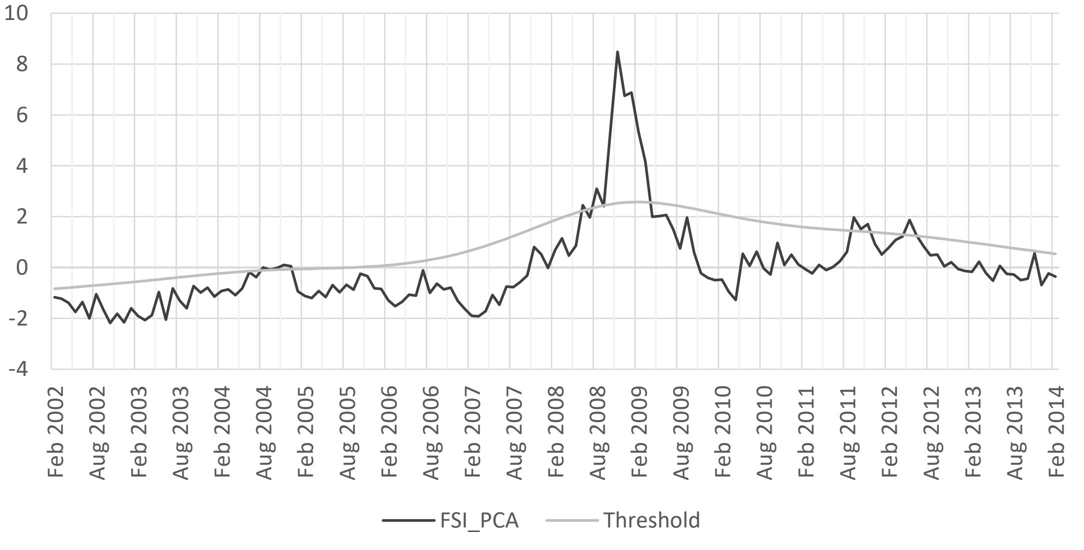
Note: EV represents equal variance aggregation, CDF is cumulative density function and PCA stands for principal component analysis.

The Figure 5.1 shows estimated financial stress index values for the Czech Republic. We apply three aggregation methods: Equal Variance, Cumulative Density Function and Principal Component Analysis. Overall, different aggregation methods convey the same message even though the values somewhat differ around the fall of Lehman Brothers in October 2008. According to our results, the most intense period of stress occurred in 2008, although we also observe mild increase in stress in late 2011 and the first half of 2012. In addition, we observe the lowest values of stress in 2007 before the outbreak of the financial crisis. The Czech economy had been growing rapidly before the crisis, inflation was typically not far from the inflation target, and the financial sector had been considered largely stable.

The difference of the PCA method compared to the other two indices during late 2008 is caused by the extreme stock market volatility (PX index) at the time. PCA gives a higher importance to observations with higher volatility. For this reason, when examining the effect of financial stress on macroeconomy within the vector autoregression model, we check whether the results depend on the choice of financial stress index. As we show below[30], the results remain unchanged no matter which index we use.

The correlation among all three indices is quite high (at minimum 0.88), thus it is not so surprising that the impulse responses give us similar results. This finding largely corresponds to Illing and Liu (2006), who find a limited effect of different aggregating methods on the resulting indices. However, due to the space limitation, we decided to present the threshold and vector autoregression results only with the index performed on PCA approach mainly due to its conservativeness, while the other VAR results are included in the Appendix E.

Figure 5.2: Czech Republic: Financial stress Index and the threshold level



Source: author's calculation

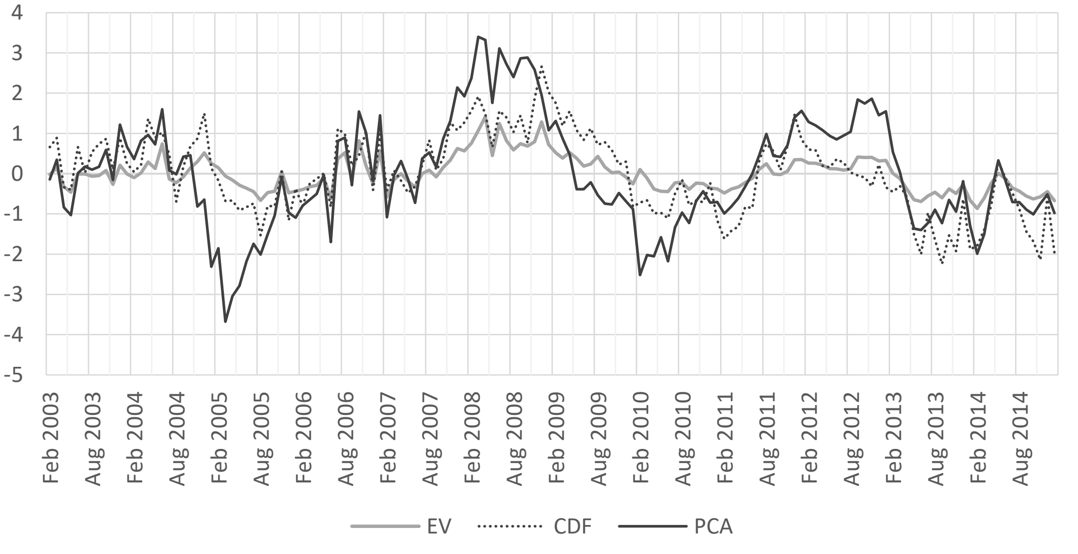
The threshold level in the Figure 5.2 separates the most intensive episodes of financial stress located above the threshold level. The more the values of FSI deviate from the historical average that is equal to zero, the higher or lower stress is expressed by the index. We may claim that periods, which are persistently under the historical average, are subjected to higher probability that financial stress will rise considerably in the following periods.

Babecký et al. (2013) develop a database of banking, debt and currency crises for 40 EU and OECD countries during 1970–2010. According to their results, there was no banking, debt or currency crisis in the Czech Republic during 2000–2014. It is worth

[30] See testing of robustness at the end of the chapter 5.3

mentioning that their findings are broadly consistent with our results. Episodes that are selected according to our threshold criterion do not necessarily escalate into the crisis but may pose a significant risk for the economy and shall serve as a warning.[31]

Figure 5.3: Slovakia: Comparison of different aggregation methods

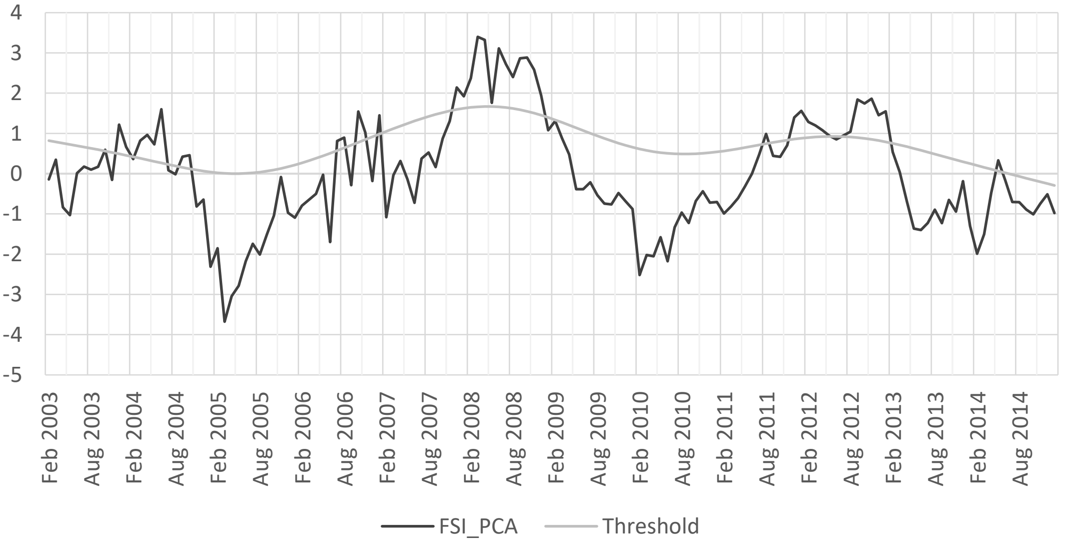


Source: author's calculation

Next, in Figure 5.3 we present financial stress index for Slovakia. As for the Czech Republic, we apply three aggregation methods and observe comparable results. According to our index, financial stress was at its highest during the second quarter of 2008 and later during 2012. Prior to the crisis we observe similarities with the Czech Republic being under the average level of financial stress in the economy. Development of domestic economy was exceptionally favourable in 2007. Because of the positive contribution of domestic and foreign demand, economic growth experienced maximum levels with inflation below 2% (NBS-FSR, 2007).

[31] Period of heightened financial stress during 2008-2009, which was identified according to our threshold criterion, was truly perceived as a recession. Commonly used definition of recession is when economy experience two consecutive quarters of declines in GDP (FRBS, 2007), as was fulfilled in the case of the Czech Republic.

Figure 5.4: Slovakia: Financial stress index and the threshold level



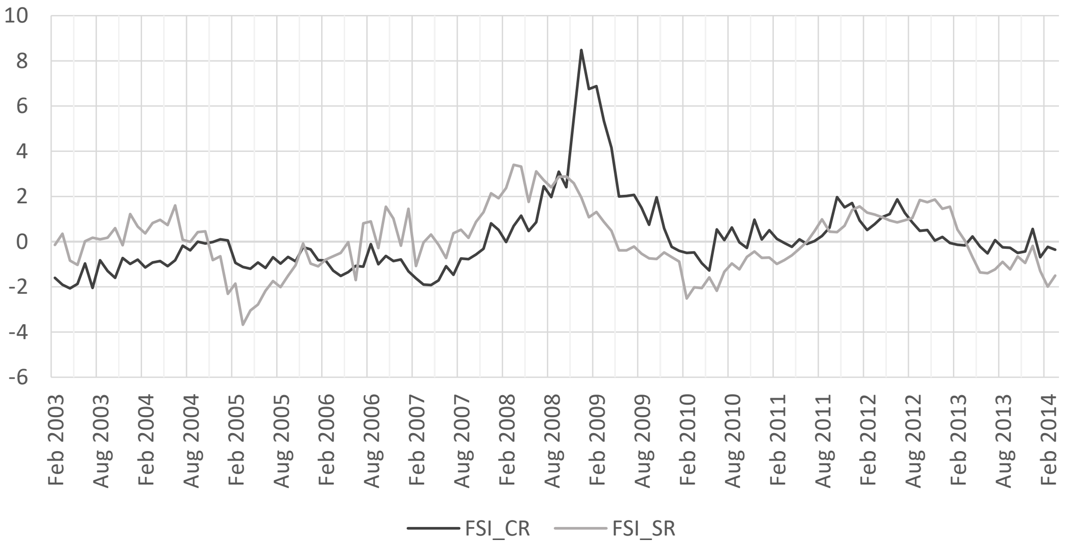
Source: author's calculation

The figure 5.4 shows computed threshold level for Slovakia separating periods with heightened financial stress. These results are largely in line with Financial Stability reports of Slovakia. Detailed description for both Czech and Slovak financial stress indices focused particularly on episode of the Global financial crisis continues in the following chapter.

5.2 Historical analysis of financial stress indices

Our index operated very well for both countries at the beginning of the Global financial crisis, where it accurately captured financial difficulties of the Bear and Sterns bank in Q1 2008. Later on we can clearly see an abrupt increase of financial stress in both cases, when US investment bank Lehman Brothers collapsed on 15 September 2008. The following day credit rating downgrades triggered fear of insolvency in the USA, which resulted in the global collapse of prices in the stock market during 6-10 October 2008. The fall of Lehman Brothers caused lack of confidence that was spilled among emerging economies and their currencies started to weaken, thus exchange rate volatility increased significantly at that time. Pressure significantly intensified at the end of 2008 where we observe the most intense episodes of financial stress in the both economies (CNB-FSR, 2009). A mild rise in the financial stress at the end of Q3 2009 depicts an increase in financial risk related to the fiscal deficits and public finance in Greece (NBS-FSR, 2009). According to our results, financial stress started more intensively in Slovakia, closely followed by the Czech Republic, although the Czech Republic was later on impacted with a considerably higher intensity.

Figure 5.5: Comparison of financial stress indices



Source: author's calculation

Although the Czech economy entered the global financial crisis and the following recession in a good financial health, it was not possible to avoid impacts of the crisis. The domestic financial sector started to be moderately affected by the fiscal reform and changing in monetary policy during 2007 (CNB-FSR, 2007). Industrial and export orientation along with open economy resulted in the fall in external demand, which led to decrease in industrial production followed by GDP. Economy got in recession in the Q4 2008 and by Q1 2009 its total output dropped by 4.1% compared to the previous quarter. A weak improvement was based on partial recovery in external demand and began in the second half of 2009 where we can see the steep decline in financial stress (CNB-FSR, 2010).

Initially, the economy and financial system in Slovakia were not considerably affected by the adverse events stemming from external environment. Moreover, analyses have not proved in any way that mortgage crisis may pose any serious direct or indirect risk for financial stability. However, due to widely open Slovak economy, financial sector could not remain unaffected. The first signals came in August and November 2007 with only a limited influence on domestic market (NBS-FSR, 2007). The influence was apparent in November and December 2008 when domestic industrial production and exports abruptly slumped. In 2008, the net profit of the banking sector dropped by almost 10% year-on-year basis. By the end of 2008, the total amount of non-performing loans increased by 29%; additionaly, the loan-to-deposit ratio dropped to 79% (NBS-FSR, 2008). Entry into the euro area in January 2009 had a profound effect on the domestic interbank market. Introduction of euro along with ongoing financial crisis had a substantial impact on banking profitability that fell year-on-year by more than 50%, moreover, it revealed another potential channel for the transmission of risk from the afflicted euro area. High uncertainty on international financial market persisted until March 2009, when extensive measures were taken by national governments and central banks. These external factors led to a contraction of Slovak economy in 2009, affecting industrial performance with GDP contracted by 4.7%. 2009 was the worst year for the Slovak banking sector since bank restructuring in 2000-2001. (NBS-FSR, 2009).

Significant increase in both indices during Q2-Q3 2010 seemingly came about due to the first financial rescue of Greece economy. Following relatively substantial recovery, global economy witnessed a moderate slowdown in the second half of 2011(CNB-FSR, 2012). At the end of September 2011 we observe in both the Czech and Slovak Republic a considerable rise in financial stress, particularly in regard to the euro area sovereign debt crisis. The acceleration of the debt crisis and concerns about public debt sustainability in several countries led to a sharp increase of financial market volatility in the second half of 2011 (NBS-FSR, 2011).

The growth of the Czech economy during 2011 slowed down and started stagnating. Increased credit risk and concerns of clients about capabilities of financial institutions to repay debts negatively affected the loan market. At the end of 2011, concerns persisted and even increased, so that protective policies took place but they even worsen availability of loans for the private sector (CNB-FSR, 2011). Economy growth was negatively affected and peaked at the end of Q2 2012 (CNB-FSR, 2012). Moderate increase in households' demand for loans was observed in the beginning of 2013. Restrained recovery appeared in Q2 and Q3 together with increased industrial production by 0.5% in Q3 and GDP growth in Q4 2013. Performance of the non-financial corporations was steadily increasing, and financial sector similarly experienced mostly positive development during 2013 (CNB-FSR, 2014).

Throughout the year 2010 and the first half of 2011, Slovak economy performed favourably. However, the second half of the year was affected by elevated pressure stemming from a number of countries that are significant recipients of Slovak exports. Domestic financial stability was further deteriorated by the fall of the Slovak Government in October 2011. The whole sitation in Slovakia at the time was perceived as serious as the collapse of Lehman Brothers in 2008 – that is apparent also from the development of the financial stresss index (NBS-FSR, 2011). During 2012, the economic situation in Slovakia was still fragile with prevailing credit risk in banking sector and uncertainty about future development of government debt (NBS-FSR, 2012). During the first half of 2013, both domestic economy and the euro area recovered, however, the risk that could lead to renewed financial turmoil was still present. Despite a downturn in economic growth in 2012, there was no further increase in non-performing loans (NBS-FSR, 2013). The situation in financial sector improved during 2014, mainly due to positive development in domestic economy. Economic growth was driven by increasing domestic consumption, industrial production and fall in unemployment (NBS-FSR, 2014).

5.3 Does financial stress have an effect on the real economy?

Previous research suggests that financial variables or financial stress have systematic effects on the real economy and that financial variables interact strongly. For instance, Hakkio and Keeton (2009) found out that an increase in financial stress resulted in more prudent behavior of credit institutions and a decrease in total loans granted, which consequently slowed economic activity in the United States. Havránek et al. (2012) examined links between financial variables and macroeconomy using block-restriction autoregression models based largely on pre-crisis data for a different set of variables rather than a financial stress index. Cardarelli et al. (2011) showed that financial stress is not always a predecessor of financial instability, and Li and St-Amant (2010) discovered that effects of monetary shocks on economy differ depending on the intensity of financial stress. Estimating a VAR model using our newly developed financial stress index is also important to examine whether the index conveys useful information and, therefore, to indirectly determine whether the index values are sensible.

In the scope of the thesis, we use VAR to examine the effects of financial stress on the macroeconomic environment in the Czech Republic. Advantages of using VAR are its simple estimation and implementation often leading to better results than theory-based systems of simultaneous equations. Moreover, there is no need for binding constraints imposed by economic theory, although there is no proper theory to choose appropriate variables (Baxa, 2012). To analyse how the selected key macroeconomic variables response to the shock in financial stress that is represented by our financial stress index, we apply the method of impulse responses.

We choose four macroeconomic variables to describe economic activity in our VAR system and order them as follows: *unemployment, inflation rate, interest rates, and financial stress index*.[32] This specification is broadly in line with previous research,

[32] Unemployment is expressed as the general rate of unemployment for those between the ages of 15 and 64 years. Inflation rate is calculated as the percentage rate of consumer price index change during

such as Borys et al. (2008) or Havránek et al. (2012).[33] The ordering is typical of studies that examine macroeconomic variables and order the variables, which do not react contemporaneously to shocks from other variables in the system (Stock and Watson, 2001). For example, our ordering implies that we assume that unemployment does not react contemporaneously to shocks from the interest rates but not *vice versa*.

We assess the stability of our VAR systems based on characteristic roots of inverse polynomial. VAR system is stable if absolute value of all roots (a number of lags multiplied by a number of variables) is less than one – they lie inside the unit circle. Formally y_t is stable if [34]

$$det(I_k - A_1 z - \ldots - A_p z^P) \neq 0 \text{ for } |z| \leq 1 \tag{4.3}$$

We find our VAR system stable (for both models); therefore, we estimate VAR in levels and do not transform it into the first differences. In acordance with suggestions of Sims et al. (1990), we do not impose possible cointegration relations explicitly.

Optimal lag length was derived according to the following tests. The first *Lag length criteria* test is based on selection of the maximum lag and then testing all lags up to the stated value, computing several information criteria (sequential modified LR test statistics, Final prediction error, then Akaike, Schwarz and Hannah-Quinn information criterion). We have chosen two lags for both countries mainly according to the Schwarz criterion that is known to perform more accurately in smaller samples (Ivanov and Kilian, 2005). The second test called *Lag Exclusion test* is based on computing the χ^2 Wald statistic for the joint significance of all dependent variables for the given lag. Results of the first test were confirmed, jointly both lags were statistically significant and therefore there is no need to exclude any lag.

If we examine correlograms, there is typically small but not significant autocorrelation, altogether less than 5% and therefore it confirms that no additional lags are needed. Regarding to the model[35], there are too many parameters estimated by the VAR model and therefore, we do not discuss the significance of each

the previous year. As a measure of interest rates, we use 3M PRIBOR published by the Czech National Bank.

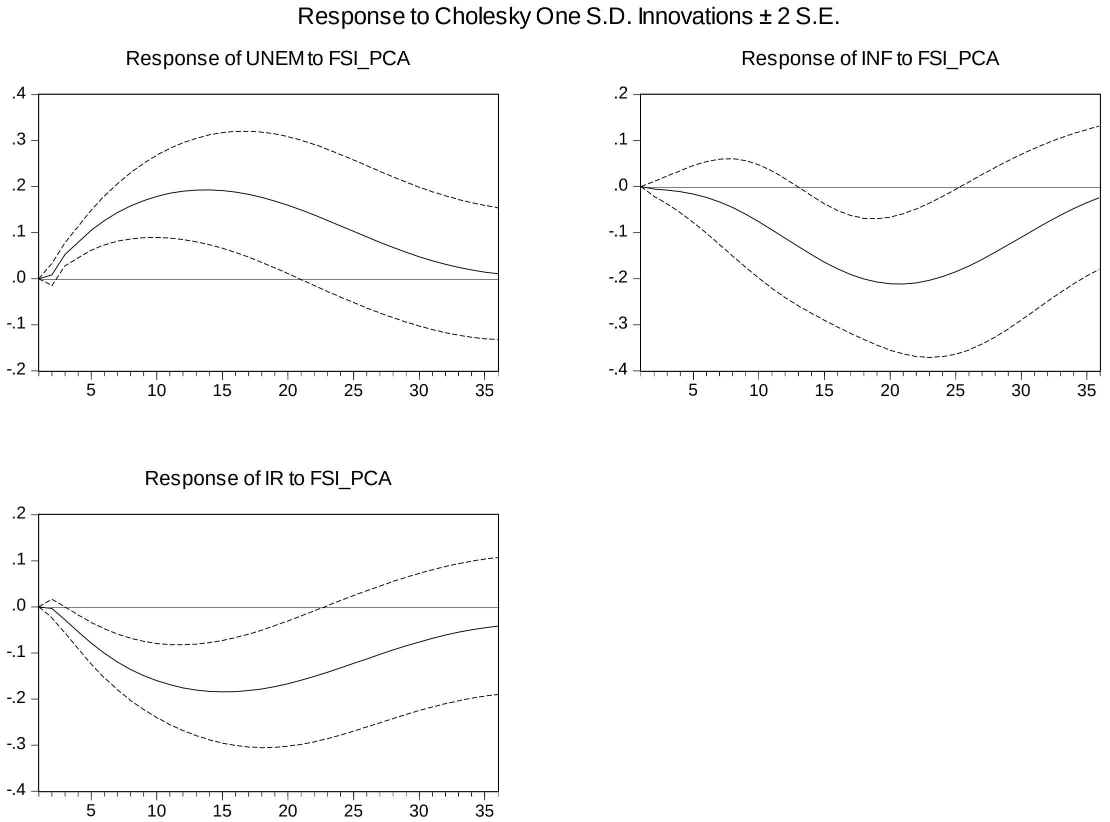
[33] We have not included GDP growth as a macroeconomic variable in our baseline specification because it is available on quarterly basis only. Unlike GDP growth, unemployment is available monthly. GDP growth would have to be transformed into monthly series using some filtering technique. Industrial production is available monthly but the share of industry is approximately 38% of GDP in the Czech Republic. Nevertheless, we conduct robustness check, where we use GDP growth instead of unemployment in the VAR estimation at the end of the chapter 5.3.

[34] See Lütkepohl (2005) chapter 2.1.1.

[35] Consider the final VAR model with FSI based on PCA.

parameter individually. Nevertheless, own lags of variables are typically significant – especially macroeconomic time series, which are known to be more persistent than e.g. financial variables. Other lags for the parameters are often significant, particularly the first lag linking the interaction between financial variables – as expected, significance is often lower with the second lag.[36]

Figure 5.6: Impulse Responses: case of the Czech Republic



Source: author's calculation

Note: FSI stands for financial stress index; UNEM for unemployment; INF for inflation; and IR for interest rates. The X-axis is in months. Dashed lines illustrate 95% standard error confidence interval.

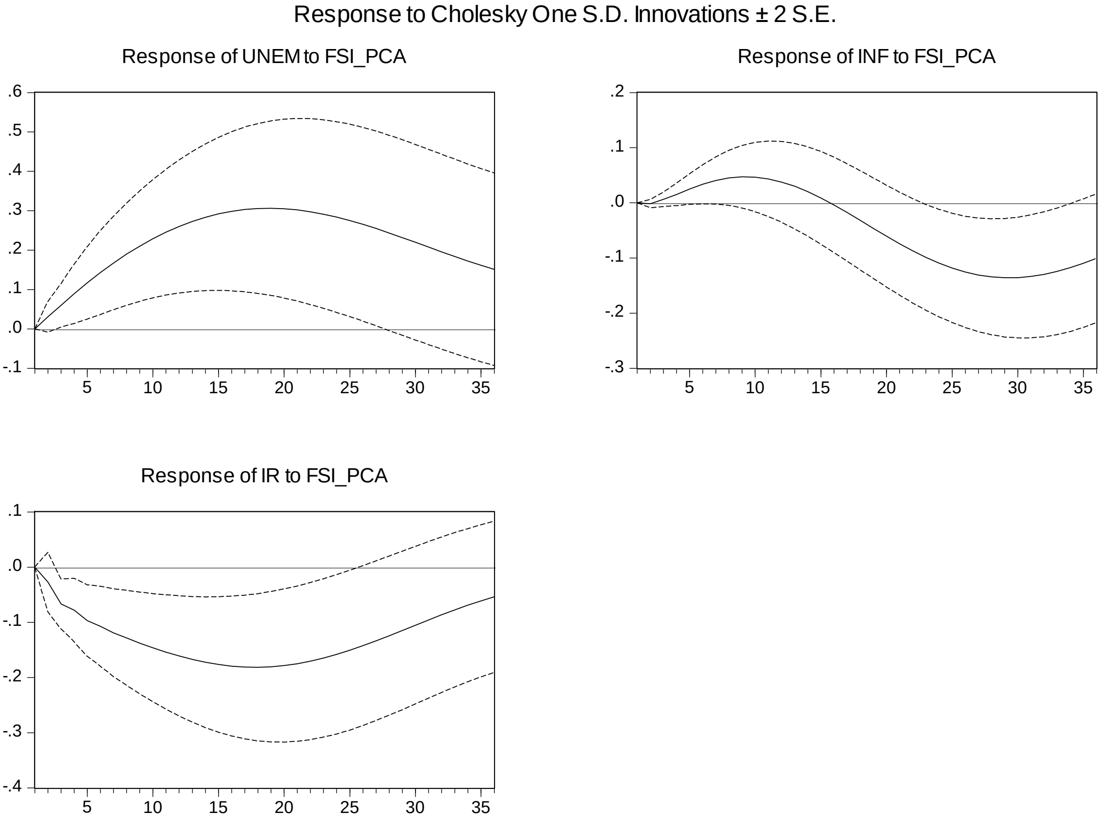
First, the Figure 5.6 shows the impulse response between the financial stress index, based on the principal components as the aggregation method, and the real economy. We can see that unemployment is rising, following unexpected increases in financial stress. The strongest effect occurs approximately one year after the shock, which is broadly in line with the results presented by Havránek et al. (2012). The minor delay at the beginning might reflect rigidity of unemployment to immediately react to the shock, which is in accordance with our expectations.

[36] All outputs are included in the Appendix C.

Next, our results suggest that prices decline during times of elevated financial stress. They show that there are significant interactions between price stability and financial stability (Horváth, 2009). For example, good historical evidence of that relationship is the notable decrease in inflation after Q4 2008, when the financial stress associated with the recession was culminating in the Czech economy. The maximum reaction of prices to financial stress appears to occur approximately two years after the shock.

Finally, we examine the reactions of short-term interest rates to financial stress. We find that higher financial stress is associated with lower interest rates. This negative response of interest rates to financial stress shock is likely a consequence of conventional monetary policy, because central banks tend to decrease their policy rates during periods of financial stress (Baxa et al., 2013). During the financial crisis, central banks used a variety of unconventional measures to support the domestic economy, but according to our results, they also used conventional measures (i.e., decreasing policy interest rates). The maximum impact on interest rates is approximately one year after the shock.

Figure 5.7: Impulse Responses: case of Slovakia



Source: author's calculation

The unemployment in the Figure 5.7 follows similar pattern as for the Czech Republic – increasing in response to unexpected rise in financial stress. The strongest effect occurs approximately one year and a half after the shock (which is a minor delay when compared to the Czech Republic) with slightly wider confidence intervals.

Heightened financial stress causes prices to slightly increase in the beginning, however, the effect is reversed approximately after one year and a half and prices start to decline with the maximum effect two years and a half after the initial shock. The rise in the beginning may be caused by a delayed response of inflation on elevated financial stress. Nevertheless, our results confirm significant connection between price and financial stability.

Last, we realize that short-term interest rates follow converse effect to increased financial stress, descending and bottom out after approximately one year and a half since the shock. We believe that according to the situation in the Czech Republic, the fall in interest rates is largely influenced by tightening central bank policy.

In conclusion, all results in relation to both the Czech and Slovak Republic are statistically significant and address the same message. To check the stability of our model, we perform the following robustness checks (for both cases): First, to generate financial stress index we estimate an identical VAR model, although with different aggregation method. Instead of principal components, we include 1) equal variance and 2) cumulative density function method one after the other into our VAR model. The impulse responses based on these two other methods yield almost identical results to those obtained by the principal components method.

Next, we estimate bivariate VAR model separately for each macroeconomic variable in order to analyse direct effect of financial stress on the economy and compare it with our current model. Unlike bivariate model, standard VAR jointly estimated with all lagged variables acquires comovements that cannot be detected by a simple univariate or bivariate model, and therefore the results are incomplete or biased (Stock and Watson, 2001). However, the bivariate model serves as a good benchmark if there is one equation wrongly specified and may bias the whole system. When comparing both bivariate and standard models for unemployment and interest rates, we observe largely similar results regarding to the shape and timing except the inflation where we examine lagged pattern with wider confidence intervals.

In addition, we check our VAR model with GDP growth[37] substituted instead of unemployment. The resulting impulse responses are similar from the economic point, but the confidence intervals for the GDP growth are larger. While estimating impusle responses, we also compare the Asymptotic and Monte Carlo approaches regarding a response of standard errors. We find results to be almost analogous, although confidence bands are sligthly wider with the Monte Carlo approach.

In the case of Slovakia, we additionally included test for structural break due to the entry into the euro area in January 2009. The results suggest that there is no significant effect of structural break in our data. Resulting impulse response functions are significant, following similar patterns, though with lesser effect on underlying macroeconomy variables compared to the standard model.[38]

[37] Similarly, as for external debt data for GDP growth is available only quarterly, therefore we apply cubic spline interpolation to obtain monthly data.
[38] Robustness tests for both models are available in the Appendix E.

6 Conclusion

The recent financial and economic crisis illustrated the strong relationship between financial stress and economic activity and emphasized the necessity to develop early warning mechanisms. A number of papers have developed financial stress indices, but only a few have been designed for Central European countries, such as the Czech Republic. We contribute to this literature by estimating a financial stress index for the Czech and Slovak Republic and examining the effects on the real economy. The advantage of the financial stress index is that it combines many underlying financial factors into a simply interpreted and comparable measure, assessing information from various sectors concurrently at any given point in time.

This article compares different methods of assessing financial stress, analyzing the Czech economic environment and, subsequently, constructing a financial stress index tailored to the environment of the Czech Republic. Although the financial stress index is designed particularly for the Czech Republic, we test its robustness by applying it on the environment of Slovakia, assuming that economic conditions are similar. Furthermore, an indicative threshold level is conservatively determined to identify serious levels of financial stress that may be concern for policymakers.

Our financial stress index identifies the episodes of heightened financial stress during 2008-2009 global financial crisis and 2011-2012 European sovereign debt crisis for both countries. Interestingly, the financial stress index decreases to nearly pre-crisis levels soon afterwards. Overall it provides valuable information about economic activity. Vector autoregression model confirms that financial stress has systematic effects on real economy. Specifically, for the Czech Republic, we find that higher stress is associated with higher unemployment, lower prices and lower interest rates, and that the maximum responses of these variables to financial stress occur approximately one to two years after the shock. In the case of Slovakia, we get very similar results in terms of shape, with lagged effect on underlying macroeconomy variables reaching the maximum impact between one year and a half and two years and a half after the shock.

These results are robust to the choice of aggregation scheme for our financial stress index. We use three different aggregation methods to generate the index and find that the impulse responses from the vector autogression model are almost identical regardless of a financial stress index we use. Furthermore, we perform additional robustness checks including structural break test and find our model stable.

In terms of future research, it would be worthwhile to extend the index to include more financial indicators, such as dividends paid, credit default swaps or corporate bonds, to further test the robustness of this financial stress index. It would also be interesting to examine the forecasting performance of financial stress indices or to evaluate the effects of financial stress in non-linear and time-varying econometric frameworks.

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Appendix A: FSI indicators

Figure A.1: Czech Republic – FSI indicators

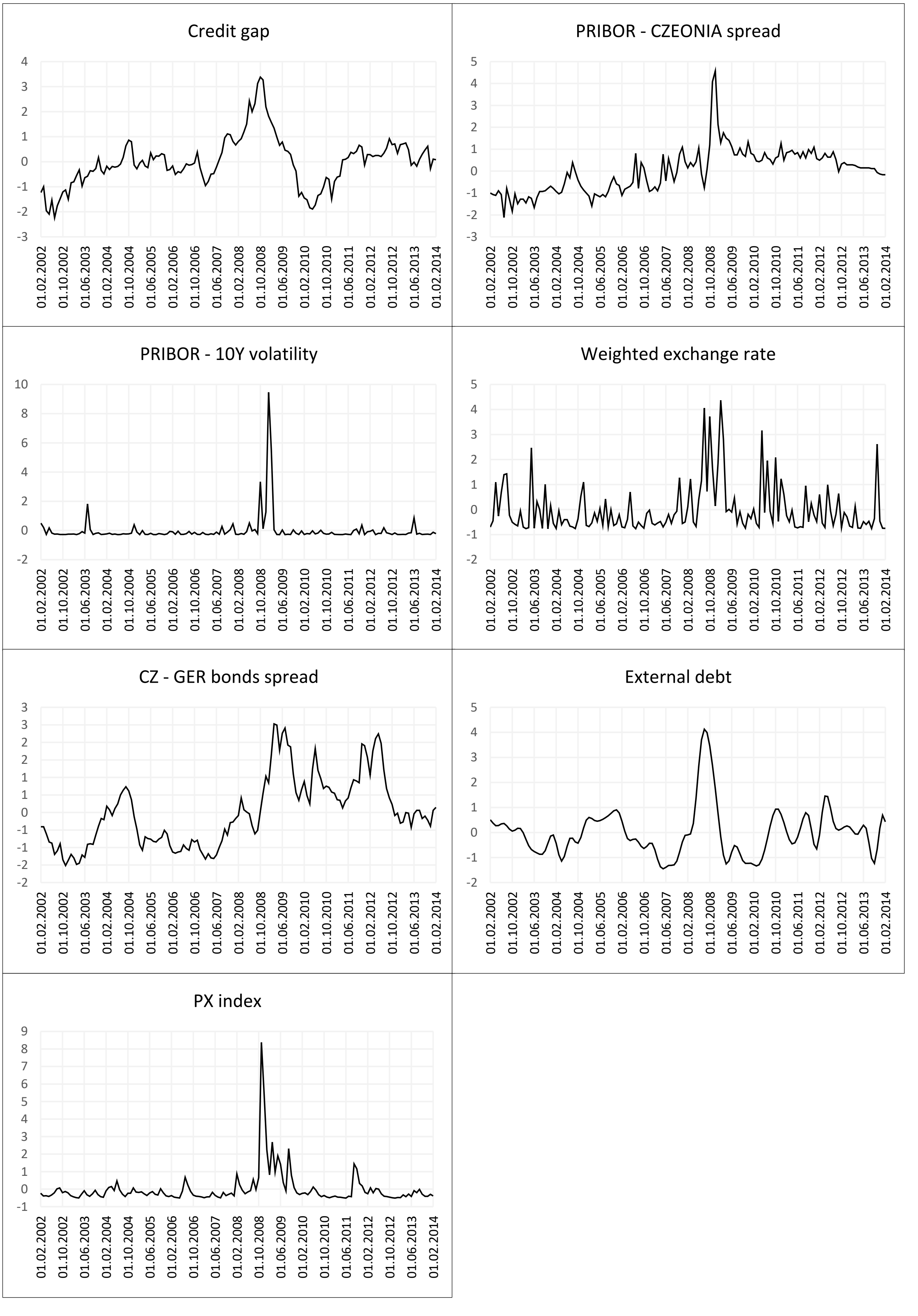
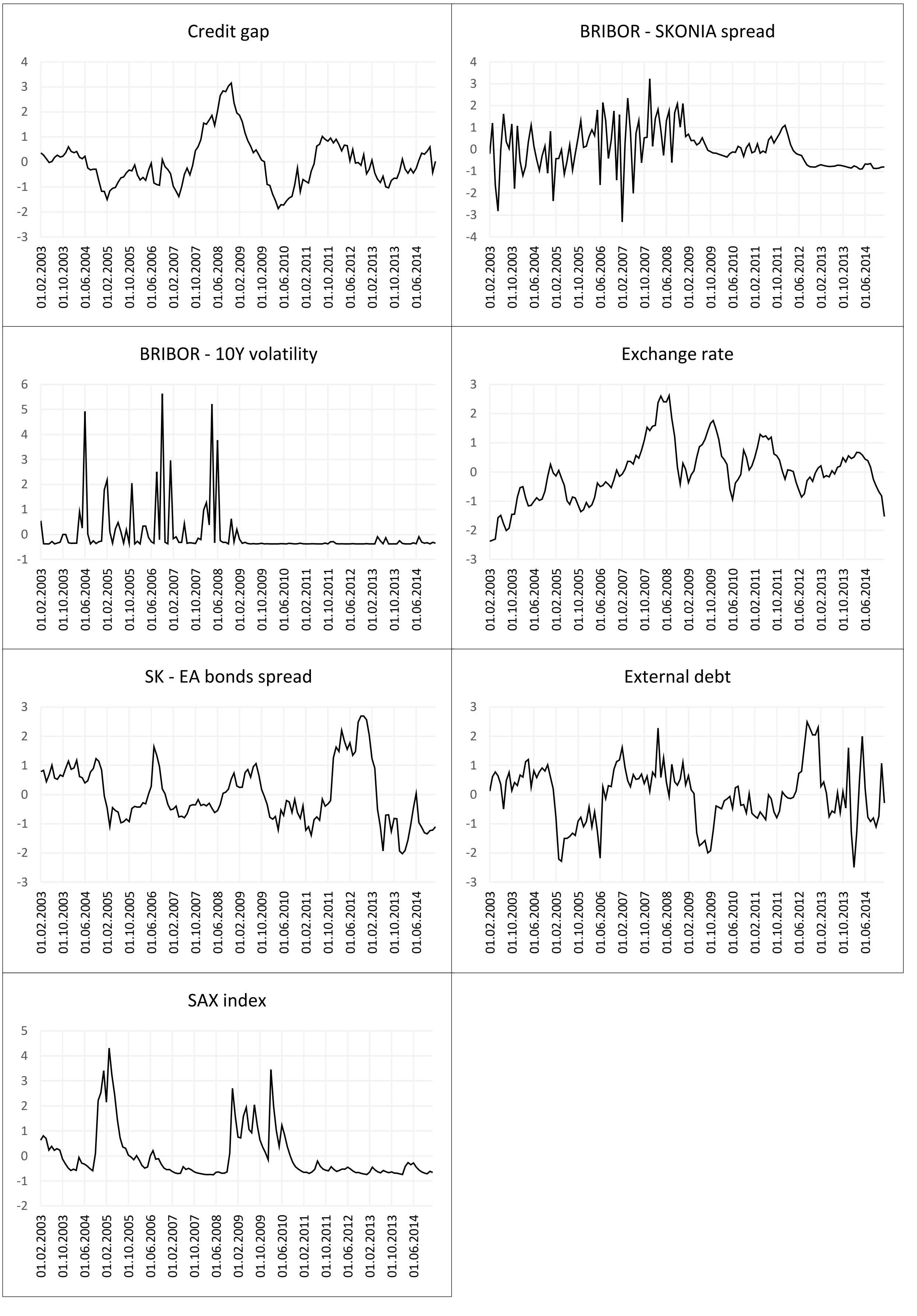


Figure A.2: Slovak Republic – FSI indicators



Appendix B: Conditional volatility tests

Case of the Czech Republic

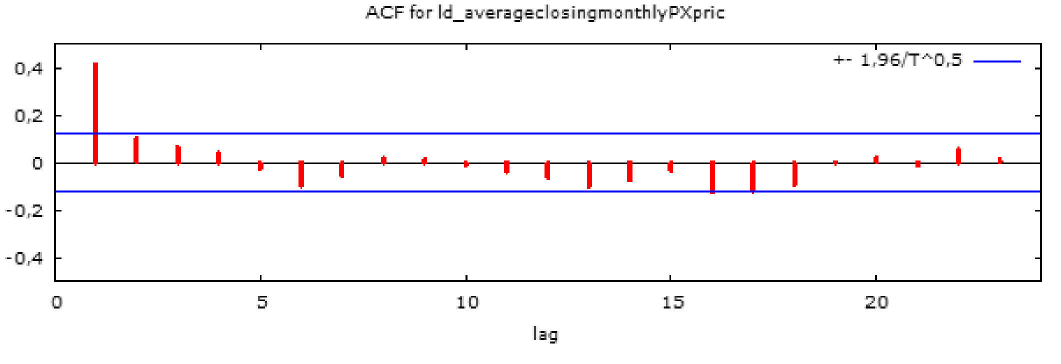
Table B.1: Augumented Dickey-Fuller test for unit roots

AUGMENTED DICKEY-FULLER TEST FOR LD_AVERAGECLOSINGMONTHLYPXPRIC
INCLUDING 9 LAGS OF (1-L)LD_AVERAGECLOSINGMONTHLYPXPRIC
(MAX WAS 15, CRITERION MODIFIED AIC)
SAMPLE SIZE 238
UNIT-ROOT NULL HYPOTHESIS: A = 1

TEST WITH CONSTANT
MODEL: (1-L)Y = B0 + (A-1)*Y(-1) + ... + E
1ST-ORDER AUTOCORRELATION COEFF. FOR E: -0,001
LAGGED DIFFERENCES: F(9, 227) = 1,782 [0,0726]
ESTIMATED VALUE OF (A - 1): -0,584855
TEST STATISTIC: TAU_C(1) = -4,41854
ASYMPTOTIC P-VALUE 0,0001

WITH CONSTANT AND TREND
MODEL: (1-L)Y = B0 + B1*T + (A-1)*Y(-1) + ... + E
1ST-ORDER AUTOCORRELATION COEFF. FOR E: -0,001
LAGGED DIFFERENCES: F(9, 226) = 1,770 [0,0749]
ESTIMATED VALUE OF (A - 1): -0,58631
TEST STATISTIC: TAU_CT(1) = -4,41152
ASYMPTOTIC P-VALUE 0,002043

Figure B.1: ACF and PACF function



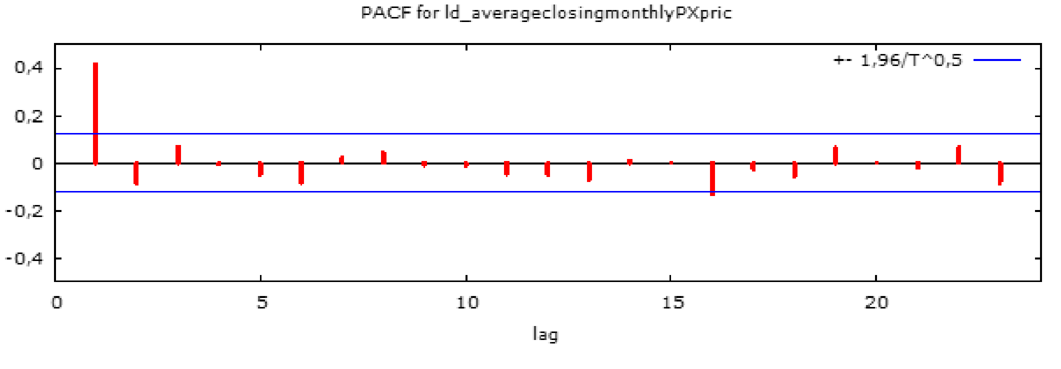


Table B.2: ARCH effect test

```
TEST FOR ARCH OF ORDER 2
         COEFFICIENT   STD. ERROR    T-RATIO    P-VALUE
 --------------------------------------------------------
 ALPHA(0)  0,00262516   0,000670999   3,912   0,0001   ***
 ALPHA(1)  0,0566941    0,0375274     1,511   0,1322
 ALPHA(2)  0,287102     0,0373862     7,679   3,90E-013 ***

 NULL HYPOTHESIS: NO ARCH EFFECT IS PRESENT
 TEST STATISTIC: LM = 53,3568
 WITH P-VALUE = P(CHI-SQUARE(2) > 53,3568) = 2,59249E-012
```

Table B.3: GARCH tests

MODEL	ARCH (1)		ARCH (2)		GARCH (1,1)		GARCH (2,1)		GARCH (2,2)	
	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE
INTERCEPT	0,0028272	7,29E-15	0,0023558	2,69E-13	0,0008565	0,0068	0,0008845	0,0035	0,0008398	0,4095
ALPHA (1)	0,558083	5,21E-05	0,471648	3,85E-05	0,388125	0,0002	0,426504	0,0001	0,315059	0,0011
ALPHA (2)			0,104944	0,0266					2,58E-12	1
BETA (1)					0,463505	3,33E-05	0,210491	0,0763	0,323413	0,7348
BETA (2)							0,205407	0,069	0,175594	0,6821
LOG LIKELIHOOD	320,2207		329,5829		334,3325		335,7923		335,054	

Case of the Slovak Republic

Table B.4: Augumented Dickey-Fuller test for unit roots

```
AUGMENTED DICKEY-FULLER TEST FOR D_L_PRICE
INCLUDING 3 LAGS OF (1-L)D_L_PRICE
(MAX WAS 14, CRITERION AIC)
SAMPLE SIZE 185
UNIT-ROOT NULL HYPOTHESIS: A = 1

 TEST WITH CONSTANT
 MODEL: (1-L)Y = B0 + (A-1)*Y(-1) + ... + E
 ESTIMATED VALUE OF (A - 1): -0,403385
 TEST STATISTIC: TAU_C(1) = -4,15185
 1ST-ORDER AUTOCORRELATION COEFF. FOR E: 0,013
 LAGGED DIFFERENCES: F(3, 180) = 6,354 [0,0004]
ASYMPTOTIC P-VALUE 0,0007927

 WITH CONSTANT AND TREND
 MODEL: (1-L)Y = B0 + B1*T + (A-1)*Y(-1) + ... + E
 ESTIMATED VALUE OF (A - 1): -0,437857
 TEST STATISTIC: TAU_CT(1) = -4,32707
 1ST-ORDER AUTOCORRELATION COEFF. FOR E: 0,013
 LAGGED DIFFERENCES: F(3, 179) = 5,778 [0,0009]
ASYMPTOTIC P-VALUE 0,002794
```

Figure B.2: ACF and PACF function

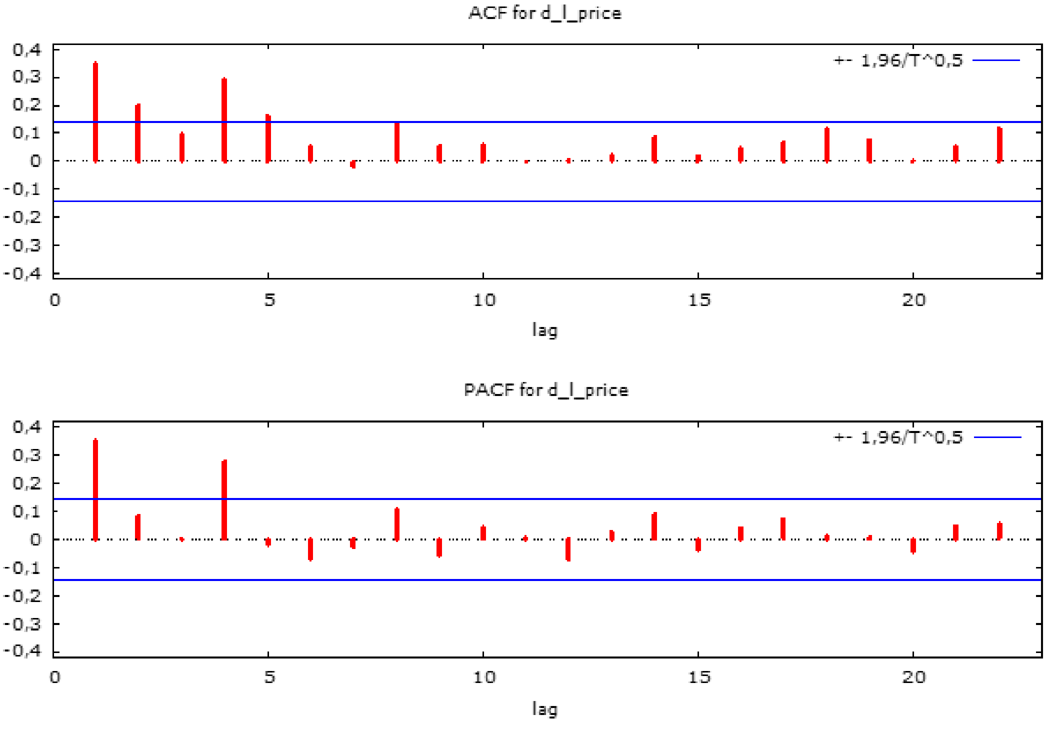


Table B.5: ARCH effect test

```
TEST FOR ARCH OF ORDER 3

           COEFFICIENT   STD. ERROR    T-RATIO   P-VALUE
 --------------------------------------------------------
 ALPHA(0)  0,00112311   0,000313355  3,584    0,0004  ***
 ALPHA(1)  0,0841147    0,0713217    1,179    0,2398
 ALPHA(2)  0,0310820    0,0714535    0,4350   0,6641
 ALPHA(3)  0,200656     0,0713079    2,814    0,0054  ***

 NULL HYPOTHESIS: NO ARCH EFFECT IS PRESENT
 TEST STATISTIC: LM = 9,99668
 WITH P-VALUE = P(CHI-SQUARE(3) > 9,99668) = 0,0185944
```

Table B.6: GARCH tests

MODEL	ARCH (1)		ARCH (2)		GARCH (1,1)		GARCH (2,1)		GARCH (2,2)	
	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE
INTERCEPT	0,00119814	1,59E-09	0,00103911	2,50E-06	0,00015	0,0350	0,000156703	0,0463	0,000170	0,3464
ALPHA (1)	0,491839	0,0070	0,429543	0,0114	0,31058	0,0061	0,387943	0,0021	0,280772	0,0096
ALPHA (2)			0,143894	0,2157					1,056E-012	1,0000
BETA (1)					0,64667	5,93E-012	0,221108	0,1296	0,320820	0,4673
BETA (2)							0,352665	0,0116	0,319022	0,1857
LOG LIKELIHOOD	328,8135		330,1886		339,003		340,7257		340,1302	

Appendix C: Vector autoregression tests

Case of the Czech Republic

Table C.1: The final VAR model

Vector Autoregression Estimates
Date: 08/07/16 Time: 20:55
Sample (adjusted): 2004M04 2014M03
Included observations: 120 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	UNEM	INF	IR	FSI_PCA
UNEM(-1)	0.843514	-0.052923	-0.040827	-0.161478
	(0.08807)	(0.06023)	(0.07431)	(0.45551)
	[9.57821]	[-0.87866]	[-0.54943]	[-0.35450]
UNEM(-2)	0.179730	0.033607	0.013135	0.040086
	(0.09117)	(0.06235)	(0.07693)	(0.47156)
	[1.97141]	[0.53898]	[0.17075]	[0.08501]
INF(-1)	-0.130401	1.816743	0.042635	0.908381
	(0.06450)	(0.04412)	(0.05443)	(0.33364)
	[-2.02162]	[41.1809]	[0.78336]	[2.72268]
INF(-2)	0.134065	-0.860809	-0.046738	-0.751865
	(0.06297)	(0.04307)	(0.05313)	(0.32570)
	[2.12907]	[-19.9879]	[-0.87967]	[-2.30848]
IR(-1)	-0.003697	0.023680	1.301000	0.767344
	(0.10334)	(0.07068)	(0.08720)	(0.53453)
	[-0.03578]	[0.33503]	[14.9200]	[1.43554]
IR(-2)	0.005842	-0.001755	-0.310108	-0.855131
	(0.10467)	(0.07158)	(0.08831)	(0.54137)
	[0.05582]	[-0.02451]	[-3.51141]	[-1.57956]
FSI_PCA(-1)	0.013287	-0.007845	-0.005735	0.713790
	(0.01812)	(0.01239)	(0.01529)	(0.09372)
	[0.73332]	[-0.63305]	[-0.37514]	[7.61655]
FSI_PCA(-2)	0.058368	0.009351	-0.030463	0.134311
	(0.01862)	(0.01273)	(0.01571)	(0.09628)
	[3.13554]	[0.73445]	[-1.93950]	[1.39495]
C	-0.578538	4.603001	0.627839	-14.98812
	(1.70833)	(1.16838)	(1.44144)	(8.83608)
	[-0.33866]	[3.93963]	[0.43556]	[-1.69624]
R-squared	0.987394	0.995850	0.990058	0.855437
Adj. R-squared	0.986486	0.995551	0.989342	0.845018
Sum sq. resids	1.883799	0.881180	1.341175	50.39799
S.E. equation	0.130273	0.089099	0.109921	0.673822
F-statistic	1086.813	3329.603	1381.728	82.10387
Log likelihood	78.97944	124.5665	99.36410	-118.2202
Akaike AIC	-1.166324	-1.926108	-1.506068	2.120337

Schwarz SC	-0.957262	-1.717046	-1.297006	2.329398
Mean dependent	6.801667	102.5275	1.967250	0.304203
S.D. dependent	1.120623	1.335801	1.064716	1.711609
Determinant resid covariance (dof adj.)		6.99E-07		
Determinant resid covariance		5.12E-07		
Log likelihood		188.0532		
Akaike information criterion		-2.534221		
Schwarz criterion		-1.697973		

Figure C.1: Stationarity test

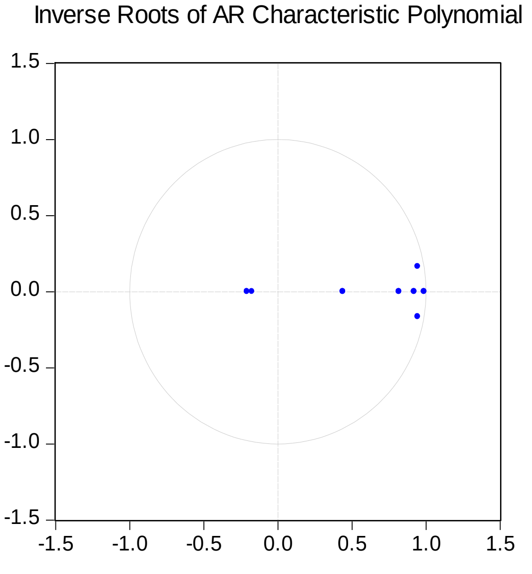


Table C.2: Lag length criteria test

VAR Lag Order Selection Criteria
Endogenous variables: UNEM INF IR FSI_PCA
Exogenous variables: C
Date: 07/31/16 Time: 21:34
Sample: 2004M02 2014M03
Included observations: 119

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-682.0944	NA	1.196610	11.53100	11.62441	11.56893
1	66.07618	1433.470	5.42e-06	-0.774390	-0.307310	-0.584723
2	186.3645	222.3817	9.40e-07	-2.527134	-1.686391*	-2.185734
3	218.0115	56.37962*	7.24e-07*	-2.790109*	-1.575703	-2.296977*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

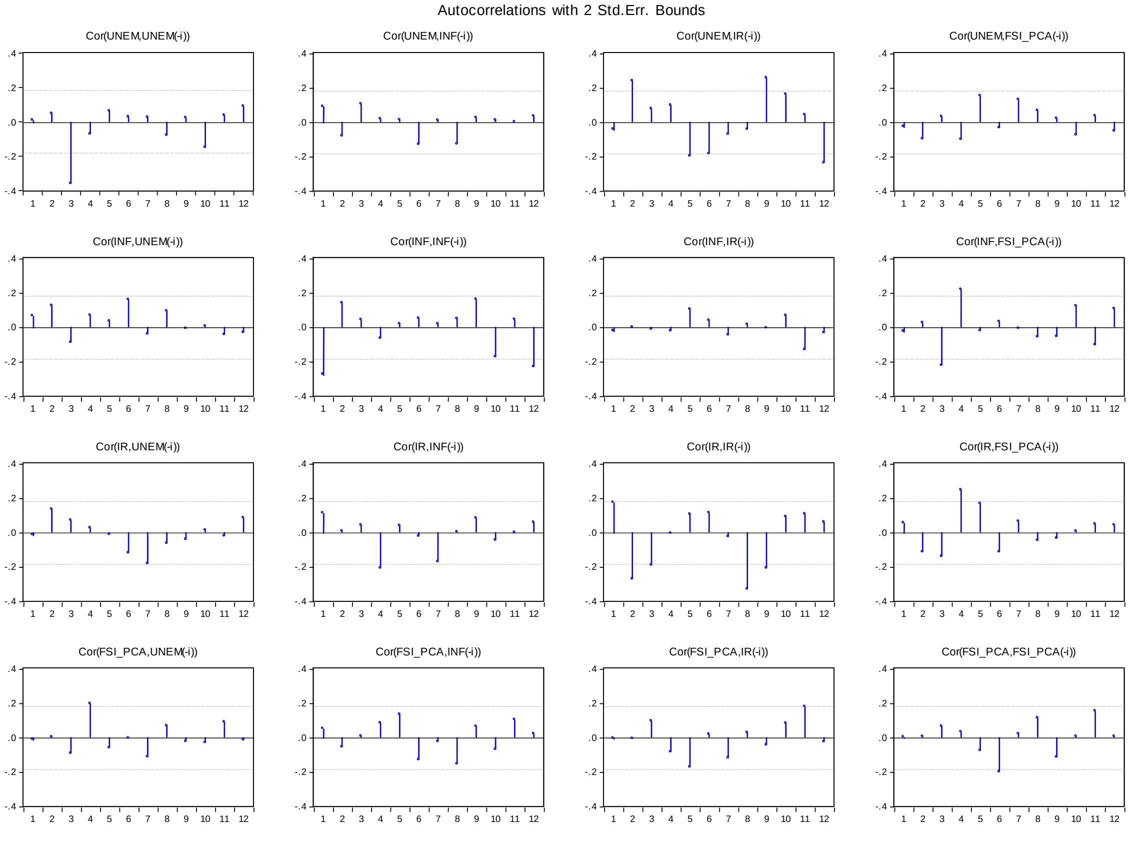
Table C.3: Lag exclussion test

VAR Lag Exclusion Wald Tests
Date: 07/31/16 Time: 21:35
Sample: 2004M02 2014M03
Included observations: 120

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	UNEM	INF	IR	FSI_PCA	Joint
Lag 1	110.4352	1862.483	241.8960	83.96362	2401.624
	[0.000000]	[0.000000]	[0.000000]	[0.000000]	[0.000000]
Lag 2	20.52994	451.5953	28.49751	9.636616	539.4178
	[0.000392]	[0.000000]	[9.89E-06]	[0.047015]	[0.000000]
df	4	4	4	4	16

Figure C.2: Correlogram



Case of the Slovak Republic

Table C.4: The final VAR model

Vector Autoregression Estimates
Date: 08/07/16 Time: 21:00
Sample (adjusted): 2004M04 2014M03
Included observations: 120 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	UNEM	INF	IR	FSI_PCA
UNEM(-1)	1.410453	-0.008618	-0.209861	-0.120401
	(0.08950)	(0.01761)	(0.12362)	(0.26114)
	[15.7598]	[-0.48926]	[-1.69764]	[-0.46106]
UNEM(-2)	-0.450450	0.013599	0.144034	0.054497
	(0.08412)	(0.01656)	(0.11619)	(0.24546)
	[-5.35475]	[0.82141]	[1.23959]	[0.22202]
INF(-1)	-0.137144	1.740806	0.775971	1.237958
	(0.26068)	(0.05130)	(0.36007)	(0.76064)
	[-0.52610]	[33.9315]	[2.15505]	[1.62753]
INF(-2)	0.162687	-0.776630	-0.802113	-1.346113
	(0.24682)	(0.04858)	(0.34093)	(0.72021)
	[0.65912]	[-15.9877]	[-2.35272]	[-1.86907]
IR(-1)	0.003821	0.025596	0.521921	0.446626
	(0.06565)	(0.01292)	(0.09068)	(0.19157)
	[0.05821]	[1.98103]	[5.75543]	[2.33145]
IR(-2)	-0.095705	-0.001594	0.364507	-0.420957
	(0.06331)	(0.01246)	(0.08745)	(0.18474)
	[-1.51159]	[-0.12794]	[4.16799]	[-2.27860]
FSI_PCA(-1)	0.048945	-0.002486	-0.043055	0.520372
	(0.03095)	(0.00609)	(0.04275)	(0.09030)
	[1.58161]	[-0.40812]	[-1.00724]	[5.76284]
FSI_PCA(-2)	0.000486	0.017194	-0.049198	0.309257
	(0.03155)	(0.00621)	(0.04358)	(0.09207)
	[0.01540]	[2.76901]	[-1.12886]	[3.35911]
C	-1.793493	3.503992	3.866900	11.76769
	(2.96658)	(0.58384)	(4.09764)	(8.65614)
	[-0.60457]	[6.00163]	[0.94369]	[1.35946]
R-squared	0.990556	0.998255	0.948458	0.813343
Adj. R-squared	0.989876	0.998129	0.944743	0.799890
Sum sq. resids	5.498253	0.212962	10.49012	46.81246
S.E. equation	0.222562	0.043802	0.307418	0.649410
F-statistic	1455.353	7936.785	255.3223	60.45919
Log likelihood	14.71106	209.7755	-24.04913	-113.7921
Akaike AIC	-0.095184	-3.346258	0.550819	2.046535
Schwarz SC	0.113878	-3.137197	0.759881	2.255597

Mean dependent	11.63997	102.3315	3.973133	0.029635
S.D. dependent	2.211907	1.012657	1.307782	1.451727
Determinant resid covariance (dof adj.)	3.19E-06			
Determinant resid covariance	2.33E-06			
Log likelihood	96.98838			
Akaike information criterion	-1.016473			
Schwarz criterion	-0.180225			

Figure C.3: Stationarity test

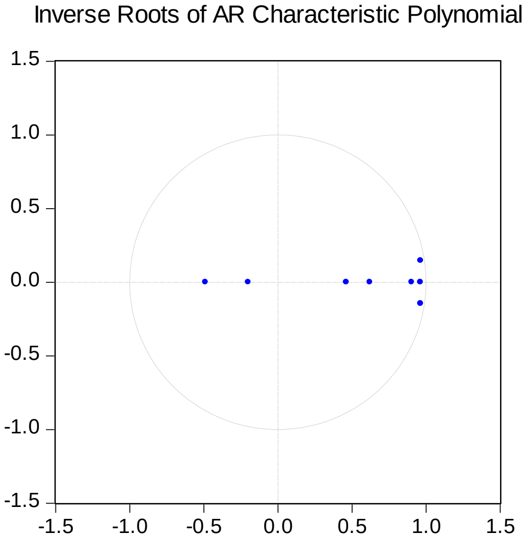


Table C.5: Lag length criteria test

VAR Lag Order Selection Criteria
Endogenous variables: UNEM INF IR FSI_PCA
Exogenous variables: C
Date: 07/31/16 Time: 19:35
Sample: 2004M02 2014M03
Included observations: 119

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-754.1819	NA	4.019054	12.74255	12.83597	12.78049
1	-14.45185	1417.298	2.10E-05	0.579023	1.046102	0.768689
2	95.25283	202.8154	4.35E-06	-0.995846	-0.155103*	-0.654447*
3	112.4159	30.57622*	4.27E-06*	-1.015393*	0.199014	-0.522261

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

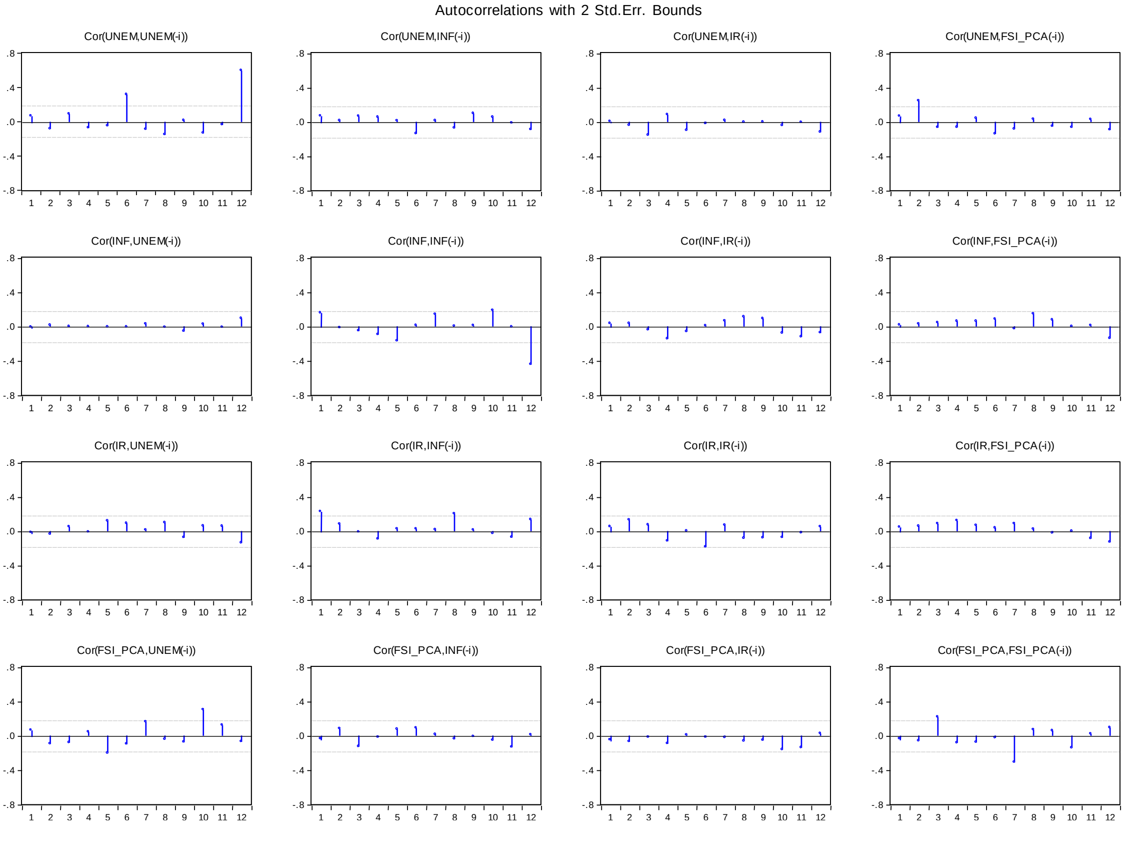
Table C.6: Lag exclussion test

VAR Lag Exclusion Wald Tests
Date: 07/31/16 Time: 19:33
Sample: 2004M02 2014M03
Included observations: 120

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	UNEM	INF	IR	FSI_PCA	Joint
Lag 1	284.8923 [0.000000]	1303.253 [0.000000]	59.58257 [3.55E-12]	53.42928 [6.93E-11]	1679.602 [0.000000]
Lag 2	32.96836 [1.21E-06]	302.2596 [0.000000]	27.08403 [1.91E-05]	25.29500 [4.39E-05]	378.2332 [0.000000]
DF	4	4	4	4	16

Figure C.4: Correlogram



Appendix D: VAR model variables

Figure D.1: Czech Republic – VAR model variables

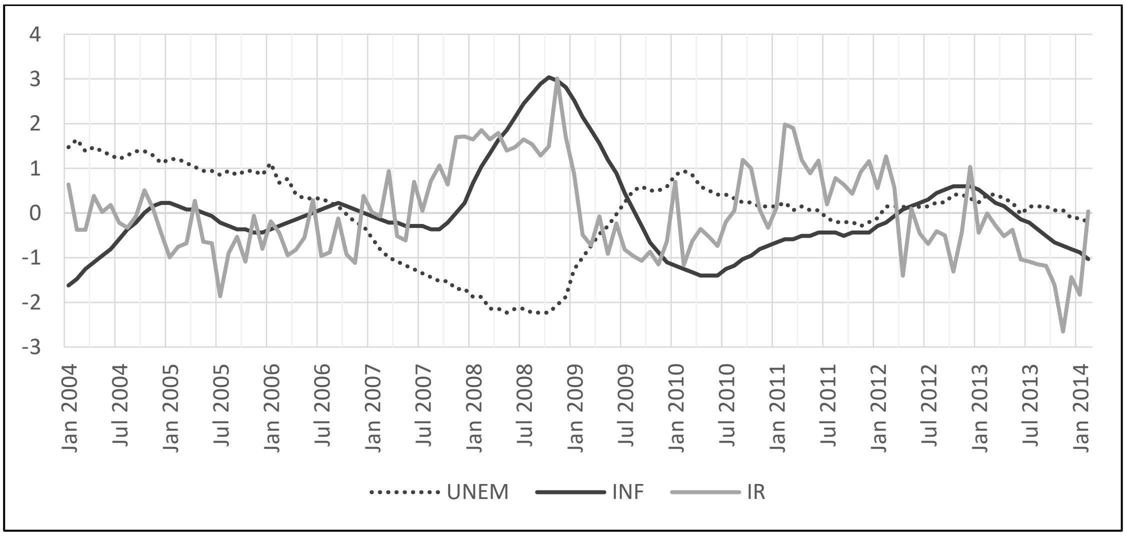
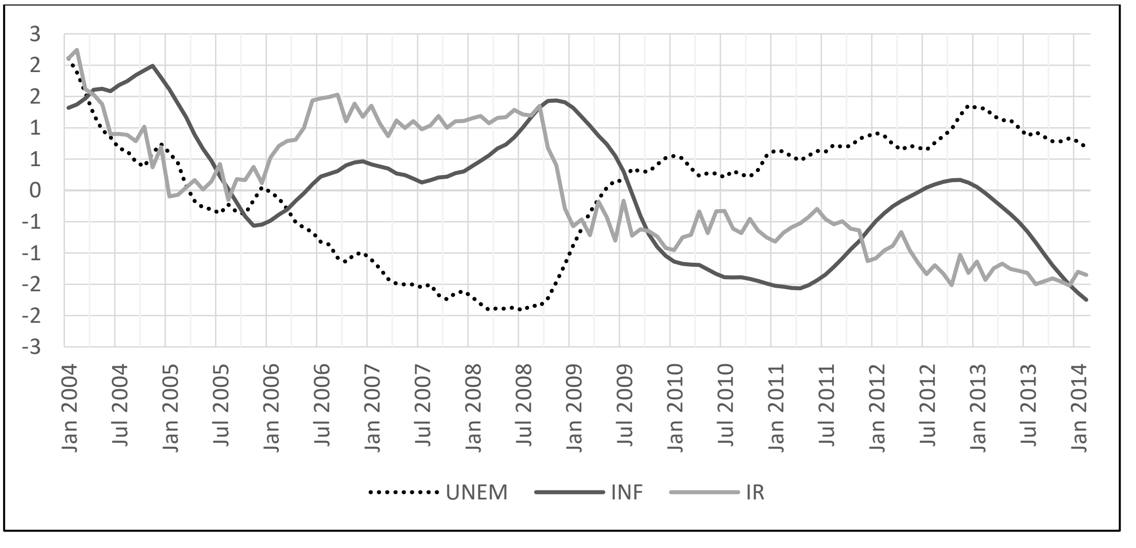


Figure D.2: Slovak Republic – VAR model variables



Appendix E: Impulse responses
Case of the Czech Republic

Figure E.1: Final model based on equal variance

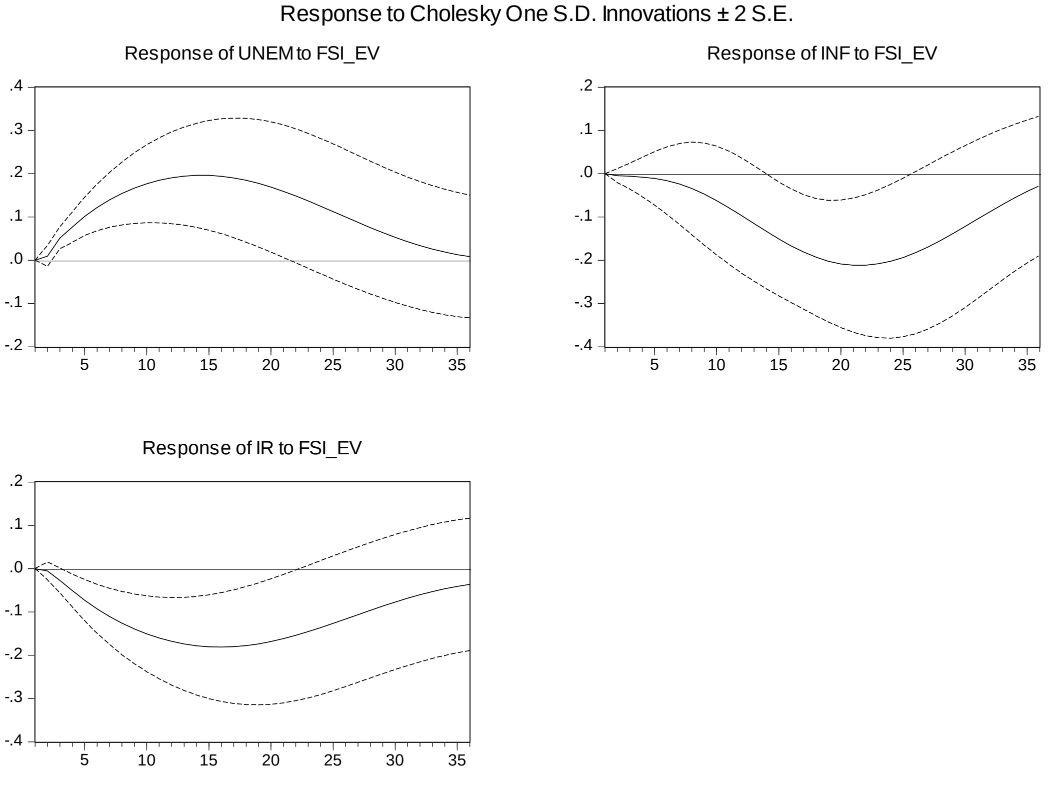


Figure E.2: Final model based on cumulative distribution function

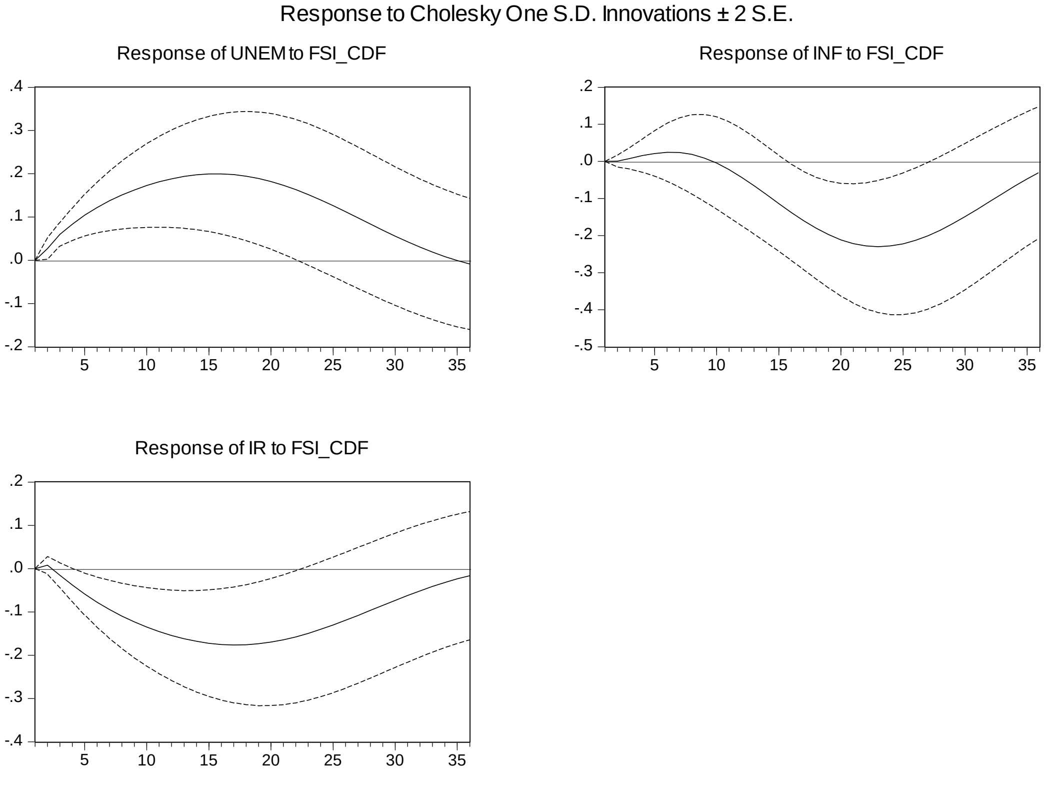


Figure E.3: Final model containing GDP growth

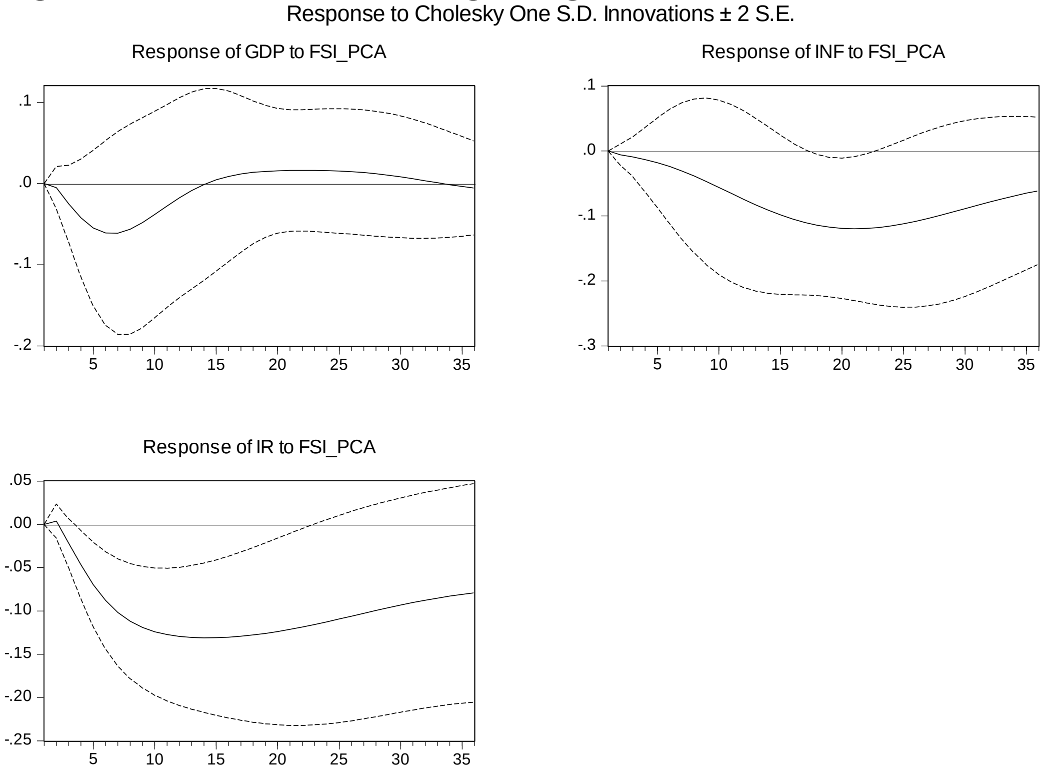


Figure E.4: Bivariate model

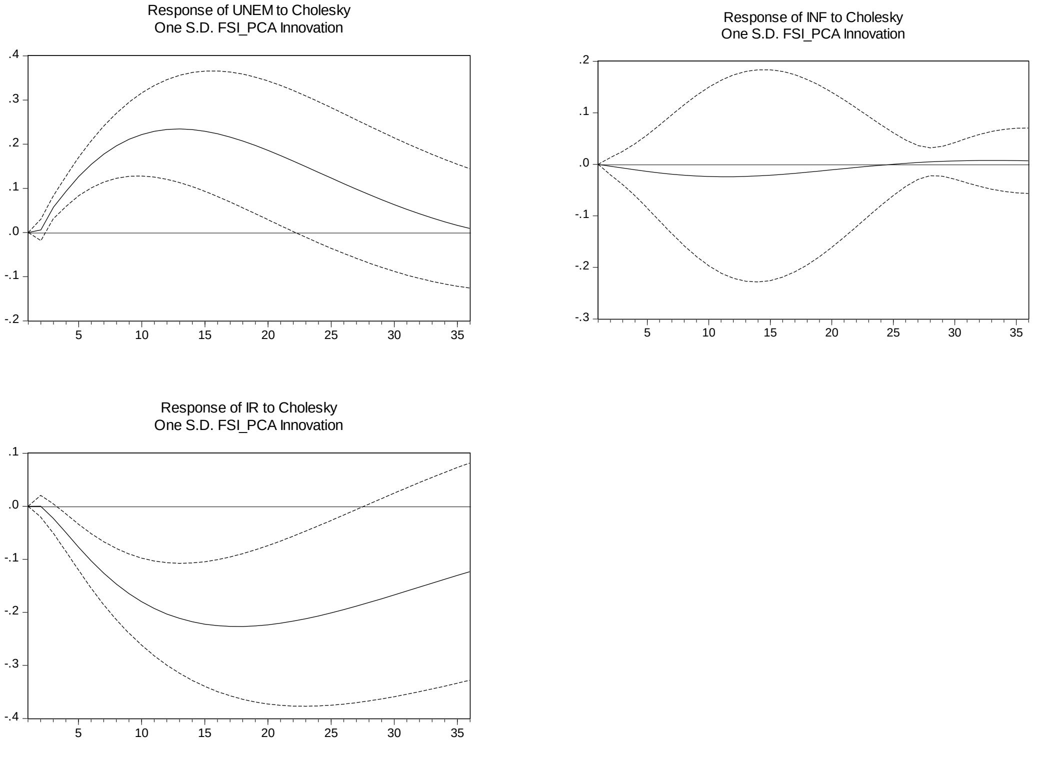
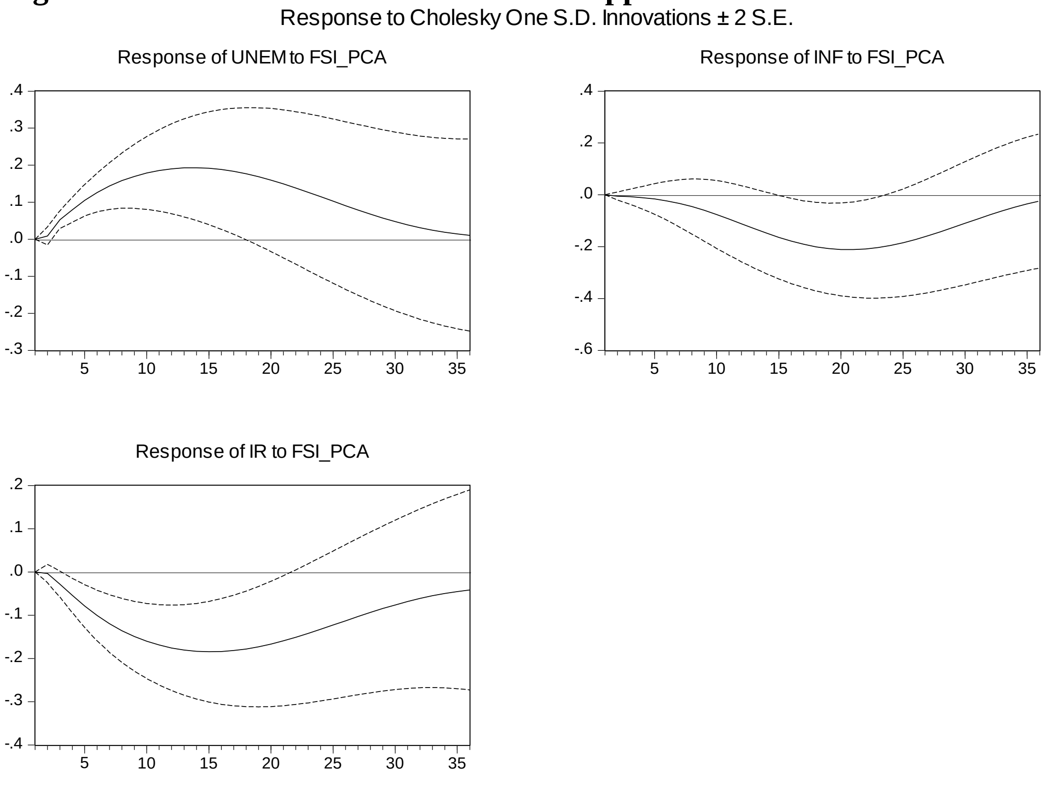


Figure E.5: Final model with Monte Carlo approach



Case of the Slovak Republic

Figure E.6: Final model based on equal variance

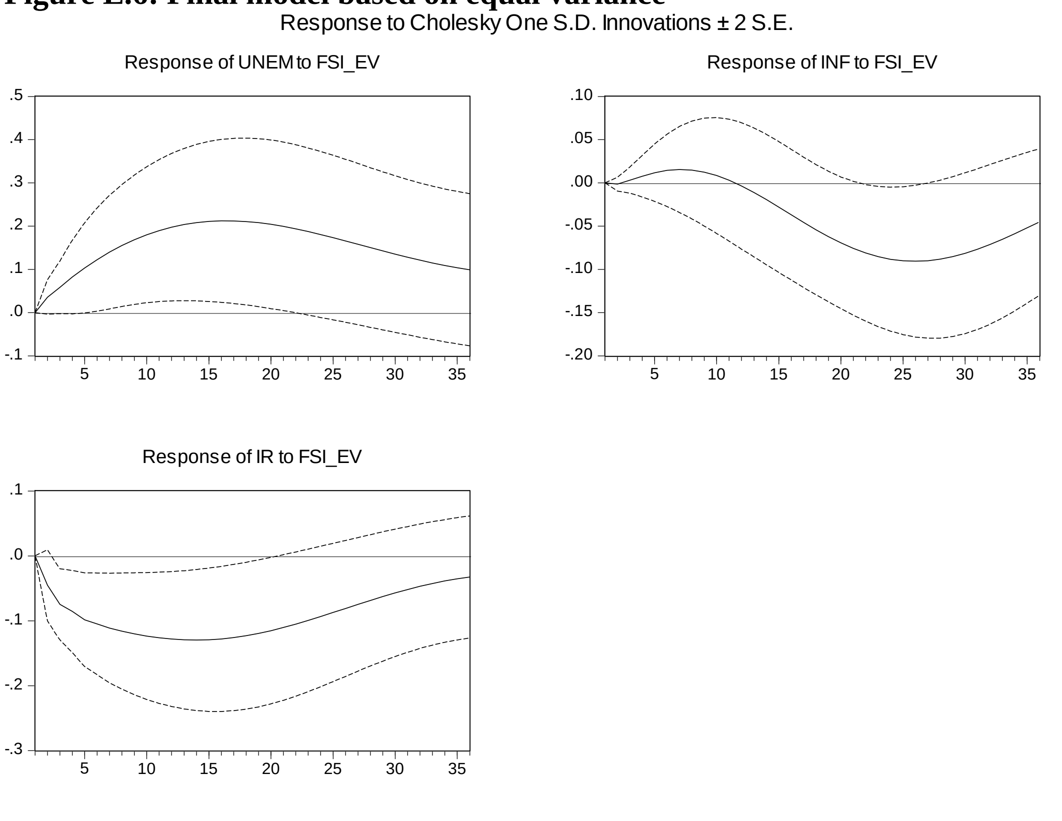


Figure E.7: Final model based on cumulative distribution function

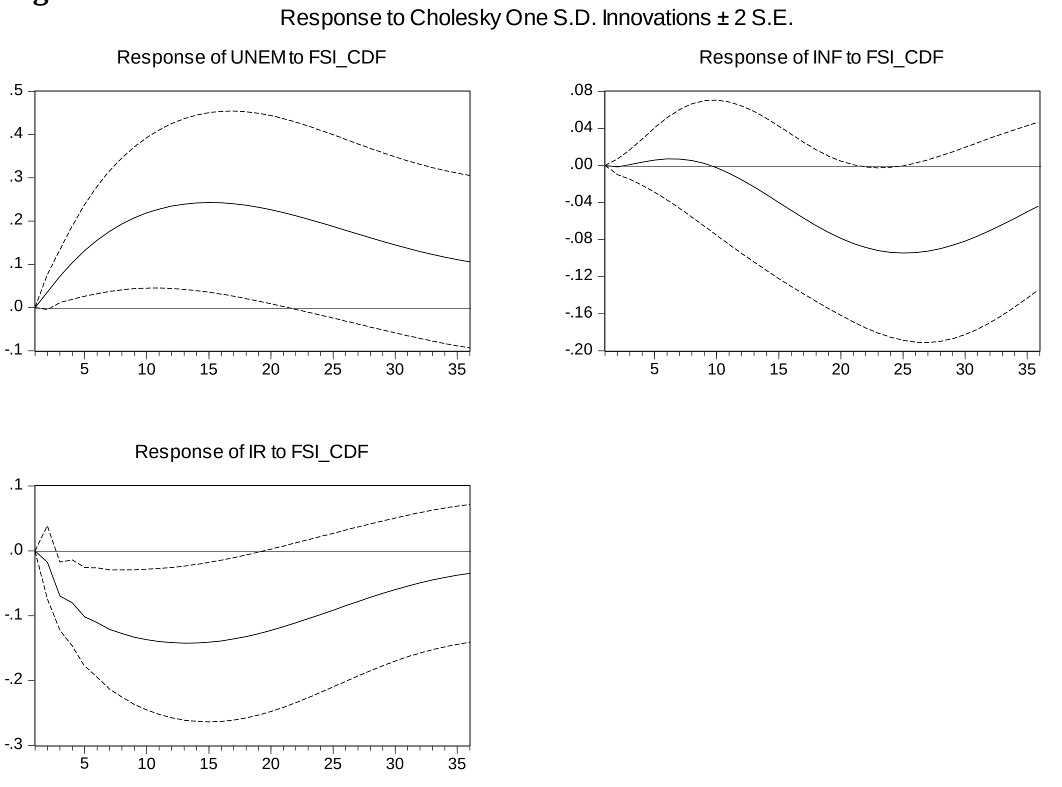


Figure E.8: Final model containing GDP growth

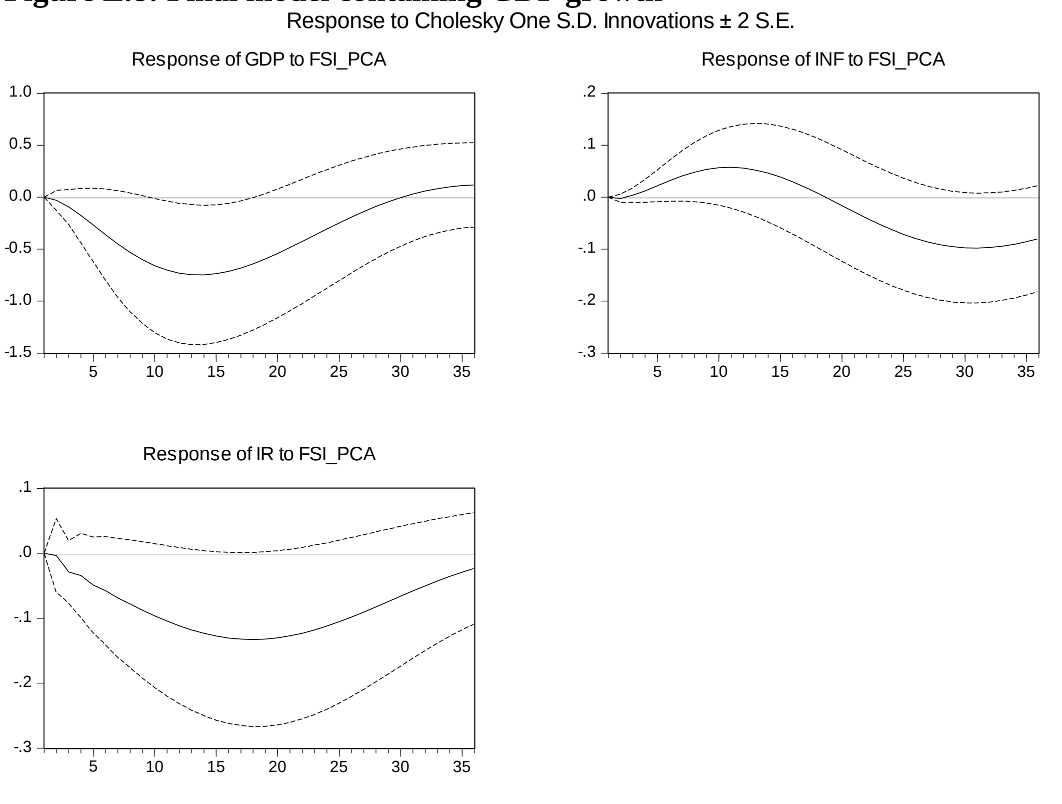


Figure E.9: Bivariate model

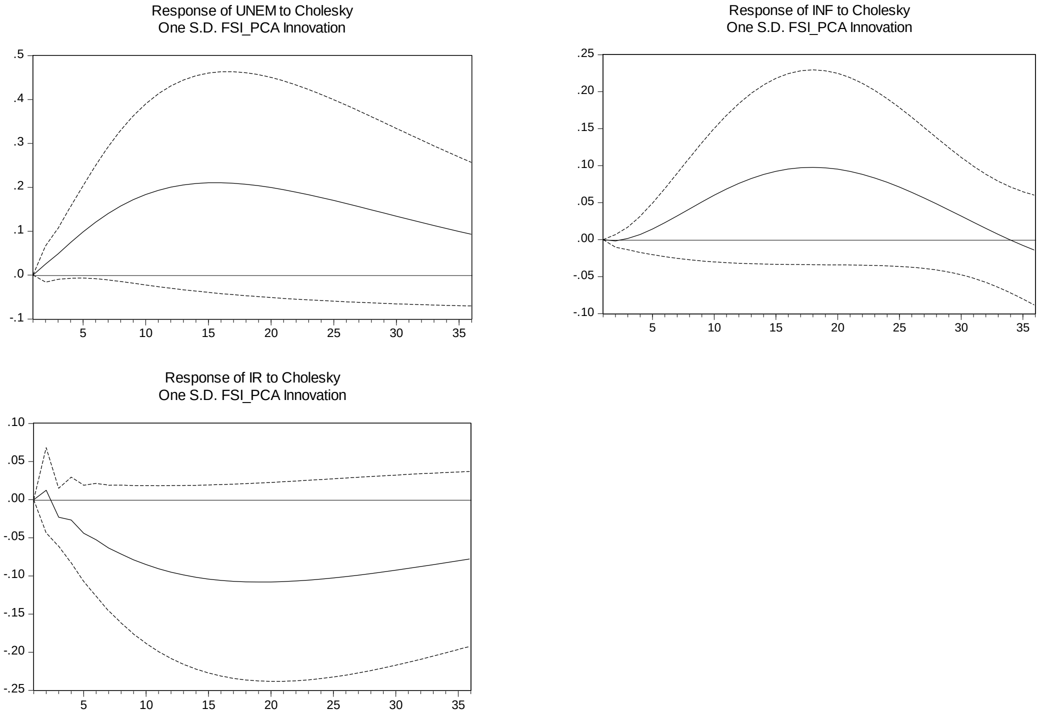


Figure E.10: Final model with Monte Carlo approach

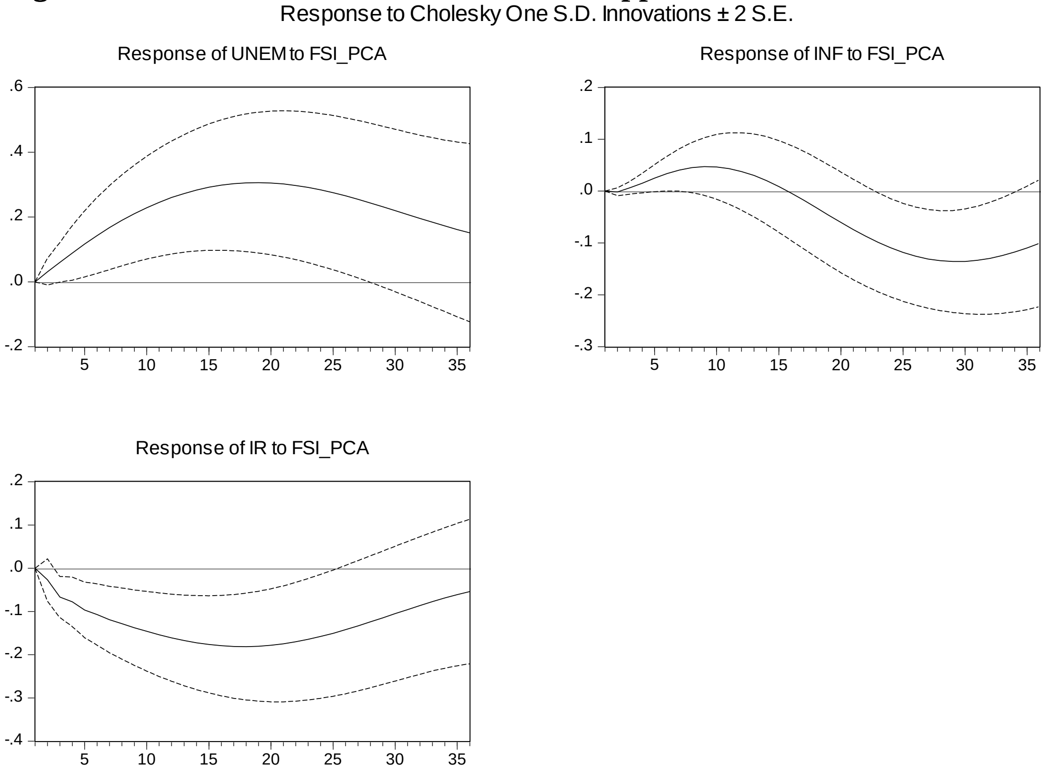


Figure E.11: Final model including dummy for structural break