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Summary

This dissertation is composed of three research papers that I have been working on during my doctoral studies in the "Doctoral Programme in Quantitative Economics and Finance" at the University of Konstanz. The three papers are empirical studies on time series analysis and empirical macroeconomics. The first article analyses the effects of fiscal policy shocks in the United States of America (U.S.). It uses additional data on the domestic economic activities that enter the usual vector autoregressive model (VAR) in the form of augmented factors. In the second paper a similar factor augmented vector autoregressive model (FAVAR) is used to assess the transmission mechanisms of monetary policy in four newly joined European Union (EU) member states. In the last article the Euro Area (EA) Gross Domestic Product (GDP) is "nowcasted" using a novel approach that combines wavelet analysis with the bridge equations model.

In the first chapter of the dissertation the effects of fiscal policy shocks in the U.S. are analysed. It is argued that the low dimensional models used by economists when analysing government spending and tax shocks are not plausible because they are missing important information. The standard VAR model is replaced by an alternative model. In the proposed model factors are extracted from a large set of economic variables representing all aspects of the U.S. economy. These factors are then added to a standard VAR model to build up the fiscal FAVAR model. In addition a novel identification scheme for fiscal policy shocks is proposed. Moreover by using the FAVAR model it is possible to rebuild the impulse responses not only of those variables that enter directly in the model, but of any economic variable that is used to estimate the factors in the FAVAR.

The empirical results from the fiscal FAVAR show that an increase in government spending boosts the U.S. economy by increasing output in the short run. This result contradicts with studies in the same field that use the standard structural VAR models but it coincides with results from event studies. In addition the reaction of GDP and

consumption on tax increase is negative in the long run but positive in the short run. That means that decreasing taxes in order to increase personal consumption is an effective fiscal policy but its effects occur with lag of almost one year. This is usually disregarded by the VAR models but captured by the event studies and the proposed FAVAR model. Another finding is that increasing taxes decreases unemployment for a longer horizon compared to a policy that increases government spending. In summary the FAVAR correctly identifies the influences of fiscal fluctuation on the U.S. economy because of its ability to consider a larger number of economic variables. In times of economic crisis, when fiscal policy is used to stimulate consumers demand, methods like the FAVAR should be used to analyse precisely the effects of fiscal innovations on the overall economy.

In the second chapter the effects of monetary policy shocks in the Czech Republic, Hungary, Poland and Slovakia within small vector autoregressive models are investigated. In particular, it is explored to what extent accounting for external economic developments in the EMU and in other acceding countries changes the results from structural VAR models.

The external developments in the European Monetary Union (EMU) are summarized by extracting factor time series using principal components from a relatively large database with time series data from eleven EMU countries. To interpret the extracted factor time series the cohesion analysis and the more traditional R^2 measure are used to investigate the dynamic correlation between the factor time series and groups of EMU time series. Consequently, the EMU factor series are used to augment the VARs for the accession countries. Using a large cross-section of time series on similar variables from the accession countries accession countries factors are extracted. To explore the role of external information in monetary analysis VAR models are augmented with either the factor series extracted from EMU data or with factors from accession country data.

The role of external information is studied by comparing the responses to contractionary monetary policy shocks from benchmark VARs with those of different FAVARs. With the exception of Poland, including EMU factors to the VAR does not substantially change the results from an impulse-response analysis. Thus, EMU economic developments do not seem to be of major importance for the monetary transmission in accession countries. This may hint to the fact that further steps need to be taken towards monetary integration of the accession countries. In contrast, including the accession country information leads to substantial changes in the impulse response pattern. Compared to the benchmark model, the responses to a monetary policy shock are more in line with theoretical expectations: output variables tend to drop, prices tend to decrease (the price puzzle disappears or is less pronounced), and the exchange rate appreciates. In some countries, a reasonable monetary transmission mechanism can only be diagnosed when the external accession country factors are included in the model.

The last chapter introduces a novel method for nowcasting euro area GDP growth. In particular the wavelet analysis is used to aid the bridge equation nowcast model used by the European Central Bank for their early estimates of GDP. The results from this study show that the wavelet based nowcasting model outperforms the bridge equation nowcast for the short term forecasts of euro area GDP growth.

Bridge equations are used by several policy institutions to obtain early estimates of quarterly GDP growth. The main idea behind the approach lies in "bridging" of information from timely monthly data to quarterly data (in this case GDP growth) in order to obtain better forecasts for the quarterly series. One should note that usually the timeliness of the monthly data is much smaller than the timeliness of the quarterly data. Since economic time series have different frequencies and timeliness it is very difficult to fit nowcasting models to the most recent available data. Usually economic data has ragged edges where the last observations of the series are missing due to lags in measurement. Economists use standard single resolution forecasting techniques to estimate the missing data and then fit it to the nowcasting bridge equation models. Here a non-parametric multi resolution wavelet analysis is used to forecast the ragged edges of the monthly variables and to aid the nowcasting bridge equations for the quarterly GDP growth.

The introduced multi-resolution approach outperforms the usual single resolution forecast framework. In this respect we use a wavelet multi-resolution analysis with the help of which each monthly time series can be decomposed into time scale components. Once this is done we forecast the ragged edges of the time series for each resolution levels and then use the properties of the wavelet transformation to reconstruct the forecast of the original time series. Once the full length monthly variables are obtained, eight bridge equations are used to obtain the final nowcasts for the euro area GDP growth. To assess the performance of the wavelet-based nowcasting method an out-of-sample forecasting exercise is performed. Three different wavelet functions are used to analyse the sensitivity of the wavelet model. The results show that the wavelet multi-resolution nowcasting model performs better than the standard single resolution nowcasting method for short run forecasts. The outcomes are supported by an encompassing test comparing the two types of forecasts.

The three papers composing the thesis share a common goal, which is to take into account the effects of external information in macroeconomic analysis. In all of the three papers additional external information plays a crucial role for the setup of the time series models and the final results. In the first and the second paper external information is compressed using factor analysis and then augmented to the empirical models in order to assess optimally fiscal and monetary policy. In the last paper external information is accommodated in forecasting GDP growth by using several bridge equations that use different information sets. The three studies show that considering external information aids the assessment of fiscal and monetary policy and should be used in practice in the future.

Zusammenfassung

Diese Dissertation besteht aus drei Forschungspapieren, an denen ich während meines Promotionsstudiums "Doctoral Programme in Quantitative Economics and Finance" an der Universität Konstanz gearbeitet habe. Die drei Papiere sind verschiedene, empirische Studien im Bereich der Zeitreihenanalyse und zur empirischen Makroökonomik. Der erste Artikel analysiert die Wirkung fiskalpolitischer Schocks in den Vereinigten Staaten von Amerika (USA). Der Artikel nutzt zusätzliche Daten zu inländischen Wirtschaftsaktivitäten, die in das normale Vektor Autoregressive Modell (VAR) in Form von Faktoren eingehen. Im zweiten Papier wird ein ähnliches mit Faktoren erweitertes Vektor Autoregressives Modell (FAVAR) verwendet, um den Transmissionsmechanismus monetärer Politik in vier Mitgliedstaaten der EU zu analysieren, die der EU kürzlich beigetreten sind. Im letzten Artikel wird das Bruttoinlandsprodukt (BIP) des Euroraums unter Verwendung eines neuartigen Nowcasting-Ansatzes modelliert, welcher Wavelet-Analyse mit einem sogenannten "Bridge-Equations"-Modell kombiniert.

Im ersten Kapitel der Dissertation wird die Wirkung fiskalpolitischer Schocks in den USA untersucht. Es wird argumentiert, dass Modelle geringer Dimension, welche üblicherweise von Ökonomen verwendet werden, um Staatsausgaben und Steueränderungen zu analysieren, nicht plausibel sind, da diese wichtige Informationen vernachlässigen. Das Standard VAR-Modell wird durch ein alternatives Modell ersetzt. Im vorgeschlagenen Modell werden Faktoren aus einer großen Menge wirtschaftlicher Variablen extrahiert, die alle Aspekte der US Wirtschaft widerspiegeln. Diese Faktoren werden dann in ein herkömmliches VAR Modell eingefügt, um das FAVAR Modell zu erstellen. Außerdem wird eine neuartige Identifikation für fiskalpolitische Schocks vorgeschlagen. Die Verwendung des FAVAR Modells ermöglicht ferner die Impulse-Antworten aller Variablen zu rekonstruieren, nicht nur für Variablen, die direkt in das Modell eingehen, sondern auch für Variablen, die verwendet werden, um die Faktoren zu schätzen.

Die empirischen Ergebnisse des fiskalen FAVARs zeigen, dass eine Erhöhung der Staatsausgaben die US-Wirtschaft fördert, indem sie dir Produktion kurzfristig erhöht. Dieses Ergebnis widerspricht anderen Studien im gleichen Feld welche ein Standard-VAR-Modell verwenden, stimmt jedoch mit den Ergebnissen von Event-Studien überein. Außerdem reagieren Bruttoinlandsprodukt und Konsum langfristig negativ aber kurzfristig positiv auf Steuererhöhungen. Die bedeutet, dass Steuersenkungen ein effektives fiskalpolitisches Mittel sind, um privaten Konsum zu erhöhen. Allerdings tritt der Effekt mit einer Verzögerung von beinahe einem Jahr auf. Dies wird von VAR Modellen in der Regel nicht erfasst, findet sich aber in Eventstudien und dem vorgeschlagenen FAVAR Modell wieder. Ein weiteres Ergebnis ist, dass höhere Steuern im Vergleich zu einer Politik höherer Staatsausgaben langfristig die Arbeitslosigkeit senken. Zusammenfassend lässt sich sagen, dass das FAVAR-Modell aufgrund der Möglichkeit eine große Anzahl ökonomischer Variablen zu berücksichtigen, die Einflüsse fiskalpolitischer Änderungen in der US Wirtschaft besser identifiziert. In wirtschaftlichen Krisenzeiten, in denen Fiskalpolitik eingesetzt wird, um den Konsum zu steuern, sollten Methoden wie FAVAR benutzt werden, um die genauen Effekte fiskalpolitischer Änderungen auf die Gesamtwirtschaft zu analysieren.

Im zweiten Kapitel werden die Effekte monetärer Politikschocks in Polen, der Slowakei, der Tschechischen Republik und Ungarn in einem kleinen vektor-autoregressiven Modell untersucht. Es wird untersucht, in welchen Umfang die Berücksichtigung externer wirtschaftlicher Entwicklungen in der europäischen Währungsunion und in anderen Beitrittsländern die Ergebnisse eines strukturellen VAR-Modells ändert.

Die externen Entwicklungen in der europäischen Währungsunion (EWU) werden durch Faktoren zusammenfasst, die mithilfe von Hauptkomponentenanalyse aus einer großen Datenbank mit Zeitreihen zu elf Ländern der EWU extrahiert werden. Um die extrahierten Faktor-Zeitreihen zu interpretieren, werden das Kohäsions-Maß und das traditionellere R^2-Maß verwendet, um den dynamischen Zusammenhang zwischen den Faktor-Zeitreihen und den Zeitreihen der EWU Zeitreihen zu untersuchen. Folglich werden die EWU Faktorzeitreihen verwendet um sie dem VAR für die Beitrittsländer hinzuzufügen. Faktoren für die Beitrittsländer werden aus einem großen Querschnitt von Zeitreihen ähnlicher Variablen aus den Beitrittsländern extrahiert. Um die Rolle externer Informationen zu untersuchen, werden die VAR Modelle zur monetären Analyse entweder mit den auf EWU-Zeitreihen beruhenden Faktoren oder mit den auf Zeitreihen anderer Beitrittsländer beruhenden Faktoren ergänzt.

Die Rolle externer Information wird untersucht, indem die Reaktionen auf kontraktionäre monetäre Politikschocks aus den Basis-VARs mit den verschiedenen FAVARs verglichen werden. Abgesehen von den Ergebnissen für Polen führt die Berücksichtigung der EWU Faktoren zu keiner substantiellen Änderung der Ergebnisse in der Impuls-Antwortanalyse. Folglich scheinen wirtschaftliche Entwicklungen in der EWU nicht von großer Relevanz für die monetäre Transmission in den Beitrittsländern zu sein. Dies kann auf die Tatsache hindeuten, dass in den Beitrittsländern weitere Schritte in Richtung monetärer Integration notwendig sind. Im Gegensatz dazu führt das Berücksichtigen der Informationen anderer Beitrittsländer zu substantiellen Änderungen im Muster der Impuls-Antworten. Verglichen mit dem Basis-Modell stimmen die Reaktionen auf einen geldpolitischen Schock mehr mit den theoretischen Erwartungen überein: Produktionsvariablen tendieren zu sinken, Preise gehen tendenziell zurück (das sogenannte "price puzzle" verschwindet oder ist weniger ausgeprägt), und der Wechselkurs wertet auf. In einigen Ländern kann ein vernünftiger monetärer Transmissionsmechanismus nur festgestellt werden, wenn die Faktoren externer Beitrittsländer in dem Modell berücksichtigt werden.

Das letzte Kapitel präsentiert eine neuartige Methode, um die Wachstumsrate des BIPs im Euroraum für die Gegenwart und die nahe Zukunft zu prognostizieren (Nowcasting). Es wird die Wavelet-Analyse benutzt, um das "Bridge-Equation"-Modell zu verbessern, welches die Europäischen Zentralbank verwendet, um frühe Schätzungen des BIPs zu erstellen. Die Ergebnisse dieser Studie zeigen, dass Wavelet-basiertes Nowcasting das kurzstfristige BIP-Wachstum im Euroraum besser prognostizieren als das "Bridge-Equation"-Modell.

"Bridge Equations" werden von verschiedene politischen Institutionen verwendet, um frühe Prognosen für das vierteljährliche BIP-Wachstum zu erhalten. Die Grundidee dieses Ansatzes liegt darin Informationen zeitnaher monatlicher Daten zu Quartalsdaten (in diesem Fall von BIP-Wachstum) zu "überbrücken" um bessere Prognosen für quartalsbasierte Serien zu erhalten. Monatliche Daten sind in der Regel viel aktueller als Quartalsdaten. Da ökonomische Zeitreihen unterschiedliche Frequenzen und Aktualität besitzen, ist es sehr schwierig die am schnellsten verfügbaren Daten für "Nowcasting-Modelle" zu verwenden. Ökonomische Daten haben üblicherweise "ausgefranste Enden" (ragged edges), bei denen die letzten Beobachtungen einer Zeitreihe aufgrund von Verzögerungen in der Messung fehlen. Ökonomen verwenden Standard-Prognosetechniken, um die fehlenden Daten zu schätzen und dann in das "Nowcasting-Bridge-Equations-Modell" einzufügen. Hier wird eine nicht-parametrische, multidimensionale Skalenanalyse verwendet, um die fehlenden Enden der monatlichen Variablen zu schätzen und das "Nowcasting" der "Bridge-Equations" für das vierteljährliche BIP-Wachstum zu ermöglichen.

Der vorgestellte Ansatz einer multidimensionalen Skalenanalyse liefert bessere Ergebnisse als übliche Prognosesysteme eindimensionaler Skalenanalysen. In diesem Zusammenhang nutzen wir eine multidimensionale Skalenanalyse mit deren Hilfe jede monatliche Zeitreihe in Zeitskalenkomponenten zerlegt werden. Danach schätzen wir die fehlenden Enden der Zeitreihen für jedes Auflösungsniveau und nutzen anschließend die Eigenschaften der Wavelet-Transformation, um die Schätzung der ursprünglichen Zeitreihe zu rekonstruieren. Nachdem die monatlichen Variablen in voller Länge gewonnen wurden, werden acht "Bridge Equations" verwendet um die endgültigen nowcasts für das BIP-Wachstum im Euroraum zu erhalten. Um das Ergebnis der Wavelet-basierten nowcasting Methode zu bewerten wird eine out-of-sample Prognose-Übung durchgeführt. Es werden drei verschiedene Wavelet-Funktionen verwendet um die Sensitivität des Wavelet-Modells zu analysieren. Die Ergebnisse zeigen, dass die Wavlet-basierte multidimensionale Skalenanalyse bessere Ergebnisse zu kurzfristigen Prognosen liefert als die übliche Prognosemethoden, die auf eindimensionalen Skalenanalysen beruhen.

Die drei Papiere, aus denen sich diese Arbeit zusammensetzt, haben ein gemeinsames Ziel, das darin besteht die Wirkung externer Informationen in makroökonomischen Analysen zu berücksichtigen. In allen drei Papieren spielen zusätzliche externe Informationen eine wichtige Rolle für die Erstellung der Zeitreihenmodelle und der Endresultate. Im ersten und zweiten Papier werden externe Informationen mithilfe der Faktoranalyse komprimiert und dann in das empirische Modell integriert, um die optimale Fiskal- und Geldpolitik abzuschätzen. Das letzte Papier verwendet externe Informationen, um das BIP-Wachstum zu prognostizieren, indem "Bridge-Equations" verwendet werden, die unterschiedliche Informationsmengen verwenden. Die drei Studien zeigen, dass die Berücksichtigung externer Informationen bei der Bewertung von Fiskal- und Geldpolitik hilft und daher in Zukunft in der Praxis verwendet werden sollten.

Chapter 1

Analysing Fiscal Policy Shocks: A Factor-Augmented Vector Autoregressive Approach

1.1 Introduction

Fiscal policy is often used to stimulate economies in recessions. There is an increasing amount of literature on the effects of fiscal shocks on the economic activity (see Perotti, 2002, 2008; Fatás and Mihov, 2001; Mountford and Uhlig, 2009). Most of the time series researchers use the structural VAR models to examine such policies.

The use of VAR models has many advantages. These models are very easy to implement and give credible results. At the same time they have several drawbacks. The first disadvantage is connected to the low dimensionality of the VAR models. Usually the VARs consist of a limited number of variables due to degrees of freedom problems. These problems are coming from the fact that VAR based impulse response functions may not be precisely estimated in case of large number of parameters and the short time series data available. This disregards data that affects the economic responses to fiscal policy shocks. Additionally in a low dimensional VAR model the responses to the policy shocks could be analysed only for the variables that are included in the model. Often economists and policy makers are interested in the influence of fiscal innovation to a wider range of variables. Defining separate VAR models for each variable of interest is burdening and not taking into account the available information set. Another concern is that the implementation of different policy shock identification schemes could lead to different responses to those fluctuations. This paper tries to relax the above limitations of the VAR models when assessing fiscal policies using U.S. data.

A number of economists investigated ways out of the dimensionality problems of the VAR models. Stock and Watson (2002b) combined the standard VAR approach with diffusion indexes, an alternative name that they use for extracting factors from large number of time series. They were inspired by Sargent and Sims (1977) who first tried to compress large data structures using the dynamic factor model. Later Forni and Reichlin (1996) used the same model applied for large cross-sectional data. More recently, Bernanke, Boivin and Eliasz (2005) combined the VAR models with factor analysis to measure the effects of monetary policy. They named their model a factor-augmented vector autoregression model (FAVAR). To our best knowledge, until now the FAVAR has not been applied as assessment tool for fiscal policy. This may be due to the fact that there is no consensus on the identification scheme of fiscal shocks. The identification procedures are getting even more complicated when factors enter the model.

In the empirical literature that uses U.S. data there are no stylized facts on the concrete effect of fiscal policy on the economy. One aspect in which the literature cannot agree is on the effect of government spending on private consumption. According to Perotti (2002, 2008) and Fatás and Mihov (2001) private consumption increases significantly after a positive government spending shock. On the other side Edelberg, Eichenbaum and Fisher (1999) and Mountford and Uhlig (2009) find that private consumption does not react significantly to similar fiscal shocks. Ramey (2011) on the other side reports a significant decrease in private consumption when government spending shock occurs. Similar contradictions also exist for the response of real wages and unemployment to an increase in government spending. In the case of a tax increase Mountford and Uhlig (2009) find that U.S. output decreases significantly, which is not supported by Perotti (2002). Very often the differences that are observed are due to different identification schemes in the structural VAR models.

There are four popular methods used to identify fiscal shocks in VAR models. Some researchers are tempted to consider the recursive approach that uses Choleski decomposition. The scheme is widely used in monetary policy VAR models. Nevertheless, this identification scheme is not always suitable for fiscal policy analysis because it imposes a recursive structure that cannot be justified theoretically. Another identification method for fiscal policies is introduced by Blanchard and Perotti (2002). They make assumptions on the reaction of the variables in the VAR based on additional economic information. In this way they calculate the effects of the fiscal indicators to different economic variables. The third identification approach that can be considered is introduced by Mountford and Uhlig (2009), who impose sign restrictions on the impulse responses and identify tax, government spending, monetary policy and business cycle shocks. An alternative way to treat fiscal policy shocks is to use event studies. For example Ramey and Shapiro (1998) and later Eichenbaum and Fisher (2005) used exogenous fiscal episodes, like increase in national military spending, to define dummy variables that were later added to their VAR models.

This paper is inspired by Stock and Watson (2002b), who showed that forecasting based on factor analysis outperforms the usual forecast methods. Another related study is the work of Bernanke et al. (2005) who resolved the price puzzle when evaluating monetary policy shocks with the FAVAR model. Here the effects of fiscal policy in the

U.S. are re-examined using the FAVAR model. Additionally a novel identification scheme for fiscal policy shocks is proposed that fits the data and the model. This paper has four main contributions. First the FAVAR model clearly shows that when government spending increases the responses of personal consumption are significantly positive for all of the twenty quarters after the shock. In addition the FAVAR shows that an increase in government spending boosts the economy by increasing output in the short run. Second, for U.S. data, increasing taxes leads to significant decrease in output in the long run. Third, when comparing how increase in government spending affects output we find significant differences in the responses when using the FAVAR and the VAR models. In the case of the FAVAR model significantly positive reaction of output is observed in the short run which contrasts to the insignificant VAR responses. Lastly, using the FAVAR to study fiscal policy shocks gives a more general view of their effect on the economy. That is due to the fact that with the FAVAR model researchers can indirectly consider the effect on a large set of economic variables and reconstruct the impulse responses of any of these variables when studying fiscal fluctuations.

This paper continues in the following way. The next section explains the methodology behind the FAVAR model. It is composed of three subsections. The first one introduces the structural VAR model, the second one presents the dynamic factor model, the next section defines the FAVAR. Section 1.3 describes in details the structure of the data and studies how different variables contribute to the formation of the factors. Section 1.4 concentrates on the identification mechanism that is chosen for the fiscal FAVAR model. Section 1.5 introduces the empirical results in the case of government spending shocks and tax shocks. Sever robustness checks are performed in section 1.6. Section 1.7 concludes the paper.

1.2 Methodology

1.2.1 VAR

The usual model considered to analyse fiscal policy shocks is the VAR model. Using notation from Lütkepohl (2005), the m-dimensional reduced form VAR model of order p, VAR(p), can be written as

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + \upsilon_t, \tag{1.1}$$

where for $t = 1, ..., T$, $Y_t = (y_{1t}, ..., y_{mt})$ is a $(m \times 1)$ vector of directly observable time series variables. For $j = 1, ..., p$, A_j are coefficient matrices with dimensions $(m \times m)$ and υ_t is a m-dimensional white noise error term. The VAR model captures the interactions of the variables in Y_t with respect to time. Equation (1.1) can be rewritten as

$$Y_t = A(L)Y_t + \upsilon_t, \tag{1.2}$$

where $A(L) = A_1L + A_2L^2 + ... + A_pL^p$ is lag polynomial of order p. L denotes a lag operator and has the following property $L^sY_t = Y_{t-s}$, for $s = 1, ..., p$.

The VAR model is widely used for monetary and fiscal policy applications due to its simplicity and ability to describe the time series dynamics. However, this approach has a couple of drawbacks. The use of different policy shock identification schemes leads to different impulse responses to those shocks. Another shortcoming of the VAR model is that the numbers of variables that can be used in the model is limited. The low dimensionality of the VAR is due to its reduced degrees of freedom. For example, when only one lag is considered in the VAR model, the number of parameters to be estimated increases to the square of the number of variables included, this can be problematic when there are not enough observations in the data set. The limited inclusion of variables ignores available data that influence the responses of key economic indicators.

Another problem that arises when using the standard VAR is that the responses to the policy shocks could be analysed only for the variables that are included in the model. Often economists and policy makers are interested in the influence of fiscal fluctuations to a wider range of variables. As proposed by Stock and Watson (2005) to relax those limitations one can combine the standard VAR approach with the dynamic factor model.

1.2.2 The Factor Model and the Principal Components Model

A widely used method for the compression of large data sets is the factor model or its extension, the dynamic factor model. As shown by Bai and Ng (2006) the dynamic factor model can be expressed as a static factor model. In this paper we estimate the factors as in Stock and Watson (2005) by using the principal components estimation method which can be easily implemented.

The factor model reduces large time series data into few unobserved factors. Here the observed variables can be partitioned into two elements: a common component and an idiosyncratic component. In this context let $X_t = (x_{1t}, ..., x_{nt})$ be an observed time series with dimensions $(n \times 1)$. X_t can be decomposed into

$$X_t = \Lambda^f F_t + \xi_t, \tag{1.3}$$

where for $t = 1, .., T$, F_t represents the latent factors with dimension $(k \times 1)$. Λ^f is matrix with the factor loadings with dimension $(n \times k)$, and the factor error term ξ_t has dimension $(n \times 1)$ and mean zero. When the principal components analysis is applied to the initial data set X_t, it consistently estimates the factors F_t along with their loadings, Λ^f. A necessary conditions for the consistent estimation of equation (1.3) is the stationarity of the variables in X_t and that the number of the observed variables in X_t are large enough (n should be much larger than the number of factors ($n >> k$) and larger than the number of time periods ($n > T$)).

The estimation of the first k principal components F_t is done using the covariance method as in Stock and Watson (2002a). Each of the variables in X_t can be presented as a linear combination of the principal components F_t. In order to extract the principal components from X_t we have to calculate the variance-covariance matrix of X_t. Let us define $\Sigma = \frac{1}{T}\sum_{t=1}^{T} X_t X_t'$. The main goal is to find k linear combinations $\hat{F}_t = \hat{S}_j' X_t$ for $j = 1, ..., k$ that maximize the variance of F_t, $\hat{S}_j'\hat{\Sigma}\hat{S}_j$, (see Schumacher, 2005). In order to identify the factors Stock and Watson (2002a) imply the following normalization $\hat{S}_j'\hat{S}_i = 1$ for $i = j$ and $\hat{S}_j'\hat{S}_i = 0$ when $i \neq j$. This normalization also implies that each factor contributes to the variance of any x_{it} from X_t. The maximization problem mentioned above is equivalent to an eigenvalue problem

$$\hat{\Sigma}\hat{S}_j = \hat{D}_j\hat{S}_j, \tag{1.4}$$

where $\hat{D}_j$ is the j-th eigenvalue and $\hat{S}_j$ is its corresponding eigenvector. The maximum number of eigenvalues is n and once calculated they are ranked in descending order based on their magnitude. The estimated factors can be written as $\hat{F} = \hat{S}'X_t$, where $\hat{S}$ is a $(n \times k)$ matrix of eigenvectors $\hat{S} = (\hat{S}_1, ...\hat{S}_k)$. The first k of the sorted eigenvalues $\hat{S}$ are equivalent to the factor loadings $\hat{\Lambda}^f$ from (1.3). Once we have estimated the factors $\hat{F}$ we can consolidate them with the observed variables Y_t and define the FAVAR model.

1.2.3 The FAVAR model

The FAVAR model combines together the standard VAR approach with the dynamic factor model. The joint dynamics of Y_t and the factors F_t from equation (1.3) can be analysed using the FAVAR model. Following the notation above one can express these dynamics as

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = B(L) \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \varepsilon_t, \tag{1.5}$$

where $B(L)$ is a lag polynomial of order p. The vector $(F_t^{'}, Y_t^{'})'$ along with equation (1.5) represents the factor-augmented vector autoregressive model. The FAVAR model is estimated by two-step principal components estimation procedure, as in Stock and Watson (2002b). In the first stage the factors $\hat{F}_t$ are estimated from equation (1.3) as explained above. Once this is done the factors from step one enter equation (1.5) which is then estimated. This estimation method was chosen over the maximum likelihood estimation (MLE) due to its computational simplicity. Another reason not to use the MLE procedure is that often it does not converge and even if it does, the results may be incorrect due to the existence of local maximum. More over as Bernanke et al. (2005) point out, when working with huge models as in this case, using MLE in not feasible in some cases from computational point of view.

At the first stage of the procedure the factors $\hat{F}_t$ are estimated using the principal components approach presented in the previous section. As a second step equation (1.5) is estimated by OLS. One concern is that at step two, $\hat{F}_t$ are regressors that are generated. The covariance matrix obtained at this stage tends to underestimate the actual uncertainty. Thus more precise standard errors may be generated by resampling. In order to construct correct confidence intervals on the impulse response functions a bootstrap algorithm proposed by Kilian (1998) is considered. The same bootstrap algorithm is also used in Bernanke et al. (2005). The nonparametric bootstrap procedure has the following steps.

1. Estimate the parameters $\hat{B}$ in equation (1.5) and construct $\hat{\varepsilon}_t$.

2. Generate a bootstrap errors ε_t^* by resampling from $\hat{\varepsilon}_t$ with replacement.

3. Generate pseudo data $[F_t^{*'} \; Y_t^{*'}]'$ of length T, using ε_t^*, $\hat{B}$, and actual pre-sample values for $[F_t^{'} \; Y_t^{'}]$.

4. Calculate the bootstrap parameter estimates $\hat{B}^*(L)$ using the pseudo data $[F_t^{*\prime}\ Y_t^{*\prime}]'$ in

$$\begin{bmatrix} F_t^* \\ Y_t^* \end{bmatrix} = \hat{B}^*(L) \begin{bmatrix} F_t^* \\ Y_t^* \end{bmatrix} + \varepsilon_t^*. \tag{1.6}$$

5. Calculate the impulse responses for the pseudo data from (1.6).

6. Repeat steps 1. - 5. depending on the bootstrap replications number[1].

7. Report the median and the percentiles to form the impulse responses along with their confidence intervals.

In order to reconstruct the impulse responses of the time series not only of the Y_t series but also the responses of any of the variables in X_t one have to assume that both Y_t and F_t are driving forces behind X_t as in (see Bernanke et al., 2005). In this respect the following equation holds

$$X_t = C(L) \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \vartheta_t, \tag{1.7}$$

where analogous to equation (1.5), C is lag polynomial of some order l. In the estimation algorithm for each step of the FAVAR calculation we also estimate in parallel the model in (1.7) in order to be able to reconstruct the responses of the observed variables of interest from X_t.

1.3 The Data and the Model

The data used in this paper consists of 93 U.S. quarterly macroeconomic time series covering the period between 1972:Q1 till 2009:Q1. The total number of observations for this time span is $T = 149$. The data is collected from the Federal Reserve Economic Data at the Economic Research Division at the Federal Reserve Bank of St. Louis, U.S. All of the considered variables are transformed. A detailed description of the variables composing the data and the applied transformations is included in the appendix. The choice of variables is based on the variables used in Stock and Watson (2005) to summarize the dynamics of U.S. economy when analysing monetary policy.

[1]The proposed bootstrap algorithm does not account for the uncertainty in the factors extraction step.

There are three indicators that enter directly in the VAR model: the log of real per capita current expenditures (g_t), the log of real per capita government current receipts $(t_t)^2$, and the log of real per capita gross domestic product (y_t). The rest of the variables are used for the extraction of factors that will be added in the VAR. The rationale for using log-transformed data for the variables entering directly the FAVAR model is due to the normality assumption and limiting possible heteroscedasticity and skewness in the level data on the estimation results. This is supported by Sims, Stock and Watson (1990) that show that even if there are non-stationary variables in systems like (1.5), the estimates will be still consistent without inducing stationarity in the series. In addition using transformations, like taking differences, could eliminate important characteristics of the series that carry information about the co-movement between the variables.

Let us denote with $Y_t = (g_t, t_t, y_t)'$ the variables that enter directly the model and with X_t the set of variables needed for the factor analysis. Since the data set X_t is built up of many variables that are measured in different units, it is not reasonable to extract factors using the raw data. Due to the significant variability of the variables and the differences of the measurement units, X_t is standardized by dividing each column by its standard deviation. The Bai and Ng (2002) criterion indicated the presence of four factors in the dataset. Section 1.4 will give more details on the estimation of the number of factors. Let us denote the factors extracted from X_t with $\hat{F}_t = (\hat{f}_t^1, \hat{f}_t^2, \hat{f}_t^3, \hat{f}_t^4)'$, then $(\hat{F}_t', \hat{Y}_t')' = (\hat{f}_t^1, \hat{f}_t^2, \hat{f}_t^3, \hat{f}_t^4, g_t, t_t, y_t)'$. The variables that enter in the model are organized such that the extracted factors are ordered first followed by the two fiscal variables and gross domestic product. This specific ordering is chosen due to the assumption that a structural shock in one of the variables in Y_t will not have immediate impact on the factors, since they are not observed. Analogously output reacts within the same period to shocks in the factors, in government spending or taxes.

Following the notation for the FAVAR model introduced in the previous section the model to be analysed can be written as

[2] Government current receipts consist mainly of current tax receipts. In addition contributions for government social insurance, income receipts on assets, current transfer receipts from business and persons, and the current surplus of government enterprises are also included.

$$\begin{bmatrix} \hat{f}_t^1 \\ \hat{f}_t^2 \\ \hat{f}_t^3 \\ \hat{f}_t^4 \\ g_t \\ t_t \\ y_t \end{bmatrix} = B(L) \begin{bmatrix} \hat{f}_t^1 \\ \hat{f}_t^2 \\ \hat{f}_t^3 \\ \hat{f}_t^4 \\ g_t \\ t_t \\ y_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{f^1} \\ \varepsilon_t^{f^2} \\ \varepsilon_t^{f^3} \\ \varepsilon_t^{f^4} \\ \varepsilon_t^{g} \\ \varepsilon_t^{t} \\ \varepsilon_t^{y} \end{bmatrix}, \tag{1.8}$$

where $B(L) = B_1L + B_2L^2 + B_3L^3 + B_4L^4$ is a lag polynomial of order $p = 4$.

Tax is plotted as share of GDP in the first panel of Figure 1.1 from the appendix. This is done for more informative data analysis; the shares do not enter the FAVAR model. There are significant fluctuations along the time span of 37 years. The greatest drop of the share is in 1975, and it is due to the so called U.S. tax rebate. During that time the taxes were cut by 33% and restored back to initial values within a quarter. The lower panel of the figure plots government spending as shares of GDP. Both graphics in Figure 1.1 show low frequency movements of taxes and expenditures. In order to account for the low frequencies of the fiscal variables, linear and quadratic deterministic trend terms are included in the model. The same deterministic terms are also used in Blanchard and Perotti (2002) and Caldara and Kamps (2008). No seasonal dummies were included since Blanchard and Perotti (2002) found that seasonalities are insignificant for fiscal policy analysis using VAR models for the U.S..

Stock and Watson (2002b) propose a method to analyse the factor structure of the data. The same exercise is repeated for the current data. All of the 90 time series that compose X_t are regressed on the extracted factors, over the whole time span. The obtained estimates of the R^2s of these 90 regressions are plotted as bar charts in Figure 1.2 in the appendix. The four sub-charts in Figure 1.2 correspond to the four principal factors that are extracted. The ordering of the 90 variables follows the listing in the appendix. As it can be seen from the chart, the first factor loads mostly on the employment and output variables. The second factor has high loadings on housing, income and the price index variables. The third factor loads mostly on interest rates. The last factor is formed by variables that describe exchange rates. According to how the variables load for each factor an economic interpretation of the factors can be build. In this respect the first factors account for real economic variables and the second factor accounts for prices. The third factor can be interpreted as summarizing information from financial and monetary indexes. On the other side the last factor is extracted from variables that are usually classified as foreign economic variables. As a summary one can conclude that the four factors extracted from the data account for the real, monetary, and international portions of the U.S. economy.

The variance explained by the first four principal components is shown in Figure 1.3. The percentage of the total variability explained by the first principal component is 60.8%, whereas for the second component the percentage is 32.1%. There is a clear cut-off between the amount of variance accounted by the first two components and the third and the fourth components. The third principal component explains 5.1% and the fourth factor explains just 1.2% of the variance. Accumulated the first four components explain more than 99% of the total variability of the time series included in X_t. The results are very similar to the results of Stock and Watson (2002b). They also use large U.S. data for the period 1959 to 1999 to extract factors. In addition the Bai and Ng (2002) criteria also indicated the presence of four factors. Additional factors after the fourth one contribute with less than 0.5% for the explanation of the variability of the data, so they are not considered in the model.

1.4 The Identification Problem in the Structural FAVAR

The error terms ε_t from equation (1.8) are reduced from residuals and a structural interpretation of the FAVAR requires the identification of the structural disturbances. To do so, one needs to define structural equations for ε_t. Denoting the structural shocks with e_t, the reduced form residuals can be expressed as a linear functions of the structural shocks. In matrix form the general relationship is

$$A\varepsilon_t = Be_t, \tag{1.9}$$

where A and B are $(k \times k)$ matrices and $e_t \sim (0, I_k)$. In the specific case of the model considered here equation (1.9) can be written as

$$A \begin{bmatrix} \varepsilon_t^{f^1} \\ \varepsilon_t^{f^2} \\ \varepsilon_t^{f^3} \\ \varepsilon_t^{f^4} \\ \varepsilon_t^{g} \\ \varepsilon_t^{t} \\ \varepsilon_t^{y} \end{bmatrix} = B \begin{bmatrix} e_t^{f^1} \\ e_t^{f^2} \\ e_t^{f^3} \\ e_t^{f^4} \\ e_t^{g} \\ e_t^{t} \\ e_t^{y} \end{bmatrix}, \tag{1.10}$$

where A and B are (7×7) matrices.

When dealing with monetary policy shocks the specification of A and B is often based on the Choleski decomposition. This is due to the fact that recursive structures are normally suitable for studies dealing with monetary policy. In this case the ordering of the variables in the system is of crucial importance. Therefore, the Choleski identification scheme is not always appropriate when analysing fiscal policy shocks. When analysing fiscal shocks the covariance matrix $\Sigma_\varepsilon = E(\varepsilon_t \varepsilon_t^{'})$ is not always diagonal because the residuals ε_t could be contemporaneously correlated. In order to orthogonalise the shocks, the relations between the variables in the VAR have to be modelled explicitly. In other words one should directly specify the form of the matrices A and B. Equation (1.9) can be rewritten as $\Sigma_\varepsilon = A^{-1}BB^{'}A^{-1^{'}}$.[3] This relation includes $k(k+1)/2$ equations. Following Lütkepohl (2005) and knowing that each of the matrices A and B has k^2 elements, in order to be able to solve the system $\Sigma_u = A^{-1}BB^{'}A^{-1^{'}}$, $2k^2 - \frac{1}{2}k(k+1)$ restrictions have to be imposed on A and B. When $k = 7$, the number of restrictions for the elements of A and B should be equal to 70. Imposing 70 linearly independent restrictions guarantees that all $2k^2$ elements of the two matrices A and B will be identified. The identifying restrictions in this study is combination of normalizing and excluding (zero) restrictions for the A and B. The matrices A and B are given as:

[3] Solving (1.9) for ε_t gives $\varepsilon_t = A^{-1}Be_t$, thus computing the covariance of ε_t gives $E(\varepsilon_t \varepsilon_t^{'}) = \Sigma_\varepsilon = A^{-1}B\Sigma_e B^{'}A^{-1^{'}} = A^{-1}BB^{'}A^{-1^{'}}$

$$A = \left[\begin{array}{cccc|ccc} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 & 0 \\ \hline a_{51} & a_{52} & a_{53} & a_{54} & 1 & a_{56} & a_{57} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 & a_{67} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 \end{array}\right], B = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & b_{55} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & b_{66} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & b_{77} \end{bmatrix}.$$

Each column in matrix A can be interpreted as being associated with a shock in certain variable, the rows in A are the responses of the variables to those shocks. As it can be seen above, the A matrix resembles a lower triangular matrix with one exception, the lower right portion of A. As it can be seen, the upper left subsection of the A matrix has entirely a lower triangular form, the upper right chunk of A has only zeros and the coefficients of the lower left portion of A are not restricted. This means that all four factors can influence the fiscal variables g_t and t_t, as well as the output y_t. Since we are interested only in the structural shocks of the fiscal variables and GDP one can impose zero restrictions for the coefficients of the upper right sub-matrix of A. By not restricting the last three rows of A, one allows all variables that enter in the FAVAR to effect the impulse responses constructed for government spending, taxation, and gross domestic product. The problem that arises is that if one considers A and B as they are defined above, the number of the restriction that are imposed are 67, which is not sufficient for the identification of the model. This means that three additional restrictions should be made in order to have a just-identified system of equations.

Blanchard and Perotti (2002) note that the coefficients of the A matrix are the elasticities between the variables in a structural VAR. In the case of FAVAR, it is difficult to define those elasticities because the extracted factors are not observed. In order to solve this problem the results from the previous subsection are used. In this respect, as it was commented on before, each factor can be interpreted as a proxy to some group of economic variables. Since the first three factors account for the highest percentage of the variability of the data, there are no zero restrictions that are imposed on their coefficients.

Another reason not to constrain those coefficients is that the first three factors summarize real economic and monetary variables that may influence the effects of fiscal shocks. Here only two coefficients for the fourth factor are restricted.

We follow simple economic justifications to set the additional restrictions for A. As noted earlier the fourth factor f_t^4 loads mostly on the exchange rates, thus it is assumed that f_t^4 is a proxy for foreign effects on the U.S. economy. Usually exchange rates react to changes in interest rates and to lags of other variables. Government expenditures and taxes are influenced by y_t thus one cannot put a zero restriction for a_{57} and a_{67}, but exchange rates should have no influence on fiscal policy decisions. Therefore it is assumed that f_t^4 has no immediate effect on g_t and t_t ($a_{54} = 0$ and $a_{64} = 0$). Additionally, the fourth factor explains the smallest percentage of the variance of the variables in X_t, so imposing zero restrictions to f_t^4 is preferable than imposing restrictions to the first three factors. The third additional zero restriction is imposed for $a_{56} = 0$. This is done because usually a shock in taxation have no immediate (within the period of one quarter) influence on government spending.

After imposing these additional restriction matrix A can be written like this

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & 0 & 1 & 0 & a_{57} \\ a_{61} & a_{62} & a_{63} & 0 & a_{65} & 1 & a_{67} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & 1 \end{bmatrix}. \tag{1.11}$$

The set of restrictions that are defined in this model correspond to 70 linearly independent restrictions, so that the model is just-identified. The estimation is done by maximum likelihood using a scoring algorithm as in Breitung, Brüggemann and Lütkepohl (2004). The estimates of the matrices A and B along with the standard errors are displayed in the appendix. As it can be seen there, some of the coefficients are not significantly different from zero. This may reflect to some extent the estimation uncertainty due to the small sample at hand. In most of the cases when the insignificant coefficients are set to zero the optimization algorithm is non-convergent. The non-convergence is again due to the small sample of the data, and it is occurring despite the fact that the model is over identified. In order to assure convergence to a global optimum the optimization problem is solved few times with different starting values. Here we will refrain from interpreting the individual coefficients due to the large standard errors.

The presented identification strategy for the fiscal shocks is influenced by the works of Perotti (2002), Favero (2002) and Blanchard and Perotti (2002), but there are two main differences between their methods and the one proposed here. First the models used in the mentioned papers use the standard structural VAR to evaluate fiscal policy, and second they calibrate a_{57} and a_{67}. Favero (2002) imposes zero restrictions for the two coefficients and Blanchard and Perotti (2002) and Perotti (2002) calculate their values using additional data. In a more recent paper, Marcellino (2006) uses an identification method closest to the one used here, but he again uses the standard structural VAR to study fiscal policy shocks and disregards the availability of additional time series. There are other identification schemes for structural VAR models analysing fiscal policies. For example Uhlig (2005) uses the sign restriction technique where restrictions are imposed on the sign of the impulse response function. Blanchard and Quah (1989) use long run restrictions for policy shocks identification. As a future extension of this present paper the two alternative identification methods are to be integrated in the FAVAR model.

1.5 Empirical Results

In this section the effects of government spending and tax shock will be examined. In addition a comparison between the results from the proposed FAVAR model and the simple VAR model will be discussed.

1.5.1 Government Spending Shock

The first column of Figure 1.4 in the appendix shows the reaction of all observed variables entering directly in the FAVAR to a positive shock in government spending. Additionally, Figure 1.6 includes responses to government spending fluctuations of selected economic variables that compose X_t. The identification method that was proposed in the previous chapter is considered when constructing the impulse responses. There are four main conclusions that can be drawn after analysing the results in the above mentioned graphics.

First, an increase in government spending has a positive effect on GDP till the third year after the spending takes place. At the last eight quarters of the 20 quarters period the effect of spending shock reaches close to the zero levels. That shows that in the long run (after 3 years) the spending shock has an insignificant influence on GDP. The findings are in tune with Blanchard and Perotti (2002), who also showed that government spending increase GDP significantly. But they do not observe that the effect is transitory. Caldara and Kamps (2008) studied the effects of fiscal policy shock in U.S. and compared the results from different VAR identification schemes. The impulse responses of GDP to spending innovation that they obtain using event studies have the same trend as the one in Figure 1.4. When they evaluated the responses of GDP to government spending shock using recursive identification, Blachard-Perotti identification and sign restriction identification they did not observe insignificance in the output responses in the long run. This result shows that the fiscal FAVAR correctly evaluates the effects of government spending on production and obtains the same results as the event studies (considered to be the most accurate ones). As shown by Caldara and Kamps (2008) the VAR models have failed to do this. This is supported by Figure 1.5 which compares the impulse responses from the FAVAR model and a simple VAR.[4] One can observe that there are differences in the impulse responses of output to government spending shock using the two models. Using the VAR model the effects of fiscal shock does not affect y_t in the short run contrary to the results from the FAVAR. The VAR shows that only after 10 quarters after shock there is a slight positive effect on y_t which is significant.

Second, taxes react positively to the government spending increase till quarter twelve and has negative impact on t_t afterwards. As in Blanchard and Perotti (2002) the response of taxes mimics the output response. As it can be seen from the first column of Figure 1.4, government spending and taxes have similar impulse responses, with lower magnitude for the tax response. The only difference is that after the twelfth quarter the effect of the spending shock on tax is significantly negative, for the same period this effect is insignificant for the production variable. On the other hand Figure 1.5 shows that based on the VAR model taxes are not affected positively by increase in government spending. The effect on taxes from the VAR is not significant in the short run. Just for the period

[4] The benchmark VAR(4) model includes a constant, a linear and quadratic deterministic terms. The Choleski identification scheme was used.

between quarter eight and fourteen after the shock taxes react negatively to increase in g_t, this effect dies out in the long run.

The tax reactions after government spending shock obtained using the FAVAR are identical to the tax reactions in the event study outcome performed by Caldara and Kamps (2008). In parallel, the results of Caldara and Kamps when using VAR models show insignificant effect of spending increase on tax for any identification scheme, this result is partially supported by Figure 1.5. The negative effect of spending on tax in the long run observed in Figure 1.4, can be very easily explained in practice. Government can increase total spending (personal and governmental) by either increasing own spending or reducing taxes and hoping that the consumers will spend their taxes on purchases. Based on event studies those two policies seem to be substitutes and lead to larger budget deficit. The proposed model captures those dynamics which are missed by the VAR models.

Figure 1.6 in the appendix, shows that consumption and personal income peak after the second year after the government spending increase takes place. Both responses are persistent. The effect of government spending on consumption and income is positive for the whole period of 20 quarters. The impulse responses of consumptions are significant for all 20 quarters and the impulse responses of income are significant for the three years after government spending shock. A different pattern is observed for unemployment, which is significantly negative for the first three quarters but then quickly achieves positive but insignificant values. This result is in tune with the economic evidence that sharp increase in government expenditure decreases unemployment in the short run. As it can be seen the increase in personal income is correlated with the increase in the average hourly earnings.

The fourth finding is connected with the responses of the monetary variables. An expansionary fiscal policy as government spending increase should push up interest rates. In our case this is observed until the fourth quarter. The increase of interest rates has a lag of one year. After the fourth quarter the impulse responses of interest rates are close to zero and insignificant. The intuition is the following, as seen from Figure 1.4, the output after a government spending shock is positive for the first three years. In this time prices start increasing, money demand increases too (also seen in Figure 1.4), which leads to increase in interest rates. When analysing the results of the fiscal VAR models using different identification methods, Caldara and Kamps (2008) note that the interest rates react significantly to fiscal policy in the long run, after the 25th quarter. Their results from the case study show that interest rates have a positive reaction to government spending shock in the short run and no significant impact in the long run. Here the results show that interest rates react immediately to fiscal policy shock and this last for approximately an year. Again the results from the FAVAR model support the outcomes of the event studies.

1.5.2 Tax Shocks

Positive shocks in tax are the other fiscal policy instrument that will be analysed. As it can be seen from the second column of Figure 1.4 in the appendix, GDP reacts positively to an increase in taxes in the first one year[5]. This reaction is insignificant only for the second year after tax increase and negative after that. Blanchard and Perotti (2002) did not observe the positive effect on GDP in the first year after tax increase, their results show a negative impact on production till quarter twelve and insignificant response afterwards. This result is the first conclusion that can be drawn when analysing government revenues shock with the FAVAR model. Indeed the output reduction due to lower budget deficit occurs with lag one year. There is a negative response of government spending due to an increase in taxes. The same line of reasoning as the one followed in subsection 1.5.1 justifies this observation.

Figure 1.5 compares the responses from the FAVAR and the VAR models. No major differences are observed in the responses of g_t, t_t and y_t in case of tax increase when using the factor augmented model and the simple VAR model. One would expect that output drops in the short run once there is an increase in taxes. An argument that could explain the positive effect in the short term is that usually increase in taxes is followed by additional stimuli in order to lessen the possible negative effects on output. Such possible stimuli are not captured by the factors since the responses of output to tax increase are very similar in the case of the FAVAR and the VAR model.

Figure 1.7 in the appendix shows the impulse responses of selected variables that were used to extract the four factors entering in the FAVAR. It should be noted that the results in Figure 1.7 are not as plausible as the results from Figure 1.6. For example personal

[5]The graphics represent the original impulse responses to a unit of one standard deviation tax increase. A possible extension that can be implemented is considering transformation of the impulse responses so that they present a dollar response of each variable to a dollar shock in one of the fiscal variables. This is not done in this paper. That is why just the direction, but not the magnitude of the responses will be discussed.

consumption reacts positively to tax shocks in the first six quarters of the considered time span. After the sixth quarter consumption decreases but the response is not significant. Personal income reacts in the same way. When consumption increases at the beginning of the 20 quarters period along with income, as a secondary effect interest rates should increase, since money demand increases. When consumption and income decrease then interest rates should follow the same pattern. This can be seen when looking at the responses of the federal funds rate. This finding is in tune with the results of Marcellino (2006) for the euro area, where the effect of tax increase on interest rates is positive for the short run. In the case of U.S. the slight increase in the interest rate can be due to the increase of the demand for money. The FAVAR shows that such an increase in interest rates does not last long, and as it can be seen from Figure 1.7 after eight quarters the federal funds rate response to tax increase is insignificant. In addition an increase in taxes leads to significant drop in unemployment which is more persistent than the one observed in the case of government spending shock. This result is not plausible, usually one would expect an increase in unemployment in case of tax increase. A possible reason for the unexpected results may lay in the indirect method used to calculate the responses in the variables from which the factors were extracted (see equation (1.7)). This result should be investigated further in order to be justified, here this will be omitted.

1.6 Robustness Checks

In this section two plausibility checks will be discussed. The first one relates to the identification scheme used in the structural model. The second one will evaluate the performance of the model in case of different number of factors.

1.6.1 Identification Schemes

In this section we will compare the impulse responses of g_t, t_t and y_t to fiscal policy shock using the FAVAR model with two different identification schemes. The main goal of this exercise is to evaluate the differences of the results which are due to the proposed identification scheme. The two FAVAR models have very similar set up, they differ only in the method used to identify the structural shocks. The general structure of the two models is the one introduced in equation (1.8). The two models include a constant, a linear and quadratic deterministic terms as before. The two identification methods that will be compared are the proposed identification scheme seen in (1.11) and the Choleski identification scheme that was discussed previously.

Figure 1.8 plots the approximate 90% confidence intervals of the impulse responses using the two FAVAR models. The main differences between the responses from the FAVAR with the new identification and the FAVAR with the Choleski identification are in the case of government spending shock. In this case the reaction of output using the Choleski identification is positive in the short run followed by an offset in the second year after the shock that lasts for an year and a half. After this period output again increases slightly. In the case of the FAVAR using the new identification the boost in y_t is much higher in the period immediately after the shock compared with the results using the Choleski identification. As it can be seen in Figure 1.8 the positive effect on output spreads for more than three years after the increase in government spending. The effect on output is offset after this period, which is in line with event studies (see Caldara and Kamps, 2008). In addition the reaction of taxes to increase of government spending also differs. This is expected since the dynamics of output and taxes are expected to be similar in case of government spending shock.

Another big difference observed when comparing the impulse responses of government spending from the two models is in the case of positive shock in output. In the case of the FAVRA with the proposed identification, g_t drops significantly in the case of increase in GDP, contrary to the results using the Choleski identification. The differences are due to the fact that in the new identification scheme there are no restrictions on the immediate impact of y_t on g_t as in the Choleski identification scheme. The results for the FAVAR with the new identification schemes are economically more plausible since one would expect that in case of GDP growth, unemployment would decrease which would lessen government spending.

1.6.2 Number of Factors

In the proposed FAVAR model we have identified a total of four factors using the Bai and Ng criteria. In this subsection we would like to analyse if reducing the number of factors that enter in the FAVAR would change the impulse responses obtained from the model. In order to do this we will compare a FAVAR model with four factors as defined in (1.10) with a FAVAR model with two factors. The decision to take just two factors is driven by the results in Figure 1.3. As it can be seen there the third and the fourth factors explain 5.1% and 1.2% of the variability of the dataset X_t. Due to the low variability that these factors explain we will consider a FAVAR model where these factors are dropped. We use the Choleski identification scheme in both models in order to obtain better comparability (note that the identification scheme proposed in (1.11) cannot be used in the FAVAR with two factors). Figure 1.9 compares the models with four and two factors and plots the approximate 90% confidence intervals of the impulse responses for the two models. No major differences in the responses could be seen from using the FAVAR with fewer factors. The benefit of using four factors comes from the fact that we can imply the new identification scheme and not calibrate a_{56} and a_{57} as done in Blanchard and Perotti (2002).

Figure 1.10 in the appendix plots the impulse responses of government spending in the case of tax shock. The Choleski identification scheme is used to identify innovations, and different number of factors were extracted from X_t and added to the FAVAR[6]. As it can be seen from the graphic, with the increase of factors included in the model the differences between the impulse responses decreases. This evidence supports Bernanke et al. (2005) that found that each increase of the number of factors in the FAVAR has limited influence on the impulse responses. From Figure 1.10 it can be noticed that the responses to tax increase, when three and four factors are included, are very similar. This is due to the fact that the explanatory power of the fourth factor is very low. It can be concluded that considering four factors instead of two does not affect much the impulse responses in our model (based on the Choleski identification scheme). In addition as pointed earlier using a four factor FAVAR aids the new identification scheme shown in (1.11).

1.7 Conclusion

The main contribution of this paper is that, when studying fiscal policy, economists may want to consider a wide range of economic variables in order to receive economically plausible results. The standard VAR models are limited because they take into account only few economic indicators. Instead of the low dimensional VAR, the FAVAR model could be beneficial in studying fiscal fluctuations. Moreover by using FAVAR one can rebuild the impulse responses not only of those variables that enter directly in the model,

[6]Figure 1.10 plots the point estimates from FAVAR with one, two, three and four factors.

but of any economic variable that is used to estimate the factors in the FAVAR.

This paper studies the effects of fiscal policy shocks in the U.S. by using the FAVAR model. An identification scheme that suits the FAVAR structure is proposed. When it comes to analysing fiscal policy shocks, there is a gap between the results obtained by the structural VAR approach and the event study approach. The main finding of this study is that the FAVAR model narrows this difference.

The FAVAR shows that an increase in government spending boosts the economy by increasing output in the short run that is the first three years after the innovation takes place. This result is supported by event studies, but contradicts studies in the same field that use the standard structural VAR with alternative identification schemes. The reaction of GDP and consumption on tax increase in the long run is negative but positive in the short run. That means that decreasing taxes in order to increase personal consumption is an effective fiscal policy but its effects occur with lag of almost one year. This is usually disregarded by the VAR models but captured by the event studies and the proposed FAVAR. In addition after comparing the results from the VAR and FAVAR models one can conclude that the VAR responses to fiscal shocks can be misleading due to disregarding other economic variables that influence those responses. This is supported by the robustness checks done in this study.

The FAVAR model gives a more global picture of the influence of fiscal fluctuation on the economy, because of its ability to consider a larger number of economic variables. In times of economic crisis, when fiscal policy is used to stimulate consumers demand, methods like the FAVAR model should be used to analyse precisely the effects of such innovations on the overall economy.

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1.A Appendix - Variables

Variables included in X_t used for the factor extraction step.

Source: Federal Reserve Economic Data from the Economic Research Division at the Federal Reserve Bank of St. Louis, USA. Quarterly data - 1972:Q1-2009:Q1. The transformation codes are in brackets: (1) indicates no transformation, (2) indicates first difference of logarithm transformation, (3) indicates logarithm of levels.

1. Moody's Seasoned Aaa Corporate Bond Yield (1)
2. Average Hourly Earnings: Construction (2)
3. Average Hourly Earnings: Manufacturing (2)
4. Average Hourly Earnings: Total Private Industries (2)
5. Aggregate Weekly Hours Index: Total Private Industries (2)
6. Average Weekly Hours: Manufacturing (2)
7. Average Weekly Hours: Total Private Industries (2)
8. Average Weekly Hours: Overtime: Manufacturing (2)
9. Moody's Seasoned Baa Corporate Bond Yield (1)
10. Board of Governors Monetary Base, Adj. for Changes in Reserve Req. (2)
11. Consumer Price Index for All Urban Consumers: Apparel (2)
12. Consumer Price Index For All Urban Consumers: All Items (2)
13. Consumer Price Index for All Urban Consumers: Energy (2)
14. Consumer Price Index for All Urban Consumers: Food and Beverages (2)
15. Consumer Price Index for All Urban Consumers: Housing (2)
16. Consumer Price Index for All Urban Consumers: All Items Less Energy (2)
17. CPI: Consumer Price Index for All Urban Consumers: All Items Less Food and Energy (2)
18. Consumer Price Index for All Urban Consumers: Medical Care (2)
19. Consumer Price Index for All Urban Consumers: Other Goods and Services (2)
20. Consumer Price Index for All Urban Consumers: Transportation (2)
21. Consumer Price Index for All Urban Consumers: Food (2)
22. Consumer Price Index for All Urban Consumers: All Items Less Food (2)
23. All Employees: Durable Goods Manufacturing (2)

24. Canada / U.S. Foreign Exchange Rate (2)
25. Japan / U.S. Foreign Exchange Rate (2)
26. Switzerland / U.S. Foreign Exchange Rate (2)
27. U.S. / U.K Foreign Exchange Rate (2)
28. FFR: Effective Federal Funds Rate (2)
29. 1-Year Treasury Constant Maturity Rate (1)
30. 10-Year Treasury Constant Maturity Rate (1)
31. 5-Year Treasury Constant Maturity Rate (1)
32. 7-Year Treasury Constant Maturity Rate (1)
33. Housing Starts: Total: New Privately Owned Housing Units Started (2)
34. Housing Starts in Midwest Census Region (2)
35. Housing Starts in Northeast Census Region (2)
36. Housing Starts in South Census Region (2)
37. Housing Starts in West Census Region (2)
38. Industrial Production Index (2)
39. Industrial Production: Business Equipment (2)
40. Industrial Production: Consumer Goods (2)
41. Industrial Production: Durable Consumer Goods (2)
42. Industrial Production: Durable Materials (2)
43. Industrial Production: Final Products (Market Group) (2)
44. Industrial Production: Materials (2)
45. Industrial Production: Nondurable Consumer Goods (2)
46. Industrial Production: nondurable Materials (2)
47. Industrial Production: Electric and Gas Utilities (2)
48. M1 Money Stock (2)
49. M2: M2 Money Stock (2)
50. ISM Manufacturing: PMI Composite Index (1)
51. All Employees: Nondurable Goods Manufacturing (2)
52. Spot Oil Price: West Texas Intermediate (2)
53. Personal Income (2)
54. Producer Price Index: All Commodities (2)
55. Producer Price Index: Crude Foodstuffs and Feedstuffs (2)

56. Producer Price Index Finished Goods: Capital Equipment (2)
57. Producer Price Index: Crude Materials for Further Processing (2)
58. Producer Price Index: Fuels and Related Products and Power (2)
59. Producer Price Index: Finished Consumer Foods (2)
60. Producer Price Index: Finished Consumer Goods (2)
61. Producer Price Index: Finished Goods (2)
62. Producer Price Index: Industrial Commodities (2)
63. Producer Price Index: Intermediate Foods and Feeds (2)
64. PPI: Producer Price Index Intermediate Materials: Supplies (2)
65. All Employees: Service-Providing Industries (2)
66. 3-Month Treasury Bill: Secondary Market Rate (1)
67. 6-Month Treasury Bill: Secondary Market Rate (1)
68. Civilians Unemployed - 15 Weeks and Over (2)
69. Civilians Unemployed for 15-26 Weeks (2)
70. Civilians Unemployed for 27 Weeks and Over (2)
71. Civilian Unemployed for 5-14 Weeks (2)
72. Civilians Unemployed - Less Than 5 Weeks (2)
73. Median Duration of Unemployment (1)
74. Unemployed (2)
75. Civilian Unemployment Rate (1)
76. All Employees: Construction (2)
77. All Employees: Education and Health Services (2)
78. All Employees: Financial Activities (2)
79. All Employees: Goods-Producing Industries (2)
80. All Employees: Government (2)
81. All Employees: Information Services (2)
82. All Employees: Leisure and Hospitality (2)
83. All Employees: Natural Resources and Mining (2)
84. All Employees: Professional and Business Services (2)
85. All Employees: Total Private Industries (2)
86. All Employees: Other Services (2)
87. All Employees: Trade, Transportation and Utilities (2)

88. All Employees: Retail Trade (2)
89. All Employees: Wholesale Trade (2)
90. Personal Consumption Expenditures (2)

Variables included in Y_t

Source: Federal Reserve Economic Data from the Economic Research Division at the Federal Reserve Bank of St. Louis, USA. Quarterly data - 1972:01-2009:01.

1. Federal Government: Current Expenditures (3)
2. Federal Government Current Receipts (3)
3. Gross Domestic Product, 1 Decimal (3)

1.B Appendix - Identification Matrices

Estimated A and B matrices

$$\hat{A} = \begin{bmatrix} 1.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ -0.54 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ -0.11 & 0.19 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.09 & -0.22 & 0.05 & 1.00 & 0.00 & 0.00 & 0.00 \\ -0.35 & 1.34 & -4.40 & 0.00 & 1.00 & 0.00 & 0.02 \\ 1.63 & 14.99 & 15.58 & 0.00 & -3.90 & 1.00 & 2.24 \\ 0.31 & 8.43 & 16.95 & 5.52 & -1.06 & -0.84 & 1.00 \end{bmatrix}$$

$$\hat{B} = \begin{bmatrix} 2.71 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.95 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.33 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.40 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 9.03 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 9.38 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 39.25 \end{bmatrix}$$

$$\hat{A}^{-1}\hat{B} = \begin{bmatrix} 2.71 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 1.46 & 0.95 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.02 & -0.18 & 0.33 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.08 & 0.22 & -0.02 & 0.40 & 0.00 & 0.00 & 0.00 \\ -0.65 & -1.90 & 1.48 & 0.01 & 8.77 & -0.05 & -0.26 \\ 1.24 & -0.19 & 3.27 & 1.72 & 4.64 & 3.23 & -30.65 \\ -13.59 & -8.33 & -1.19 & -0.74 & 13.19 & 2.65 & 13.22 \end{bmatrix}$$

<u>The standard errors of the estimated A and B matrices</u>

$$\hat{A}_{SE} = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.03 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.02 & 0.03 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.03 & 0.04 & 0.10 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.60 & 3.28 & 1.89 & 0.00 & 0.00 & 0.00 & 0.40 \\ 8.16 & 29.61 & 58.18 & 0.00 & 12.65 & 0.00 & 3.85 \\ 2.74 & 5.32 & 13.85 & 14.19 & 2.64 & 0.73 & 0.00 \end{bmatrix}$$

$$\hat{B}_{SE} = \begin{bmatrix} 0.16 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.06 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.02 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.02 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 5.25 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.38 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 22.64 \end{bmatrix}$$

1.C Appendix - Figures

Figure 1.1: Government spending and taxes as shares of GDP. Sample 1972:Q1-2009:Q1.

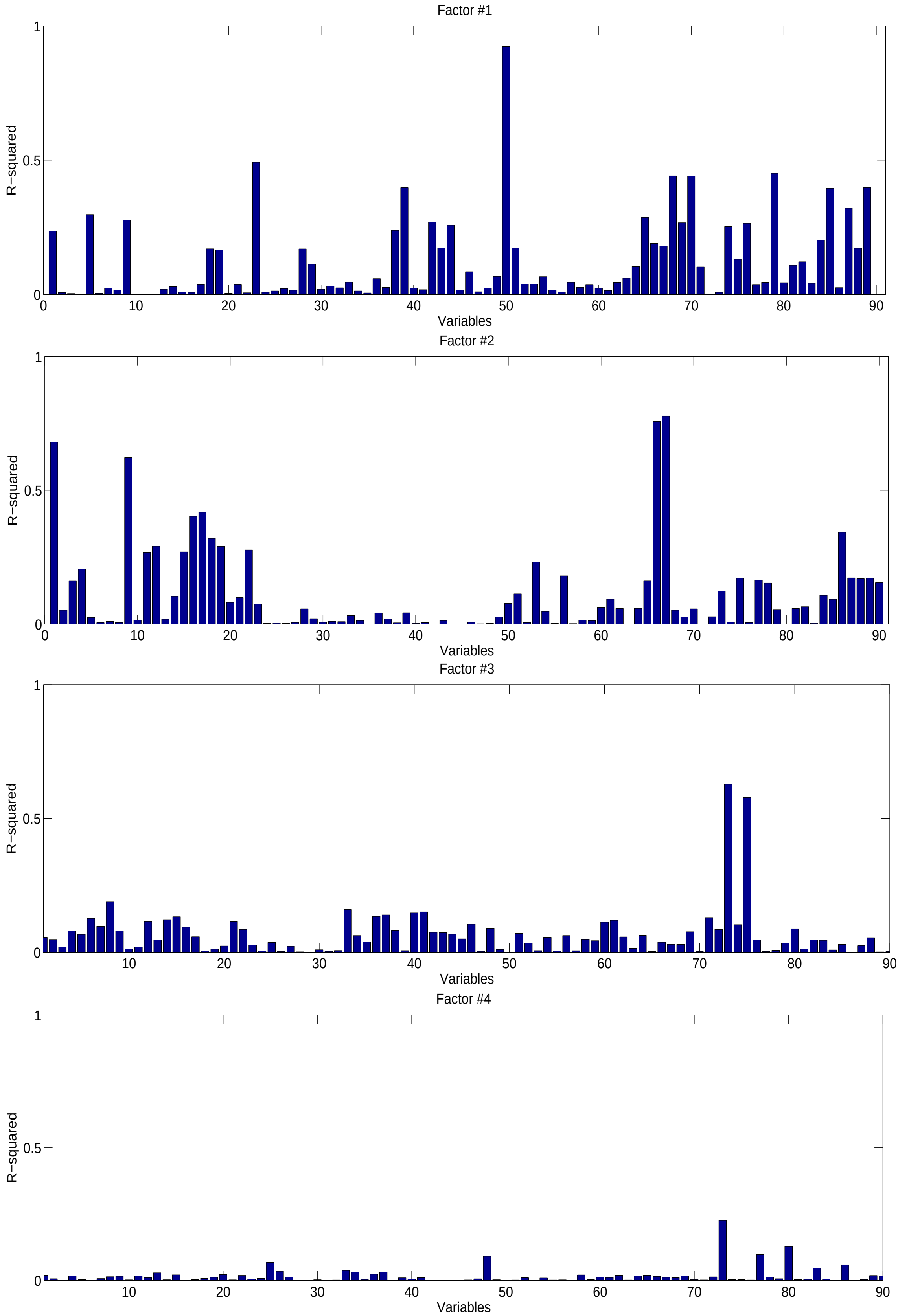

Figure 1.2: The R^2s of regressing each variable in X_t on the four principle components $(\hat{f}_t^1, \hat{f}_t^2, \hat{f}_t^3, \hat{f}_t^4)$. Sample 1972:Q1-2009:Q1. The number on the horizontal axis corresponds to the numbering of the variables in Appendix 1A.

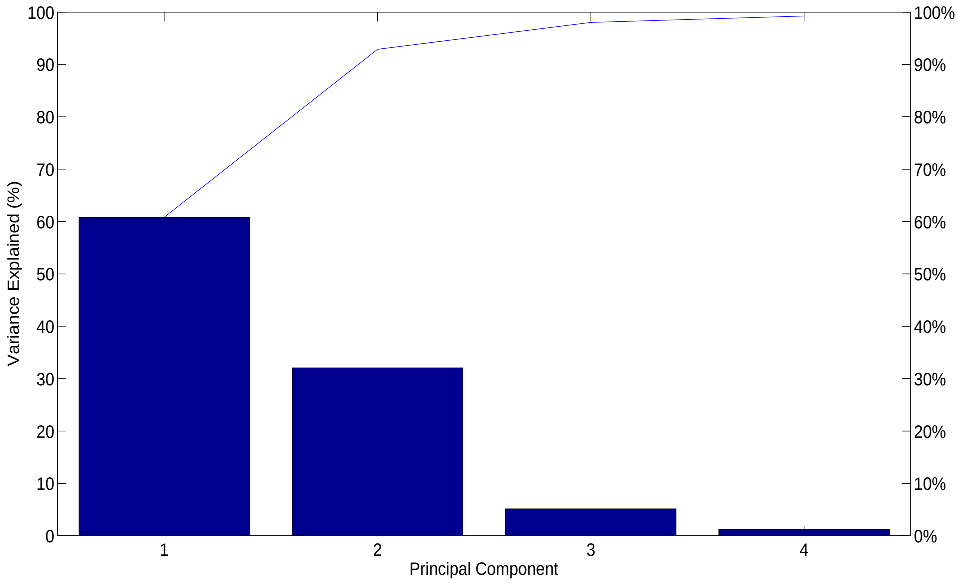

Figure 1.3: Estimated variance for each principal component. The line above the bars shows the cumulative percentage. The principal components are extracted from X_t, which includes the 90 variables listed in Appendix 1A. Sample 1972:Q1-2009:Q1.

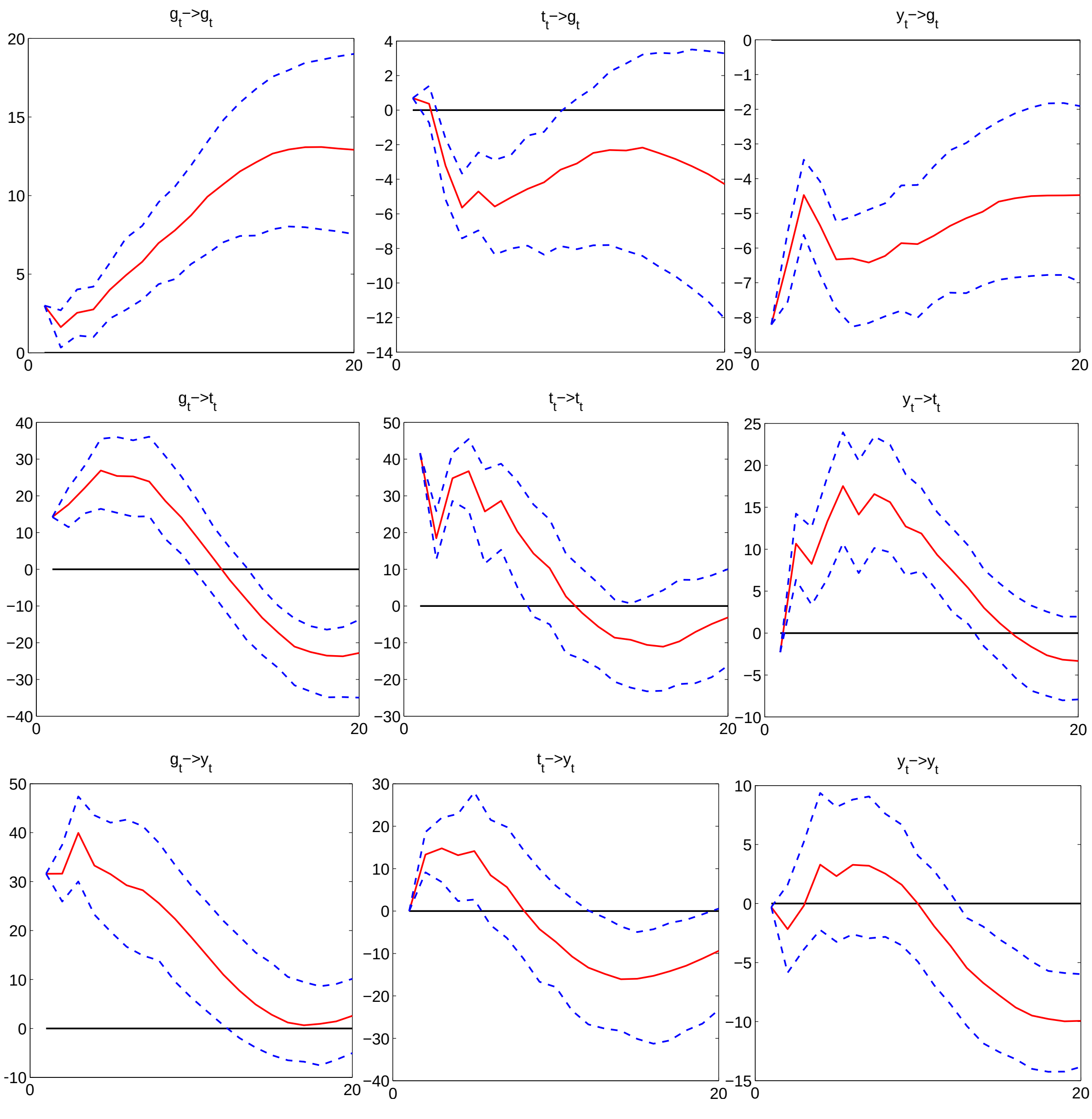

Figure 1.4: Responses of government spending (g_t), taxes (t_t), and output (y_t) to shocks in government spending (first column), taxes (second column), and GDP (third column). The point estimate is reported together with an approximate 90% confidence intervals based on the bootstrap method explained in section 1.2.3. The model used is a FAVAR with four factors, the identification scheme is the one introduced in (1.11). Sample 1972:Q1-2009:Q1.

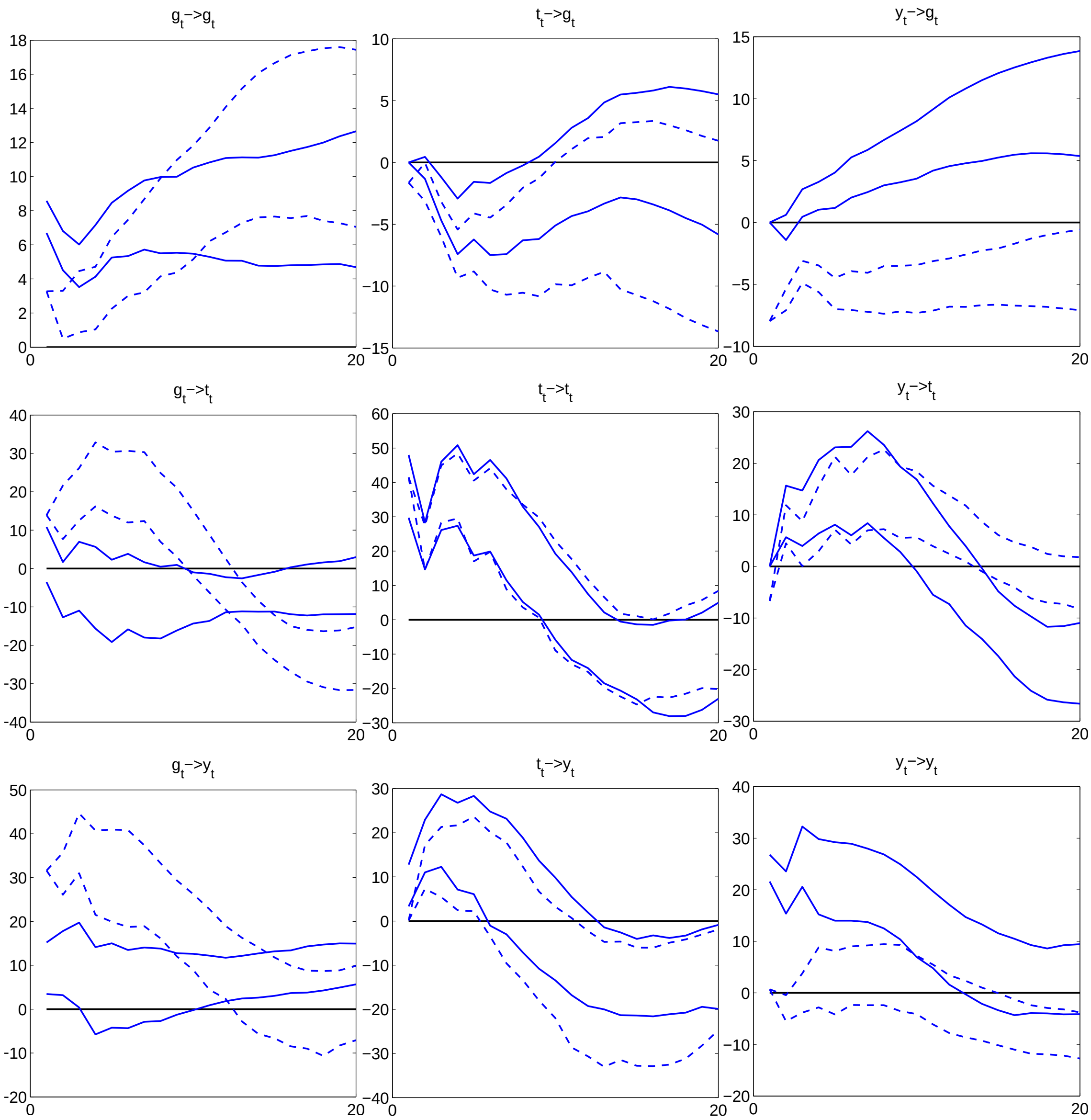

Figure 1.5: Responses of government spending (g_t), taxes (t_t), and output (y_t) to shocks in government spending (first column), taxes (second column), and GDP (third column). The approximate 90% confidence intervals based on the bootstrap method explained in section 1.2.3 are reported. The dashed line are the confidence bands for FAVAR model with four factors, the identification scheme is the one introduced in (1.11). The solid line represents the confidence bands for VAR model, the Choleski identification scheme is used. Sample 1972:Q1-2009:Q1.

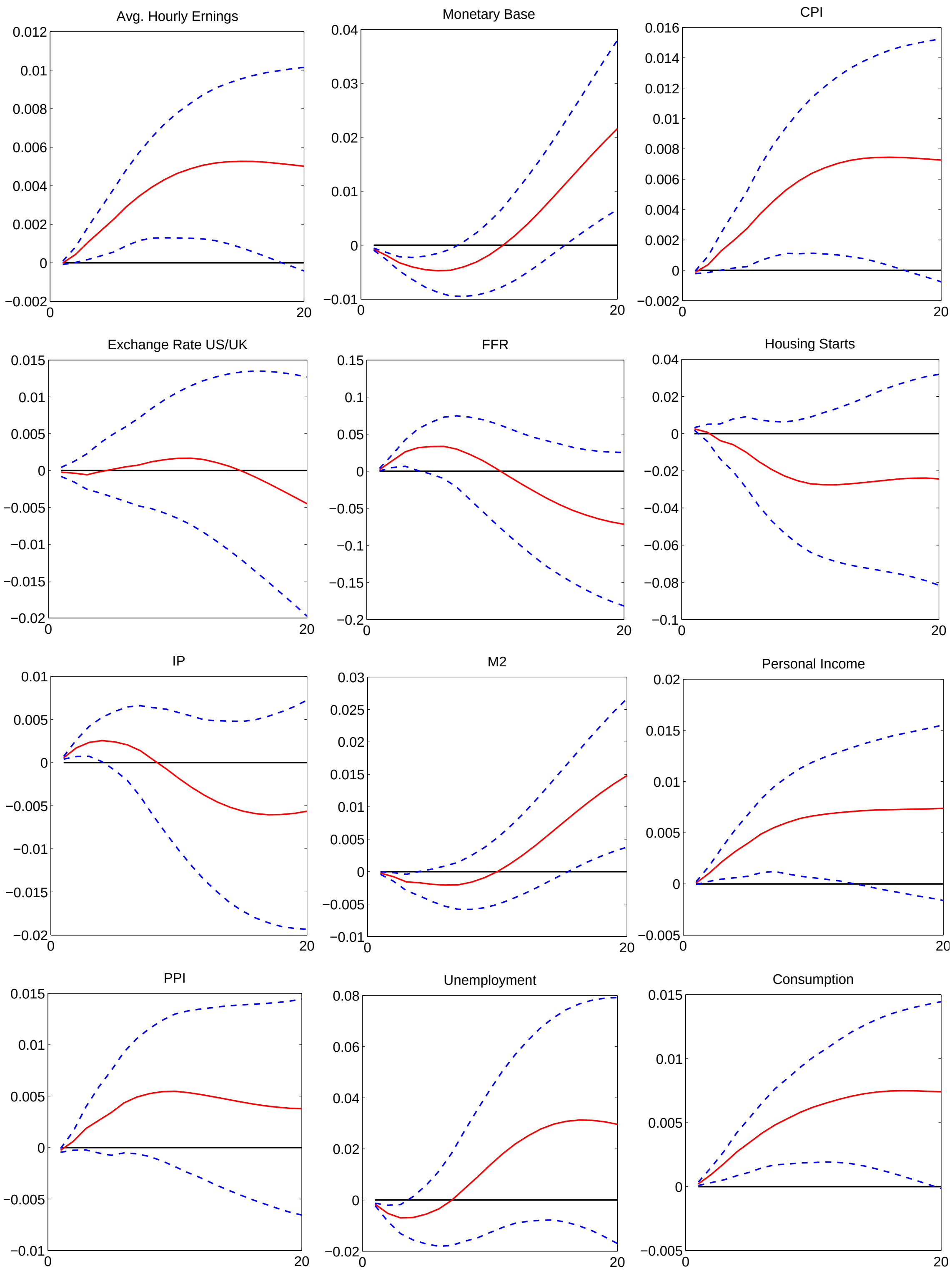

Figure 1.6: Responses of selected variables composing X_t to shock in government spending. The point estimate is reported together with an approximate 90% confidence intervals based on the bootstrap method explained in section 1.2.3. The model used is a FAVAR with four factors, the identification scheme is the one introduced in (1.11). Sample 1972:Q1-2009:Q1.

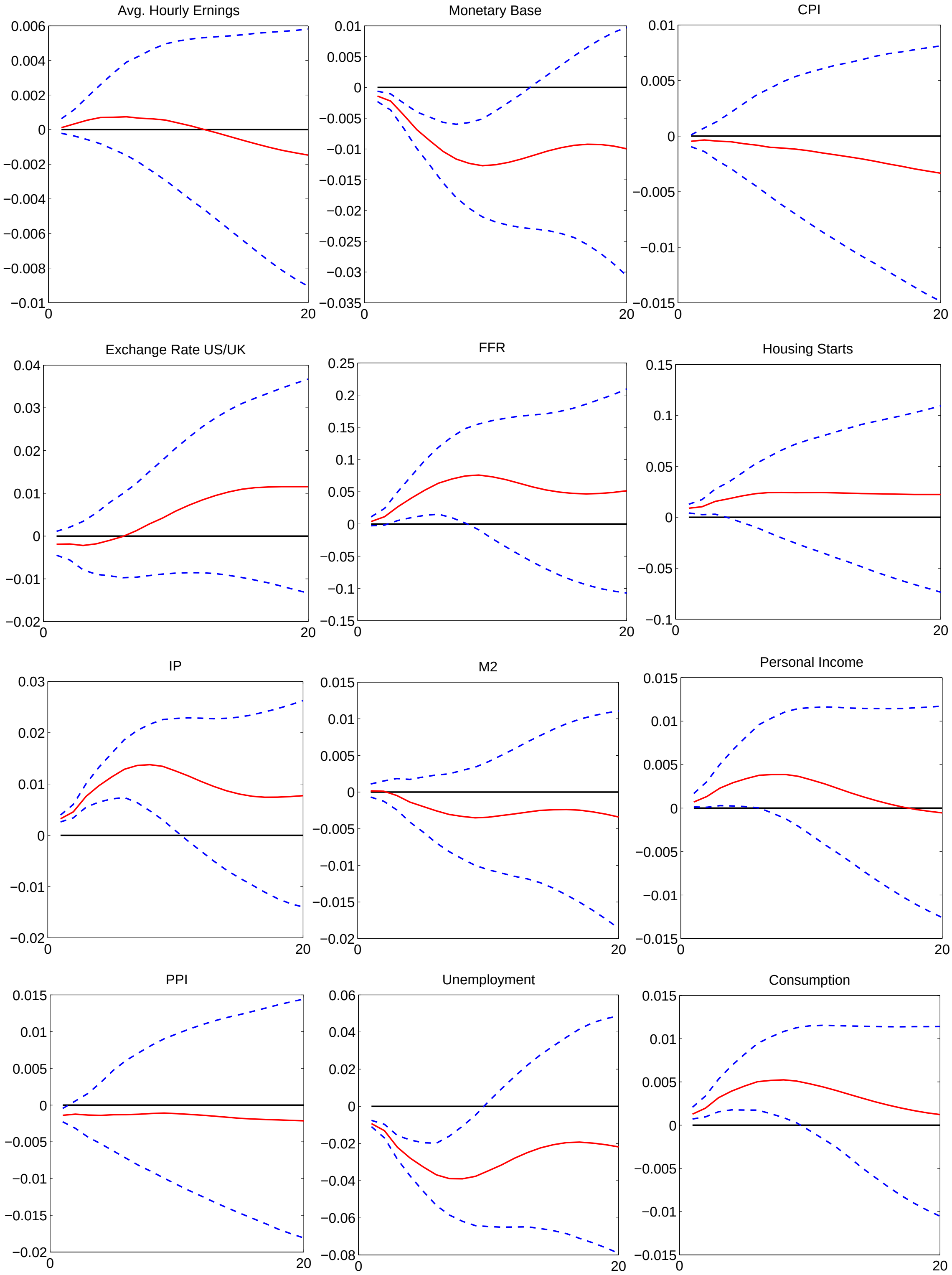

Figure 1.7: Responses of selected variables composing X_t to shock in taxes. The point estimate is reported together with an approximate 90% confidence intervals based on the bootstrap method explained in section 1.2.3. The model used is a FAVAR with four factors, the identification scheme is the one introduced in (1.11). Sample 1972:Q1-2009:Q1.

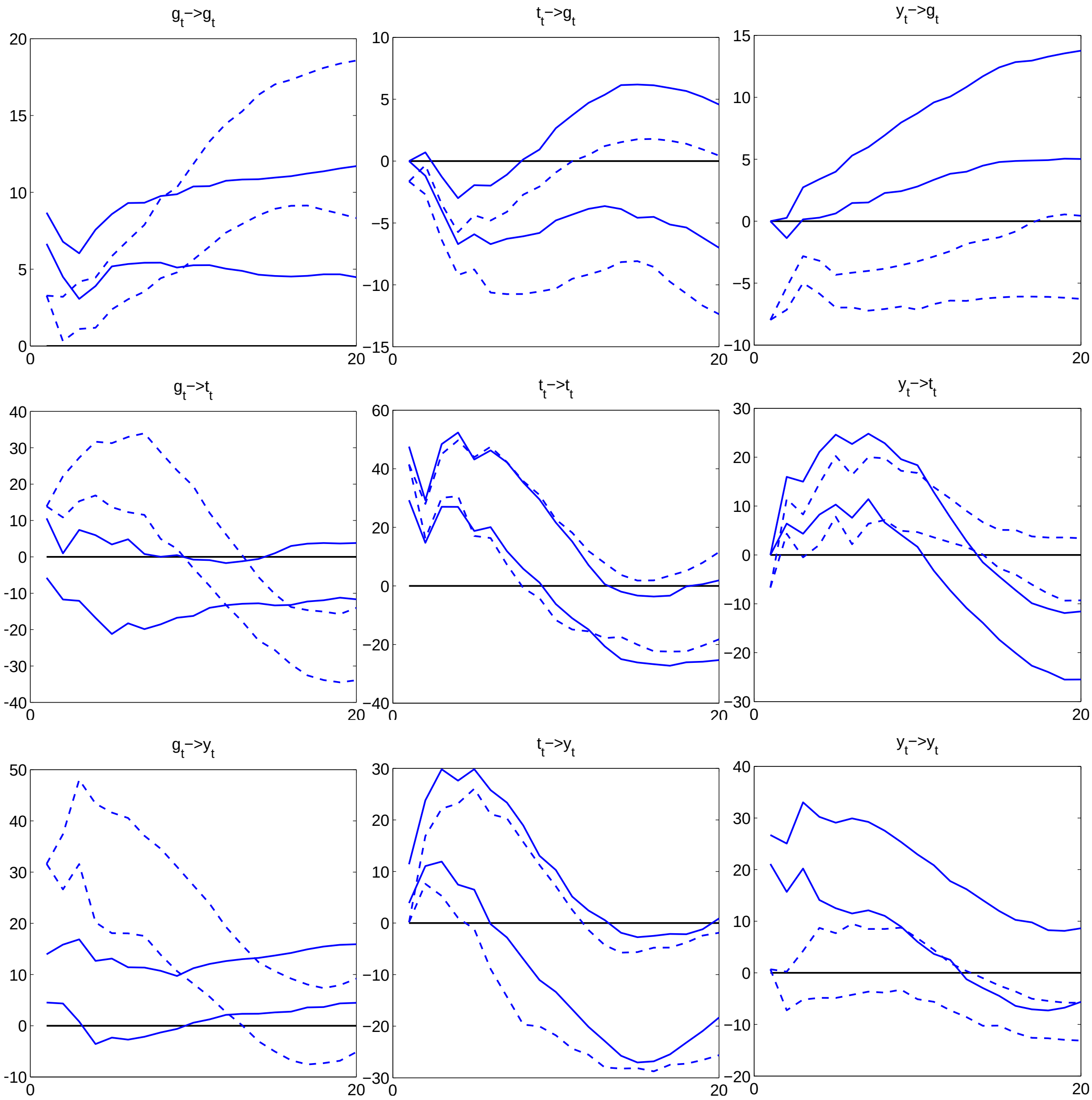

Figure 1.8: Responses of government spending (g_t), taxes (t_t), and output (y_t) to shocks in government spending (first column), taxes (second column), and GDP (third column). The approximate 90% confidence intervals based on the bootstrap method explained in section 1.2.3 are reported. The solid line are the confidence bands for the FAVAR with Choleski identification, the dashed lines are the confidence bands from the FAVAR using the identification presented in (1.11). Sample 1972:Q1-2009:Q1.

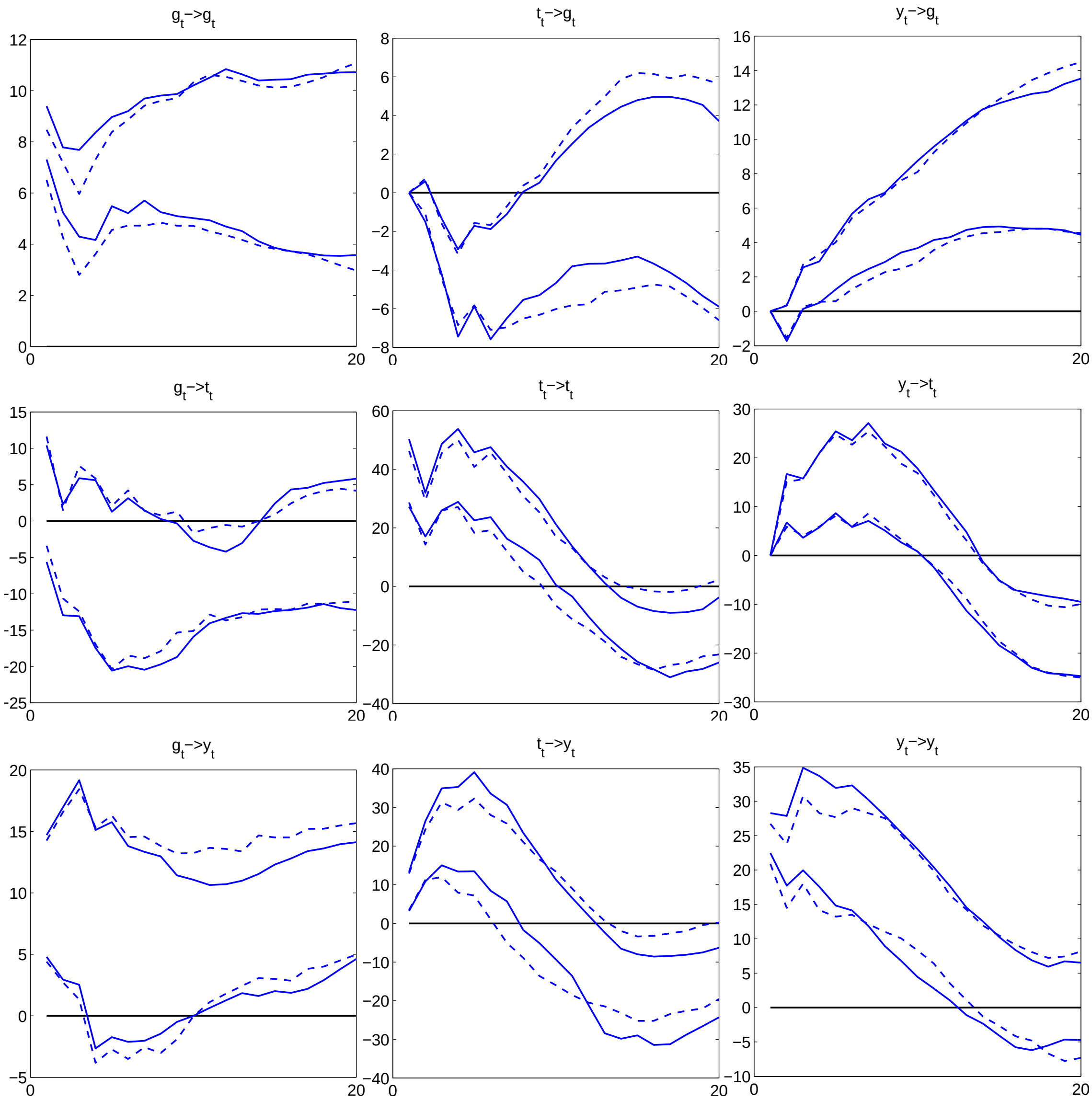

Figure 1.9: Responses of government spending (g_t), taxes (t_t), and output (y_t) to shocks in government spending (first column), taxes (second column), and GDP (third column). The approximate 90% confidence intervals based on the bootstrap method explained in section 1.2.3 are reported. The dashed line are the confidence bands for the FAVAR with four factors and the solid line indicates the confidence bands for FAVAR with two factors. Choleski identification is used for both models. Sample 1972:Q1-2009:Q1.

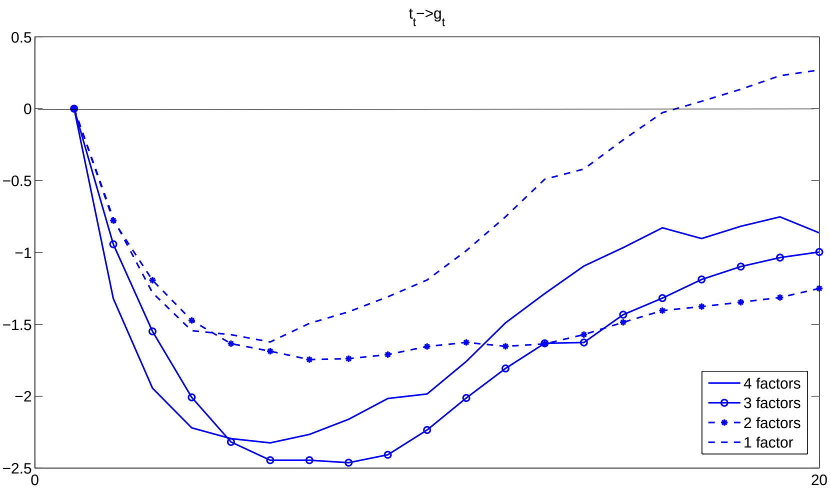

Figure 1.10: Responses of government spending to one standard deviation shock in taxes when using FAVAR with four, three, two and one factors. The variables in the FAVAR are ordered as follows: extracted factors, government spending, taxes, and gross domestic product. Sample 1972:Q1-2009:Q1.

Chapter 2

External Information and Monetary Policy Transmission in New EU Member States: Results from FAVAR Models

2.1 Introduction

On May 1, 2004 eight Central and Eastern European (CEE) countries have entered the European Union (EU), among them the three largest CEE economies Czech Republic, Hungary and Poland. EU membership may be seen as the first step towards European economic and monetary integration of accession countries. In fact, many of the new member states have plans to become members of the European Monetary Union (EMU) and to adopt the Euro as a common currency in the future. Moreover, some of the new member states (Slovenia, Slovakia, and Estonia) have already adopted the Euro.

Economists argue that successful EMU membership requires the countries of the monetary union to be sufficiently similar as otherwise common monetary policy may be difficult to implement (see e.g. Dornbusch, Favero and Giavazzi, 1998). Against this background, one aspect of economic integration that has received some attention in the literature is related to differences in the monetary transmission mechanisms. Understanding how monetary transmission differs among (potential) EMU members is particularly relevant in the context of currency unions. Empirically, the effects of monetary policy shocks are usually investigated within small identified vectorautoregressive (VAR) models using techniques of innovation accounting such as impulse response analysis. For instance, a number of studies focus on possible heterogeneity in the transmission mechanism in economies that formed the EMU in 1999 (see e.g. Smets and Peersman, 2001; Mojon and Peersman, 2001; Angeloni, Kashyap, Mojon and Terlizzese, 2003; Mihov, 2001; Ciccarelli and Rebucci, 2002; Ehrmann, Gambacorta, Martinez-Pagés, Sevestre and Worms, 2003). Similarly, some attempts have been made to characterize and compare the monetary transmission mechanism in individual EU acceding countries. Examples for studies on acceding countries include the work of Ganev, Molnar, Rybinski and Wozniak (2002), Gavin and Kemme (2009), Coricelli, Égert and MacDonald (2006), Elbourne and de Haan (2006), Anzuini and Levy (2007). The reported results for the individual countries are often ambiguous and sometimes the authors do not find evidence for a sensible monetary transmission mechanism. For instance, in addition to positive price responses to contractionary monetary policy shocks (the so-called 'price puzzle') the papers also report counterintuitive positive output responses for some of the countries. Thus, only few robust conclusions emerge from the mentioned studies.

We argue that some of the counter-intuitive results for the accession countries found in the literature are due to mis-specification of the small VARs, as some important (external) variables are likely to be missing from the information set. The point of missing variables in the VAR is particularly relevant in the case of EU accession countries, because the work for those countries typically uses very small VAR systems often including not more than four variables. This is due to the fact that available time series are still relatively short and is in contrast to studies for the US or other European countries. Using larger VARs is prohibitive as the degrees of freedom in these models quickly exhaust.[1] Moreover, the close trade links among the accession countries themselves and the links with other EMU countries suggest a prominent role for additional external variables in the VARs.

Therefore, in this paper we explore to what extent accounting for external economic developments in the EMU and in other acceding countries changes the results from structural VAR models and the conclusion about the effects of monetary policy shocks. We do so by augmenting standard VAR models with factor time series that summarize parsimoniously the information from a large cross-section of time series from EMU or acceding countries as explained below. This approach differs markedly from just including a few exogenous variables.

To summarize the external economic developments, we first condense the information contained in a large cross-section of time series into a few factor time series using the techniques suggested by e.g. Stock and Watson (2002b) and Bai and Ng (2004). To facilitate the interpretation of the factor time series, we relate the factor time series to groups of variables using a cohesion measure (see e.g. Croux, Forni and Reichlin, 2001), which is a measure of dynamic correlation that has been used in the literature to study the synchronization of eastern and western European economies (cf. Eickmeier and Breitung, 2006; Camacho, Perez-Quiros and Saiz, 2006). In addition, we relate the factor time series to the underlying time series by regressing the stationary factors on the individual variables. We then include the factor time series into the VARs of the acceding countries and do so in two different ways. In a first variant we adapt the factor-augmented VAR (FAVAR) approach of Bernanke, Boivin and Eliasz (2005) and augment the VARs with factor time series (see also Marcellino, Favero and Neglia, 2005 for a related study). Since

[1] VAR based impulse response functions may not have been precisely estimated given the relatively large number of parameters and the short time series data available. To mitigate this problem, Jarocinski (2010) suggests a Bayesian framework. See also Gavin and Kemme (2009) for a similar approach. While this may help to reduce the estimation uncertainty, the problem related to missing important variables cannot be resolved by this approach.

some of the time series in the VARs are likely to be driven by stochastic trends and are also possibly cointegrated, we prefer to use VARs for the levels of the variables. This preserves all potential cointegration relationships. Correspondingly, we include the non-stationary factor time series obtained from the approach by Bai and Ng (2004). In the second variant, we include the non-stationary factor time series as exogenous variables with lags. To our best knowledge, none of these types of augmentations have been used in the literature so far.

In the empirical analysis, we report and compare impulse response functions (IRFs) for the four accession countries Czech Republic, Hungary, Poland, and Slovakia. We identify monetary policy shocks either using a recursive structure or using sign restrictions (as in Jarocinski, 2010) and document the role of external information by comparing the responses to contractionary monetary policy shocks from benchmark VARs with those of different FAVARs. We investigate the respective roles of external information coming from EMU countries and of information coming from the other accession countries. In other words, we use different FAVARs either using the factor time series from EMU countries or using the factor time series from accession countries.

We find that including EMU factor time series in the VAR does not greatly change the pattern of the IRFs. In contrast, including the accession country information leads to substantial changes in the impulse response pattern. Compared to the benchmark model, the responses to a monetary policy shock are then more in line with theoretical expectations: output variables tend to drop, prices tend to decrease (the price puzzle disappears or is less pronounced), and the exchange rate appreciates. In some countries, a reasonable monetary transmission mechanism can only be diagnosed when the external accession country factors are included in the model. Our results suggest that the external economic developments in the other accession countries are more important for the monetary transmission than the economic ongoings in the euro area. Overall, our results highlight the importance of taking these external developments properly into account.

The remainder of the paper is organized as follows. In Section 2.2 we introduce the econometric framework. Section 2.3 contains the empirical results from the factor and cohesion analysis as well as from the FAVAR impulse response analysis. Section 2.4 concludes.

2.2 The Econometric Framework

We use factor-augmented VAR models in the empirical analysis. Therefore, in Section 2.2.1 we briefly review the framework for the factor analysis, which corresponds to the first part of the empirical analysis in Section 2.3. Section 2.2.2 explores the economic meaning of the extracted factor time series. The way how the factors enter the VAR and how we use this model to compute IRFs is explained in 2.2.3.

2.2.1 Stationary and Non-Stationary Factor Models

Factor models that condense the information from a large cross-section of times series have been introduced in the context of forecasting (see e.g. Stock and Watson, 2002a,b) and this framework has been extended by Bai and Ng (2004) to the case of non-stationary factors.

We assume that the N-dimensional time series X_t is driven by a small number of L unobserved common factors F_t and an idiosyncratic component e_t, i.e. the vector of time series may be written as

$$X_t = \Lambda F_t + e_t, \quad t = 1, \dots, T,$$

where X_t is a $N \times 1$ vector, Λ is a $N \times L$ matrix of factor loadings, F_t is the $L \times 1$ vector of common factors and e_t is an $N \times 1$ vector of idiosyncratic components. We follow Bai and Ng (2004) and allow for possible non-stationarity in both F_t and e_t. If we use principal components to estimate the above equation the estimates of the factors F_t will not be consistent if the elements of e_t, denoted as e_{it}, are $I(1)$. Bai and Ng (2004) show that in this case applying the method of principal components to the first-differenced data leads to consistent estimation of the factors. To be precise, we define $x_t = X_t - X_{t-1} = \Delta X_t$ for $t = 2, \dots, T$ and the $(T-1) \times N$ matrix of stationary variables $x = (x_2, \dots, x_T)'$ with the t-th row being x_t'. Moreover, we let $f_t = F_t - F_{t-1} = \Delta F_t$ and $f = (f_2, \dots, f_T)'$ is the $(T-1) \times L$ vector of differenced factors. The principal components estimator of f is given as

$$\tilde{f} = \sqrt{T-1}V, \tag{2.1}$$

where V is the matrix of the L eigenvectors corresponding to the first L largest eigenvalues of the matrix xx'. The factors are normalized such that $\tilde{f}'\tilde{f}/(T-1) = I_L$ holds and we refer to these normalized factors as $\hat{f}$. Using this normalization the loadings are estimated as

$$\hat{\Lambda} = x'\hat{f}/(T-1).$$

The corresponding estimator for F_t is given by cumulating the stationary PC component factors $\hat{f}_t$, i.e.

$$\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s. \tag{2.2}$$

By using this approach we obtain estimates of the F_t which retain their order of integration regardless if e_{it} is $I(0)$ or $I(1)$. We refer to equations (2.1) and (2.2) as the stationary and non-stationary factor time series, respectively.

2.2.2 Relating Factors to Groups of Time Series

In the empirical analysis of the paper we include some of the non-stationary factor time series into VAR models in order to analyse the monetary transmission mechanism of the acceding countries. To give some insight, on what these factor time series represent we would like to relate these factor series (i) to the original time series data from which the factors have been extracted (ii) to the variables included in the VARs.[2] The latter gives a first indication which economic variables may be important in the VAR for the acceding countries.

In order to get a better understanding of what these factors represent we use two different techniques. The first one is a simple R^2 measure that has also been used by Stock and Watson (2002b). In this approach, the individual stationary factor series $\hat{f}_t$ are regressed on each of the $i = 1, \ldots, N$ series x_{it} used in the factor extraction step and the R^2 of the corresponding regression is reported. The second method is based on the *cohesion* measure, proposed by Croux et al. (2001) as a novel way to analyse dynamic comovement of many variables. In the context of time series cohesion is closely related to cointegration. The main benefits of the former method is that it is not binary (usually two series are cointegrated or not, but one cannot establish certain magnitude association). Moreover, the method can also be applied if the number of time series under investigation is larger, i.e. the methods works also when reduced rank methods based on VARs cannot

[2]Clearly, the factors are only identified up to a rotation and here we use a standard statistical normalization that is used in the FAVAR context (cf. e.g. Bernanke et al., 2005). Given this normalization, we try to relate these factor series to different economic time series. Evidently, the corresponding factor interpretation should be regarded with some caution as it is not based on a structural model. Nevertheless, the results based on this approach are still helpful to understand the results from the impulse response analysis of 2.3.3.

be applied anymore.

The cohesion measure can be interpreted as an extension of the dynamic correlation concept. Given two time series y_t and x_t with mean zero and with spectral density functions $S_y(\lambda)$ and $S_x(\lambda)$ and cospectrum function $C_{xy}(\lambda)$, the dynamic correlation between y_t and x_t at frequency λ is

$$\rho_{xy}(\lambda) = \frac{C_{xy}(\lambda)}{\sqrt{S_y(\lambda) S_x(\lambda)}}.$$

For the multivariate case where x_t is a vector of n variables, i.e. $x_t = (x_{1t}, x_{2t}, \dots, x_{nt})'$ cohesion equals a weighted average over dynamic correlations

$$coh_x(\lambda) = \frac{\sum_{i \neq j} w_i w_j \rho_{x_i x_j}(\lambda)}{\sum_{i \neq j} w_i w_j}.$$

This measure is not very informative since $\rho_{x_i x_j}(\lambda) \in [-1, 1]$ and some terms within the sum may cancel. Therefore, Croux et al. (2001) considered a cohesion measure based on the absolute values of the dynamic correlations

$$coh_x^*(\lambda) = \frac{\sum_{i \neq j} w_i w_j |\rho_{x_i x_j}(\lambda)|}{\sum_{i \neq j} w_i w_j}, \tag{2.3}$$

where we have used $w_j = 1, \forall j$ to give equal weights to the different variables. Clearly, when considering the absolute value of the correlation the information regarding the direction of the correlation is also lost. This is not a problem for our application where we are interested in the magnitude of the correlation and not in its sign. To our knowledge, up to now the cohesion measure has not been used to determine co-movement between group of variables and extracted factors. To avoid spurious cohesion among the non-stationary factors and variables, we compute the cohesion among shocks driving the factors and shocks driving the variables. These shocks are measured as the residuals from autoregressive models fitted to the factors and variables, respectively.[3]

[3]These type of shocks have also been used in the study of correlations among factors and variables presented in Eickmeier (2005).

2.2.3 Factor-Augmented VARs

The monetary transmission mechanism is analysed within the VAR framework. The starting point is a standard VAR with intercept of the form

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{2.4}$$

where y_t is a $K \times 1$ vector of endogenous variables, ν is a $K \times 1$ vector of intercepts, $A_1, \ldots, A_p$ are $K \times K$ fixed VAR coefficient matrices and u_t is the reduced form innovation vector with mean zero and fixed, non-singular covariance matrix Σ_u. In what follows, we discuss the two variants of factor augmentation that we use in the empirical analysis.

The first approach follows the idea of Bernanke et al. (2005) and Stock and Watson (2005). In their set-up, the estimated stationary factor time series $\hat{f}_t$ are added as variables to a VAR model. In contrast to this, we include the non-stationary factor time series $\hat{F}_t$ in the VAR. Also note that in our application the group of variables from which the factors are extracted does not contain the variables y_t as for a particular country we only use data from other foreign countries (EMU or other accession countries) for factor extraction. Our first setup is obtained by defining the $(L+K) \times 1$ vector as $y_t^* = (\hat{F}_t', y_t')'$ and then formulating the factor-augmented VAR as

$$y_t^* = \nu^* + A_1^* y_{t-1}^* + \cdots + A_p^* y_{t-p}^* + u_t^*, \tag{2.5}$$

where $A_i^*, i = 1, \ldots, p$ are now $(L+K) \times (L+K)$ fixed coefficient matrices. u_t^* is now a $(L+K) \times 1$ innovation vector with covariance matrix Σ_u^*. Including the non-stationary factors in the model has the advantage that possible cointegration relationships between the factors F_t and the VAR variables in y_t are implicitly accounted for. In addition, in this approach the factor time series and y_t are likely to be of the same order of integration and hence we look at a type of balanced regression. Estimation of the VAR with levels of the variables and the non-stationary factor time series seems warranted given the points made by Sims, Stock and Watson (1990).

Alternatively, we include the factor time series in form of exogenous variables. To be more precise, we use VAR models of the form

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 \hat{F}_t + \cdots + B_s \hat{F}_{t-s} + u_t, \tag{2.6}$$

where y_t is a $K \times 1$ vector of endogenous variables and $\hat{F}_t$ is the $L \times 1$ factor variable vector. $B_0, \ldots, B_s$ are fixed $K \times L$ coefficient matrices related to the exogenous variables. As before, u_t is the reduced form innovation vector with mean zero and fixed, non-singular covariance matrix Σ_u. Estimation of the VAR in levels of the variables and the non-stationary factor time series seems warranted as long as $s \geq 1$ (see Sims et al., 1990).

The VAR models given in (2.4)-(2.6) are reduced form models. The effects of structural shocks are typically investigated using the structural VAR (SVAR) framework (see e.g. Breitung, Brüggemann and Lütkepohl, 2004 for an overview of these models). In order to identify the monetary policy shocks suitable restrictions have to be imposed on the model. We describe the two identification schemes used in the empirical analysis in the following:

The basic idea in both identification schemes is that the reduced form disturbances u_t are regarded as linear combinations of a set of structural shocks ε_t, such that

$$u_t = G\varepsilon_t. \tag{2.7}$$

Once the matrix G has been determined, impulse responses to monetary policy shocks can be computed using the standard formulas laid out e.g. in Lütkepohl (2005, Section 2.3)

The first identification scheme that we use is the well-known recursive scheme, in which G is a lower triangular matrix obtained from a Choleski decomposition of the covariance matrix Σ_u. Clearly, with this recursive identification scheme the results may depend on the ordering of the variables. In the empirical baseline model of Section 2.3, we have a four-dimensional VAR model with $y_t = (q_t, p_t, r_t, e_t)'$, where q_t is the log of industrial production, p_t is the log of the consumer price index (CPI), r_t is the short-term interest rate and e_t is the log of the exchange rate measured as local currency per US Dollar. Monetary policy shocks are related to the equation in r_t and therefore using the recursive scheme implies that monetary policy shocks may have an immediate impact on the the exchange rate, while output and prices can only be affected with a lag of one period. This identification scheme is quite standard in the literature (see e.g. Christiano, Eichenbaum and Evans, 1999). Once factor time series are included in the VAR as in (2.5), we order them first, i.e. we use $y_t^* = (\hat{F}_t', y_t')'$. This implies that the interest rate shock in a particular accession country has no immediate impact on the external development in either the EMU or the other accession countries.

In small VARs with recursive identification schemes, contractionary monetary policy shocks often lead to positive responses of price measures. This effect is known as the 'price puzzle'. As e.g. noted by Kim and Roubini (2000) for countries other than the USA the 'price puzzle' is observed if one does not control for the immediate reactions of exchange rates to fluctuations in interest rates and vice versa. To avoid potential problems related to the price puzzle in our context, we follow Jarocinski (2010), who combines a sign restriction approach and with a recursive identification and adapt his approach for our FAVAR specifications. The main assumption on which this identification rests is that exchange rate and interest rate are allowed to react immediately in the presence of innovations in r_t and e_t, respectively. To be more precise, in a VAR without factors (or with factors entering exogenously), equation (2.7) is given as in Jarocinski (2010):

$$\begin{pmatrix} u_t^q \\ u_t^p \\ u_t^r \\ u_t^e \end{pmatrix} = \underbrace{\begin{pmatrix} + & 0 & 0 & 0 \\ * & + & 0 & 0 \\ * & * & + & + \\ * & * & - & + \end{pmatrix}}_{G} \begin{pmatrix} \varepsilon_t^q \\ \varepsilon_t^p \\ \varepsilon_t^r \\ \varepsilon_t^e \end{pmatrix} \tag{2.8}$$

where $*$, $+$, and $-$ denotes that the corresponding coefficient is unrestricted, restricted to be positive and restricted to be negative, respectively. Column (3) of the matrix G implies that output and prices do not react within a month (as in the recursive scheme), while an immediate negative impact of contractionary monetary policy shocks ε_t^r to the exchange rate equation is imposed. Similarly, if the factors are included, we write equation (2.7) as

$$\begin{pmatrix} u_t^F \\ \hline u_t^q \\ u_t^p \\ u_t^r \\ u_t^e \end{pmatrix} = \underbrace{\left(\begin{array}{c|c} G_{11} & G_{12} \\ \hline G_{21} & G \end{array}\right)}_{G*} \begin{pmatrix} \varepsilon_t^F \\ \hline \varepsilon_t^q \\ \varepsilon_t^p \\ \varepsilon_t^r \\ \varepsilon_t^e \end{pmatrix} \tag{2.9}$$

where u_t^F and ε_t^F are $L \times 1$ vectors of reduced form and structural innovation vectors related to the factor equations, G_{11} is a $L \times K$ lower triangular matrix with positive diagonal elements, $G_{12} = 0$ is a $L \times L$ zero matrix, G_{21} is a $K \times L$ matrix with unrestricted coefficients and the lower right-hand side block G is given as in equation (2.8). The zero block $G_{12} = 0$ implies that the non-stationary factors, which summarize the foreign economic development, do not respond immediately to fluctuations in the home country variables and consequently do not respond immediately to a monetary policy shock in the home (accession) country. This corresponds to the recursive identification scheme explained above. Thus, the identification of the monetary policy shocks is equivalent to the model without the factors included. Note, the lower-triangular structure of the upper left-hand block G_{11} does not affect our results, as it does not impact the identification of the monetary policy shock. In summary, this identification combines a recursive scheme with sign restrictions given in the lower 2×2 block of G.

This sign restriction approach is similar to Uhlig (2005) and implies sign restrictions on the impulse responses on impact. The appropriate factorizations will be obtained by means of a rotation matrix. As argued by Jarocinski (2010) the difficulty of finding an appropriate factorization disappears due to the fact that we combine zero restrictions with sign restrictions. In this respect the factorization G^* can be represented as multiplication of two matrices, the Choleski decomposition of Σ_u^*, denoted as $\mathrm{chol}(\Sigma_u^*)$ and a rotation matrix for the last two columns of G, i.e.

$$G^*(\theta) = \mathrm{chol}(\Sigma_u^*) \cdot R(\theta), \tag{2.10}$$

where $R(\theta)$ is a rotation matrix of form

$$R(\theta) = \begin{pmatrix} I_{K+L-2} & 0_{(K+L-2)\times 2} \\ 0_{2\times(K+L-2)} & V(\theta) \end{pmatrix}$$

and

$$V(\theta) = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix}$$

If we let c_{ij} be the ij-th element of the lower 2×2 block of $\mathrm{chol}(\Sigma_u^*)$, then multiplying the lower 2×2 block of $\mathrm{chol}(\Sigma_u^*)$ to $V(\theta)$ and using the sign restrictions implies a system of equations of the form

$$\begin{aligned} c_{11}\cos(\theta) &> 0 \\ -c_{11}\sin(\theta) &> 0 \\ c_{21}\cos(\theta) + c_{22}\sin(\theta) &< 0 \\ -c_{21}\sin(\theta) + c_{22}\cos(\theta) &> 0, \end{aligned}$$

which can be solved for the set of admissible solution for the rotation angle θ that depends on c_{21}:

$$\theta \in \begin{cases} \left(-\frac{\pi}{2}, \arctan\left(-\frac{c_{21}}{c_{22}}\right)\right), & \text{when } c_{21} > 0 \\ \left(\arctan\left(\frac{c_{22}}{c_{21}}\right), 0\right) \quad , & \text{when } c_{21} < 0 \end{cases} \tag{2.11}$$

In the practical implementation, $\text{chol}(\Sigma_u^*)$ is estimated from the estimated reduced form residuals, the range of admissible solutions for θ is computed according to (2.11). Then the rotation angle θ is chosen randomly from a uniform distribution over the range of admissible solutions. This is repeated 1000 times and the 5th and 95th quantiles of the resulting distribution of impulse responses are shown as error bands.

2.3 Empirical Results

In this section we report empirical results on the effects of monetary policy shocks for the accession countries Czech Republic, Hungary, Poland and Slovakia. For each country we compare the results from the baseline specification without taking into account the external information and compare the results with those from models that either include EMU factor or accession country factor time series.

2.3.1 Data

As mentioned earlier, the baseline VAR model specification for an accession country is a four-dimensional VAR model with $y_t = (q_t, p_t, r_t, e_t)'$, where q_t is the log of industrial production, p_t is the log of the consumer price index (CPI), r_t is the short-term interest rate and e_t is the log of the exchange rate measured as local currency per US Dollar. For each country, monthly time series data ranging from 1995M01 to 2007M12 have been used in the baseline specification. The sample of the baseline specification ends in 2007M12 to abstract from effects of the financial crisis. Precise data sources are given in the appendix. Time series plots for the accession country data series are given in Figures 2.1-2.4. It is obvious from Figures 2.1-2.4 that at least some variables show trending behaviour. A unit root analysis (results not shown) indicates that the unit root hypothesis cannot be rejected for the all the considered time series and that most of them can be characterized as integrated of order 1, I(1). Against the background that the variables may be cointegrated, we follow the standard practice in this line of the literature and specify VAR models for the levels of the variables. This avoids the false cancelation of long-run relationship between the variables. Also note that the beginning of the sample is characterized by more volatile movements e.g. in interest rates, most likely due to effects related to transitional processes. For instance, Czech Republic and Slovakia abandoned the fixed exchange rates to the Deutsche Mark an inflation-targeting framework was adopted by the Czech national bank in December 1997 and in October 1998 a similar policy was adopted by the National Bank of Slovakia.

To account for external influences we extract factor time series from (a) a large set of macroeconomic time series from EMU countries and (b) from sets of accession countries. To extract the EMU factors we use data from 11 EMU member states[4] on industrial output, CPI and producer price index, short- and long-term interest rates, exchange rates, share prices, unemployment, imports and exports. Again, the data sources are listed in the appendix. The EMU data set is composed of 107 time series.[5].

Similarly, for a similar set of variables we collect data for the four accession countries Czech Republic, Hungary, Poland and Slovakia. The list of variables coincides with the one given for the EMU countries except that we have no observation on the long-term interest rates. Thus for each country we have only 9 variables available.

2.3.2 EMU and Accession Country Factors Time Series

For the factor extraction step, the time series have to be transformed to stationarity. We follow the standard practice in the factor literature (see e.g. Stock and Watson, 2002b) and transform the variables to stationarity by either taking first differences or first differences

[4]The countries used are the original 11 EMU members Austria, Belgium, Finland, France, Germany, Italy, Ireland, Luxembourg, Netherlands, Spain and Portugal.

[5]There are no series for the short term interest rate and share prices for Luxembourg, and no unemployment series for Austria is available. Consequently, the EMU data consists of 10 time series for each 11 countries minus three ($10 \times 11 - 3 = 107$).

of the logarithm. The corresponding transformation codes can be found in Table 2.1.[6] The transformed data is then demeaned and normalized to have unit variance before the principal components are extracted.

Factor Time Series from EMU Data Starting with EMU data set, the information criteria of Bai and Ng (2002) point to up to six factors. The first 6 factors explain about 48% of the variance in the EMU data set. To get a better understanding of what these 6 factors mean, we have regressed the six stationary factors $\hat{f}_t$ on the 107 (stationarity transformed) variables in the original data set and recorded the R^2 of the corresponding regression. The results are depicted in Figure 2.5 and show a clear pattern. The first factor seems to be an important determinant of imports, export and the exchange rate. Thus we refer to this factor as the trade related factor. The second factor influences most strongly the two interest rates, while the third factor has relatively large R^2s in regression on share prices and consequently, might be referred to as a financial factor. Factor 4 and 5 seems to be related to prices, while the last factor may tentatively associated with movements in industrial output. In addition, we have also applied the cohesion measure $coh_x^*(\lambda)$ to analyse the co-movement between the stationary factors and groups of EMU variables and give the results in Table 2.2. In line with the results of the R^2 measures, the cohesion analysis shows that the first factor may be interpreted as a trade related factor, with the largest cohesion ranging from 0.4 to 0.51 for imports, exports and exchange rates.[7] Similarly, the second factor may represent the interest rate movements (cohesion with the group of interest rates is 0.45 and well above those of other variable groups) and the third can be interpreted as financial factor.

As we want to investigate the importance of EMU economic developments for the accession countries, we also regress the stationary EMU factor time series to the stationary-transformed variables of the four accession countries to get a first indication on which of the EMU factors is most important. The R^2 measures are graphed in Figure 2.6. Interestingly, only for the first of the EMU factors (the trade related factor) and the exchange rate variables one finds sizable R^2 values (0.64 for Czech, 0.57 for Slovakia, 0.22 for Hungary and 0.30 for Poland). Most other R^2s are fairly small, often below 10%. Based on this result we decided to only include the first EMU factor time series in the VAR analysis of

[6] The transformation applied is also backed up by a unit root analysis on the individual series.

[7] We have also looked at the cohesion between the non-stationary factors and the results are very similar to the ones shown in Table 2.2.

Section 2.3.3.

Factor Time Series from Accession Country Data When analysing the monetary transmission of policy shocks for a particular accession country, we would like to explore the role of external developments in the other accession countries. In order to not mix internal and external developments, we do not use data from the country under investigation when we extract the factors. For example, we augment the VAR model for Czech Republic (CZ) used in Section 2.3.3 with factor time series that have been extracted using only data from Hungary, Poland, and Slovakia (HN, PO, SX). Thus, we extract separately factors from the following four set of country combinations: (HN, PO, SX), (CZ, PO, SX), (CZ, HN, SX), (CZ, HN, PL) and summarize the results briefly.

To facilitate the comparison in the VAR analysis and to use parsimoniously specified models (cf. Section 2.3.3), we have decided to use only two principal components for each of the accession country data set.[8] The following discussion is structured accordingly.

The first two principal component factors explain between 26% and 31% of the variance in the respective data collection. In Table 2.3 we list the cohesion among the first two stationary factor time series and groups of variables from the respective accession countries. Similarly to what we have observed for the EMU data, the first principal component (factor) seems to reflect a trade related factor. The cohesion with imports, exports and exchange rate variables are clearly the largest and range (depending on the data set) between 0.4 and 0.7.[9] The interpretation of the second factor is to some extent less clear. Using data on (CZ, PO, SX) and (CZ, HN, SX) the largest cohesion is found with the price measures, while for data sets (HN, PO, SX) and (CZ, HN, PL) also the second factor seems to most closely related to imports and export and to a some extent to industrial production. Looking at the resulting R^2 (results not shown), shows that the second factor has much higher R^2 in regressions with the price variables than with imports and exports. One exception is the (CZ, HN, PL) variant, where both regressions using price variables and imports/exports have similar measures of fit. Overall, we would interpret the second accession country factors as a price/inflation factor.

[8] This choice is also supported by the Bai and Ng (2002) information criteria. One exception is the set (CZ, HN, PL) in which one of the criteria suggests to use four factors.

[9] We have also looked at R^2s in regressions of acceding country variables on acceding country factor time series which lead to the same conclusion. Consequently, the results are not shown for sake of brevity.

2.3.3 FAVARs and the Response to Monetary Policy Shocks

To analyse and compare the effects of contractionary monetary policy shocks, we start with baseline VAR models for $y_t = (q_t, p_t, r_t, e_t)'$, where q_t is the log of industrial production, p_t is the log of the consumer price index (CPI), r_t is the short-term interest rate and e_t is the log of the exchange rate measured as local currency per US Dollar. As explained earlier, we use monthly data over the sampling period from 1995M01 to 2007M12. The start of the estimation sample is governed by data availability and the sample end is chosen to not include the recent crisis period, as we do not want our results to be driven by specific developments of the crisis. The VARs always include an intercept and the lag length is determined by using the Schwarz (SC) information criterion (cf. Schwarz, 1978 and Lütkepohl, 2005, Ch. 4) and points to using $p = 3$ lags for Czech Republic and Poland while two lags are suggested for Hungary and Slovakia.

In addition to results from this baseline specification we also report results for FAVAR models, in which the non-stationary factor time series $\hat{F}_t$ enter either endogenously or exogenously as explained in Section 2.2.3. Using factor time series from EMU data, we have included only the first factor in accordance with the analysis of Section 2.3.1. If this factor enters exogenously, we have to include the contemporaneous value and its first lag, i.e. $s = 1$ in (2.6).[10] If we use accession country factors, the two first factor time series are used in the VAR models and if the factors enter exogenously, we include the contemporaneous value and the first lag ($s = 1$).

To facilitate the comparison between impulse responses obtained from different models, we provide plots of Hall's percentile bootstrap confidence intervals with nominal coverage of 90% from the benchmark as well as the two factor-augmented VARs.[11] To make our main points, we discuss the results of the recursive identification scheme in detail, while providing the results of the sign restrictions approach in the Appendix along with a brief discussion on the changes in the results.

Figures 2.7-2.10 show the intervals for impulse responses to a contractionary monetary policy shock (with size of one standard deviation) using the benchmark VAR, the FAVAR with endogenous factors, and the FAVAR with exogenous factors. The first column in

[10] Including at least one lag is necessary in order to capture the non-stationary of the factors appropriately (see e.g. the discussion of Sims et al., 1990). We have also tried more exogenous lags but only the first lag entered the models significantly.

[11] See Breitung et al. (2004, Section 4.5) for details on the construction of Hall percentile intervals. We have used 1000 bootstrap replications.

each figure reports results of VARs with EMU factors, the second column shows results of VARs with accession country factors. Both columns also include the intervals from the benchmark VAR to facilitate the comparison. The discussion of the results follows along the four different countries.

The results for Czech Republic show that the inclusion of the EMU factor time series does not change the results greatly compared to the benchmark VARs (see columns (1) of Figure 2.7). After the monetary policy shock output does not respond significantly for about two years and a significant depreciation (a negative response) of the exchange rate is observed. The only substantial change is that the response of output is no longer significantly different from zero in the estimated FAVAR with endogenous factors. All other responses are qualitatively similar. In particular, a significant price puzzle is observed even when the EMU factor time series is included. The left column shows the responses to a monetary policy shock from models that add accession country factors to the benchmark specification. Note, that the addition of the two accession country factor time series changes the results quite a bit. In particular, one now observes a significantly negative response in output and the price puzzle vanishes. The positive response of prices in the first few periods after the shock is no longer significant. For both FAVAR variants a clearly significant negative response of prices is observed after about six months, which has not been observed in the benchmark model. Moreover, the response of the exchange rate seems to be slightly more pronounced when the endogenous factors are added to the model. Note that although we have not imposed any sign restrictions, the model using the external information from the other accession countries does not show the price puzzle and the responses are now in line with what to expect from economic theory. Obviously, accounting for development in the other accession countries seems more important than accounting for developments in the EMU.

Figure 2.8 shows similar results for Hungary. The model without factors indicates no significant reaction in output or prices after the monetary policy shock, while we observe an appreciation of the exchange rate. Adding EMU factors to the model again leaves the responses largely unchanged (cf. column (1)). One exception is the significant price drop observed in the model with exogenous factors. In contrast, using the accession country factors has a more substantial impact. Now both FAVARs indicate a significant and permanent decrease in output after about 6-8 months and a significant drop in prices after about one and a half year. Also note that in the FAVAR models the exchange rate returns faster to the level before the shock. Thus, we find again that accounting for the developments in other accession countries seems to be of importance in the VAR analysis.

The results for Poland are given in Figure 2.9. In the benchmark VAR we find a significant and permanent drop in output after about 10 months. At the same time a pronounced price puzzle with prices increasing for almost one and a half year is visible. Moreover, the benchmark VAR indicates a significant depreciation of the exchange rate which seems at odds with standard economic theory. Adding the external EMU factor exogenously we find that the counter-intuitive exchange rate response is no longer significant in the model with exogenous factors (see column (1)). Thus, adding the EMU factors to the Polish VAR leads to more reasonable results although the price puzzle is still visible. Also note that the observed change of the exchange rate response is in line with our trade related interpretation of the EMU factor time series in Section 2.2.1. The change in the exchange rate response may indicate that Poland is affected more strongly by external developments in the EMU (compared to Czech Republic and Hungary). Adding the accession country factors leads to substantial changes as well (column (2)). To be more precise, the output responses show a less persistent pattern and the initial positive response of prices is much less pronounced (in particular in the FAVAR with exogenous factors). Both FAVARs lead to a significant drop in prices after one and a half year. Interestingly, adding the accession country factors to the VAR also leads to more reasonable responses of the exchange rates with a significant drop (appreciation) of the exchange rate. Therefore, we again find that adding the accession country factors helps to generate responses that are in line with economic theory.

Figure 2.10 shows the results for Slovakia. Note that the figure reports results for a sample starting in 1999. Using the full sample period results in a completely unreasonable impulse response pattern with strongly increasing prices and a strong depreciation of exchange rate. This may be due to model misspecification in the rather volatile periods from 1995 to 1997 where market interest rates fluctuated strongly. We therefore decided to only show the results for the shorter subsample.[12] Even with this shorter sample period, the baseline model suggests an immediate significant increase in output and an increasing price level after about one and a half year. The exchange rates depreciates starting three

[12]The results for the full sample are not shown to conserve space but are available on request.

month after the shock. Adding the EMU factors does not alter the response patterns in a substantial way although a significant price puzzle is no longer observed in the model with exogenous factors. The situation is again quite different if the accession country factors are added (see column (2) of the figure). With this external information included, the counterintuitive positive response of output disappears and a significant drop in output is diagnosed about a year after the shock. In addition, the augmented models do not show any signs of the pronounced price puzzle. In fact, prices drop significantly in the FAVAR with endogenous factors about 18 months after the shock. Moreover, compared to the benchmark VAR also the response of the exchange rate changes quite a bit. The appreciation is now less pronounced and the exchange rate returns to its initial level after about one year. Since some of the responses in the benchmark are at odds with economic expectations, the results for Slovakia may partly be driven by a type of model misspecification. Thus, the results should be interpreted with caution.

As a robustness check we have also computed responses to monetary policy shocks that are identified by the sign restriction approach. The corresponding results are given in Figures 2.11-2.14 in the Appendix. Naturally, changing the identification scheme leads to some changes in the impulse responses. For Czech Republic the only substantial change is that the output response in the benchmark VAR is not significantly different from zero. Apart from that the effects of adding the factors are very similar to the ones described above. Using the sign restrictions for Hungary we find that the impulse responses are generally less informative with relatively wide error bands. For example, adding the accession country factors does not lead to significant responses in output and prices although this seems to push the responses into the 'right direction'.[13] Due to the sign restriction used for identification, the counter intuitive response of the exchange rate reported above for Poland and the price puzzle are no longer visible. Moreover, no significant effect on output is obtained in the benchmark model. For Slovakia, using the sign restriction approach results in very similar results as using the recursive identification, with the exception that the significant positive response of output observed in the recursive benchmark system is no longer visible when using sign restrictions. This again reflects that models with our sign restrictions seem to be less informative compared to the recursive setup.

[13] The literature on sign restrictions often reports 68% error bands corresponding to roughly ± one standard error bands. Using 68% bands (results not shown) one finds again that adding the factors leads to a significant change in the response of output and prices. In line with the results of the recursive systems, however, we prefer to report 90% bands here.

In summary, our results indicate that using external information from a large set of EMU variables typically does not lead to large changes in the impulse response pattern in Czech Republic and Hungary. A possible interpretation is that the monetary transmission in these countries is not greatly affected by the economic EMU developments. This may hint to the fact that further steps need to be taken towards full monetary integration. The situation seems to be slightly different in Poland, where we find that a model that accounts EMU developments leads to a more reasonable response of the exchange rate. This could be an indication that Poland is slightly more oriented towards EMU than Czech Republic and Hungary.

Moreover, we find evidence for a major role of external development in other accession countries. Typically, including the other's accession country information leads to substantial changes in the impulse response pattern. Compared to the benchmark model, the responses to a monetary policy shock are more in line with theoretical expectations: output variables tend to drop, prices tend to decrease (the price puzzle disappears or is less pronounced), and the exchange rate appreciates. In some countries, a reasonable monetary transmission mechanism can only be diagnosed when the external accession country factors are included in the model. Our results suggest that for the analysis of monetary policy shocks the external economic developments in the other accession countries are more important than the economic developments in the euro area. This may reflect the traditionally close links in trade among the countries under consideration. Overall, our results highlight the importance of taking external developments properly into account.

2.4 Conclusions

We investigate the effects of monetary policy shocks in Czech Republic, Hungary, Poland and Slovakia within small vector autoregressive models. In particular, we explore to what extent accounting for external economic developments in the EMU and in other acceding countries changes the results from structural VAR models.

The external developments in the EMU are summarized by extracting factor time series using principal components from a relatively large database with time series data from eleven EMU countries. To interpret the extracted factor time series we use cohesion analysis to investigate the dynamic correlation between the factor time series and groups of EMU time series. The cohesion analysis together with more traditional R^2 measures suggest that the first EMU factor can be interpreted as a trade related factor as it is most closely related to imports, exports and the exchange rate. We find that this factor is the only one that loads onto variables from the accession countries. Consequently, we use this factor series to augment the VARs for the accession countries. Using a large cross-section of time series on similar variables from the accession countries, we find that the first principal component may again be interpreted as a trade related factor, while the second one could be seen as a price/inflation factor.

To explore the role of external information in monetary analysis, we augment standard VAR models with either the factor series extracted from EMU data or with factors from accession country data and compare the results. Factor-augmented VARs (FAVARs) are specified in two different ways: First, we include the factors as an endogenous variable into the VARs. While the principle idea follows Bernanke et al. (2005), we use the non-stationary factors from the Bai and Ng (2004) approach in the VAR in order to preserve any cointegration relations among the variables and the factors. In a second variant, we include the non-stationary factor series as exogenous variables which leads to more parsimonious models. To our best knowledge, none of these types of augmentations have been used in the literature so far.

We explore the role of external information by comparing the responses to contractionary monetary policy shocks from benchmark VARs with those of different FAVARs. With the exception of Poland, we find that including the EMU factors does not substantially change the results from an impulse-response analysis. Thus, EMU economic developments do not seem to be of major importance for the monetary transmission in accession countries. This may hint to the fact that further steps need to be taken towards monetary integration of the accession countries.

In contrast, including the accession country information leads to substantial changes in the impulse response pattern. Compared to the benchmark model, the responses to a monetary policy shock are more in line with theoretical expectations: output variables tend to drop, prices tend to decrease (the price puzzle disappears or is less pronounced), and the exchange rate appreciates. In some countries, a reasonable monetary transmission mechanism can only be diagnosed when the external accession country factors are included in the model.

We have taken implicitly care of any cointegration relations among the variables by using non-stationary factors and variables in levels in the VAR models. Clearly, if cointegration is present, taking them explicitly into account would be beneficial. Modelling the monetary transmission mechanism in factor-augmented vector error models is therefore an interesting direction of future research.

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2.A Appendix - Variables and Data Sources

The data consists of monthly data for the period 1995:M01-2007:M12. All series are obtained from the IMF-IFS statistics (via Datastream) and the precise Datastream mnemonics are available on request.

For the accession country VARs we use data on log of industrial production, the log of a consumer price index, the interest rate and the exchange rate (local currency to US dollar).

To extract the EMU factor time series, we use data from 11 EMU members (Austria, Belgium, Finland, France, Germany, Italy, Ireland, Luxembourg, Netherlands, Spain and Portugal). The variables are industrial output (IP), unemployment rate (UN), imports and exports (IMP and EXP), consumer and producer price index (CPI and PPI), short- and long-term interest rates (RS and RL), exchange rates (EXR), and share prices (SP). The same variables (except the long-term interest rates) have been used from the accession countries to extract the accession country factor time series. The transformation used before the factor analysis is given in Table 2.1.

Table 2.1: Variable Groups and Their Transformation

Variable group	Transformation
IP	first difference of logs
UN	first difference
IMP	first difference of logs
EXP	first difference of logs
CPI	first difference of logs
PPI	first difference of logs
RS	first difference
RL	first difference
EXR	first difference of logs
SP	first difference of logs

2.B Appendix - Tables and Figures

Table 2.2: Cohesion of Stationary Factors and Groups of Variables for EMU Data

Group	coh^*_{f1}	coh^*_{f2}	coh^*_{f3}	coh^*_{f4}	coh^*_{f5}	coh^*_{f6}
IP	0.14	0.17	0.23	0.20	0.19	0.22
UN	0.15	0.17	0.16	0.15	0.15	0.17
IMP	0.37	0.20	0.16	0.13	0.11	0.20
EXP	0.40	0.20	0.19	0.12	0.12	0.23
CPI	0.13	0.15	0.19	0.18	0.21	0.19
PPI	0.14	0.21	0.16	0.22	0.16	0.20
RS	0.12	0.23	0.13	0.23	0.25	0.16
RL	0.12	0.45	0.13	0.26	0.12	0.20
EXR	0.51	0.22	0.09	0.13	0.20	0.16
SP	0.22	0.20	0.30	0.15	0.21	0.24

Note: Table shows the values of cohesion as in (2.3) (cf. Croux et al., 2001) of stationary factor time series extracted from EMU data and the corresponding groups of EMU variables. The reported numbers are the average cohesion values over all frequencies. $coh^*_{f1}, \ldots, coh^*_{f6}$ denote the cohesion measures for the first through sixth factor, respectively. Variable names: IP: industrial production, UN: unemployment, IMP: imports, EXP: exports, CPI: consumer price index, PPI: producer price index, RS: short-term interest rate, RL: long-term interest rate, EXR: exchange rate, SP: share prices. Sample period: 1995M01-2007M12.

Table 2.3: Cohesion of Stationary Factors and Groups of Variables for Accession Country Data

Data:	(HN, PO, SX)		(CZ, PO, SX)		(CZ, HN, SX)		(CZ, HN, PO)	
	coh^*_{f1}	coh^*_{f2}	coh^*_{f1}	coh^*_{f2}	coh^*_{f1}	coh^*_{f2}	coh^*_{f1}	coh^*_{f2}
IP	0.24	0.31	0.30	0.31	0.22	0.24	0.19	0.30
UN	0.17	0.19	0.20	0.18	0.18	0.17	0.13	0.22
IMP	0.49	0.37	0.59	0.18	0.58	0.28	0.39	0.50
EXP	0.53	0.34	0.58	0.13	0.57	0.17	0.45	0.46
CPI	0.13	0.25	0.15	0.31	0.12	0.33	0.16	0.29
PPI	0.21	0.27	0.12	0.38	0.13	0.29	0.28	0.26
RS	0.17	0.20	0.17	0.29	0.17	0.26	0.17	0.22
EXR	0.58	0.14	0.69	0.26	0.63	0.25	0.65	0.28
SP	0.11	0.13	0.12	0.18	0.09	0.17	0.15	0.13

Note: Table shows the values of cohesion as in (2.3) (cf. Croux et al., 2001) of stationary factor time series extracted from accession country data given and first row of the table and the corresponding groups of accession country variables. The reported numbers are the average cohesion values over all frequencies. coh^*_{f1} and coh^*_{f2} denote the cohesion measure for the first and second factor, respectively. Variable names: IP: industrial production, UN: unemployment, IMP: imports, EXP: exports, CPI: consumer price index, PPI: producer price index, RS: short-term interest rate, EXR: exchange rate, SP: share prices. Sample period: 1995M01-2007M12.

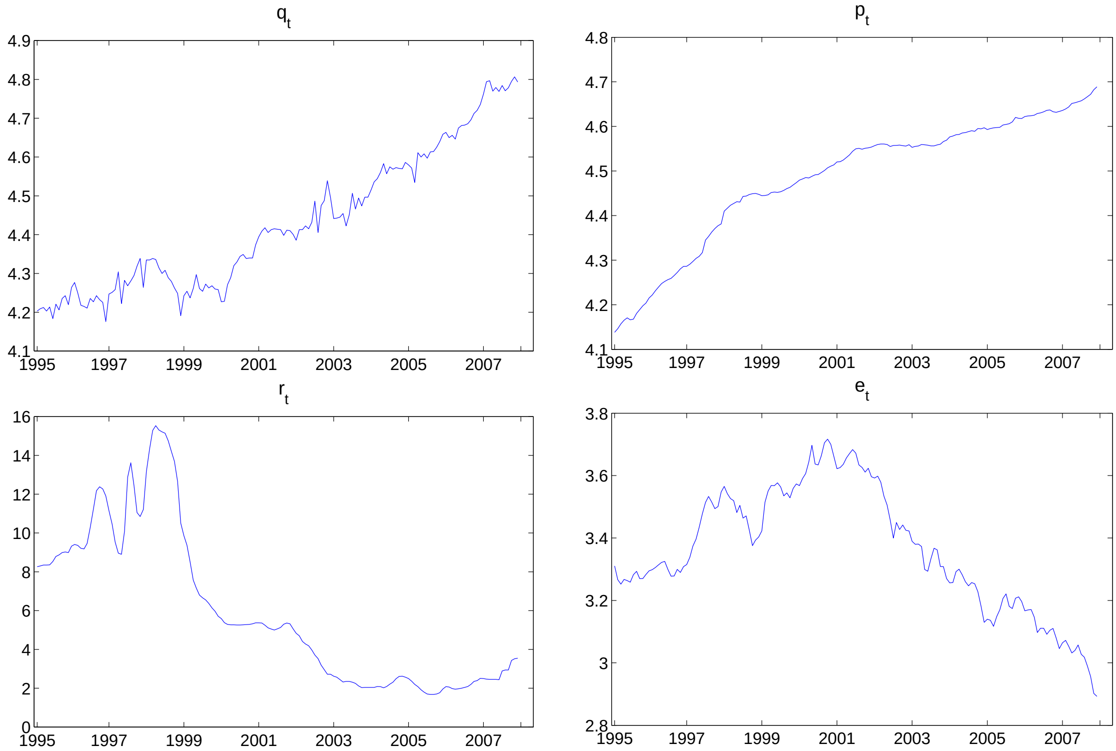

Figure 2.1: Time series plots for Czech Republic: The log of industrial production (q_t), the log of the consumer price index (p_t), the short-term interest rate (r_t) and the log of the exchange rate measured as local currency per US Dollar e_t. 1995M01-2007M12.

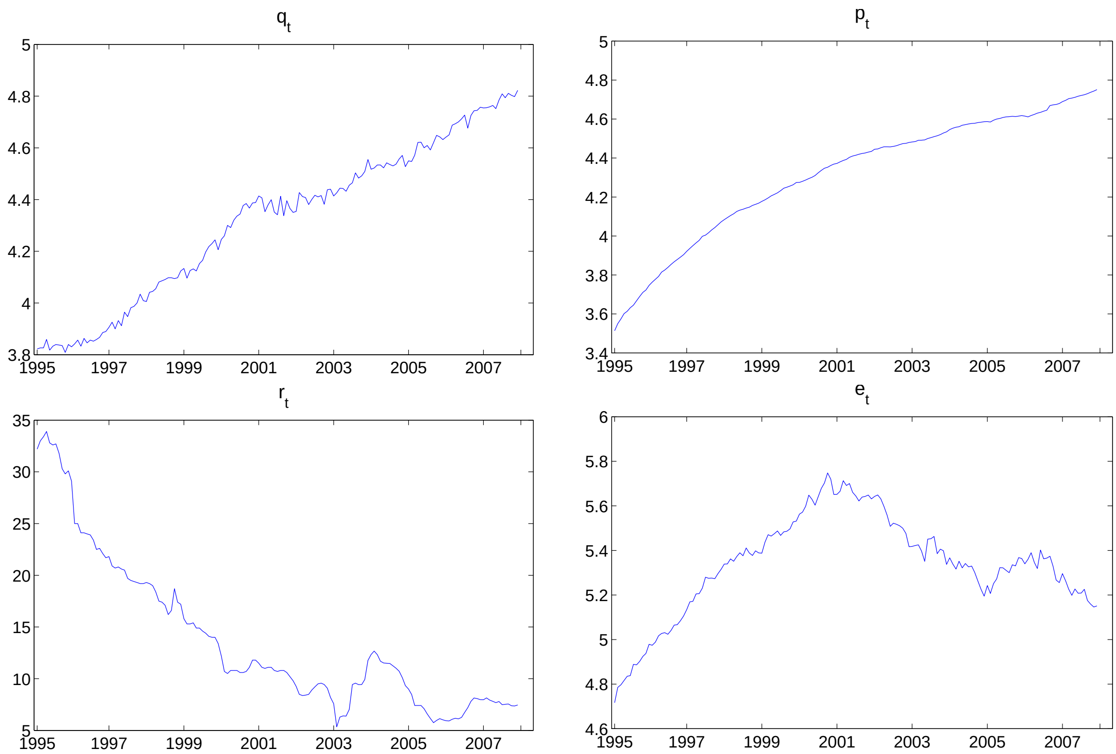

Figure 2.2: Time series plots for Hungary: The log of industrial production (q_t), the log of the consumer price index (p_t), the short-term interest rate (r_t) and the log of the exchange rate measured as local currency per US Dollar e_t. 1995M01-2007M12.

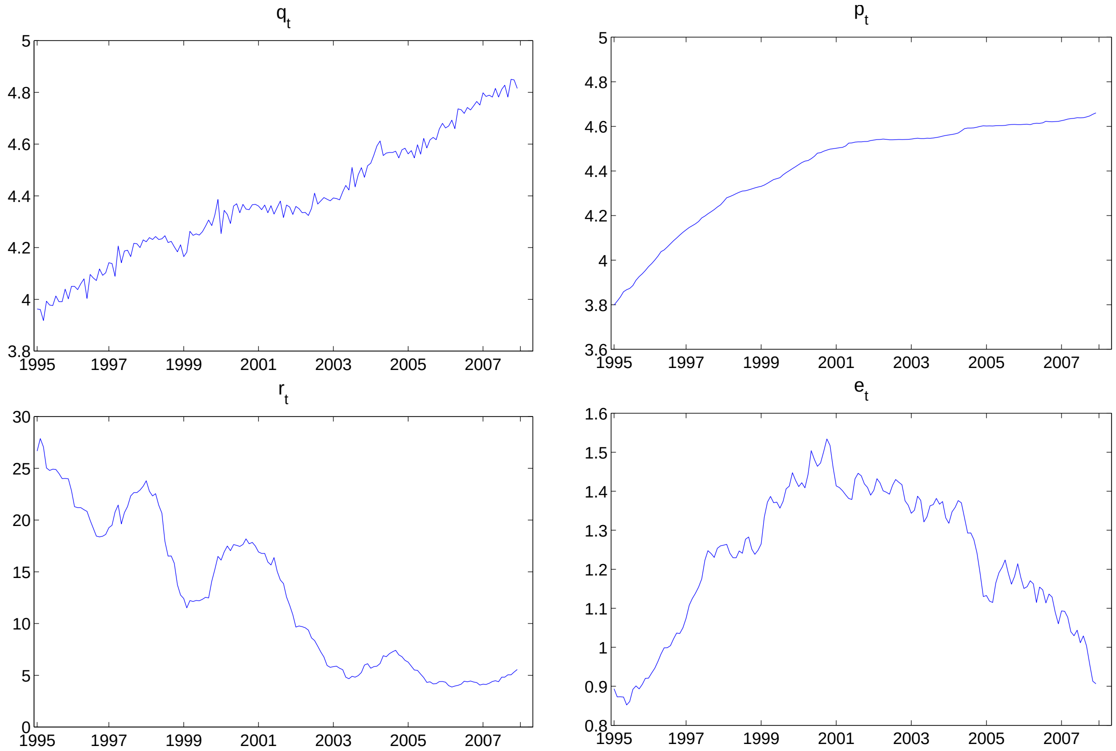

Figure 2.3: Time series plots for Poland: The log of industrial production (q_t), the log of the consumer price index (p_t), the short-term interest rate (r_t) and the log of the exchange rate measured as local currency per US Dollar e_t. 1995M01-2007M12.

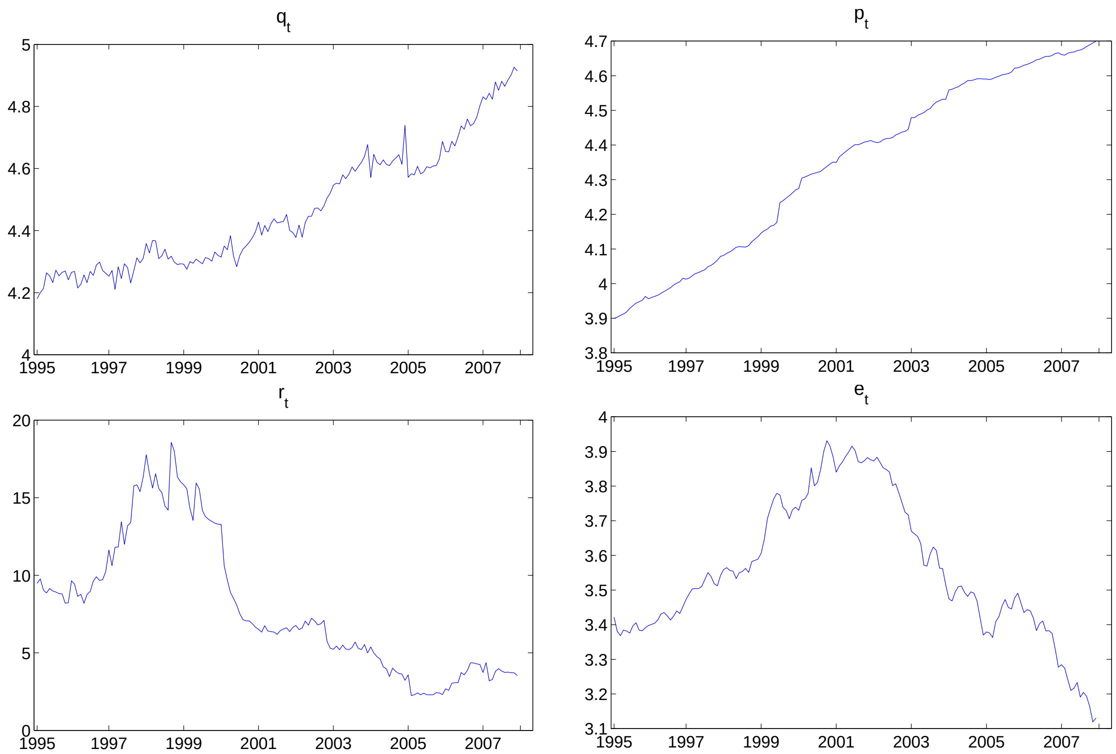

Figure 2.4: Time series plots for Slovakia: The log of industrial production (q_t), the log of the consumer price index (p_t), the short-term interest rate (r_t) and the log of the exchange rate measured as local currency per US Dollar e_t. 1995M01-2007M12.

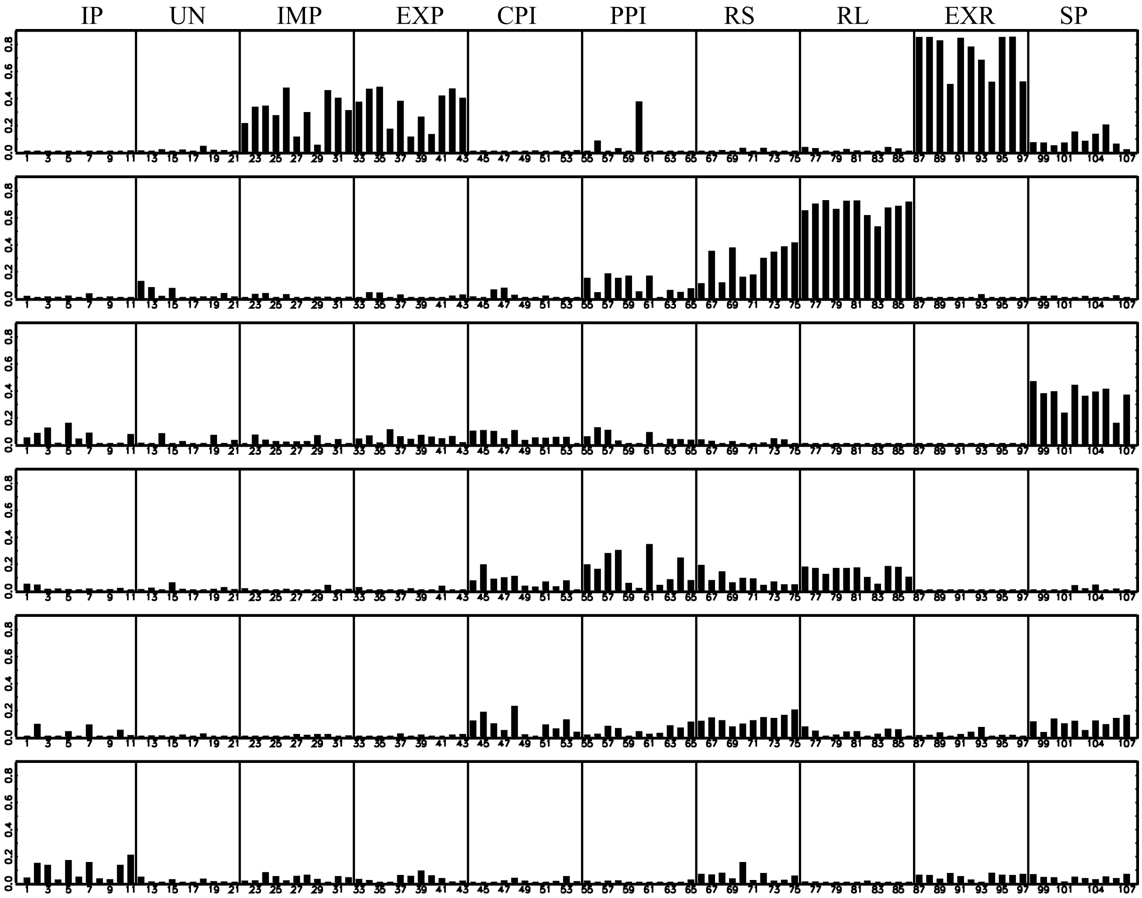

Figure 2.5: R^2s from regressions of the first 6 stationary factor time series on the individual stationary-transformed EMU time series. Row 1: $\hat{f}_1^{\text{EMU}}, \ldots$, row 6: $\hat{f}_6^{\text{EMU}}$. Groups of variables: Industrial production (IP), unemployment (UN), imports (IMP), exports (EXP), consumer and producer prices (CPI and PPI), short- and long-term interest rate (RS and RL), exchange rate (EXR), share prices (SP). Sample period: 1995M01-2007M12.

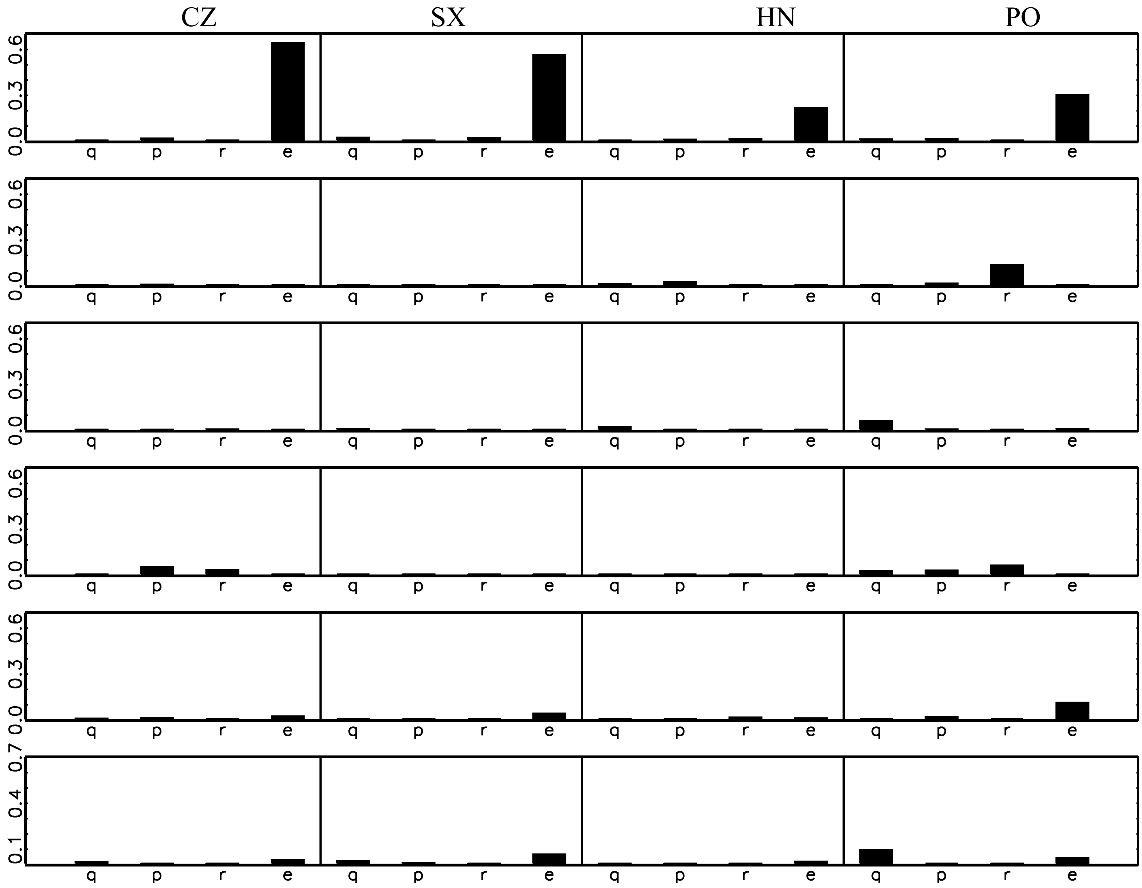

Figure 2.6: R^2s from regressions of the first 6 stationary factor time series on the stationary-transformed accession country data time series. Row 1: $\hat{f}_1^{\mathrm{EMU}}, \ldots$, row 6: $\hat{f}_6^{\mathrm{EMU}}$. Groups of variables: Industrial production (IP), unemployment (UN), imports (IMP), exports (EXP), consumer and producer prices (CPI and PPI), short- and long-term interest rate (RS and RL), exchange rate (EXR), share prices (SP). Sample period: 1995M01-2007M12.

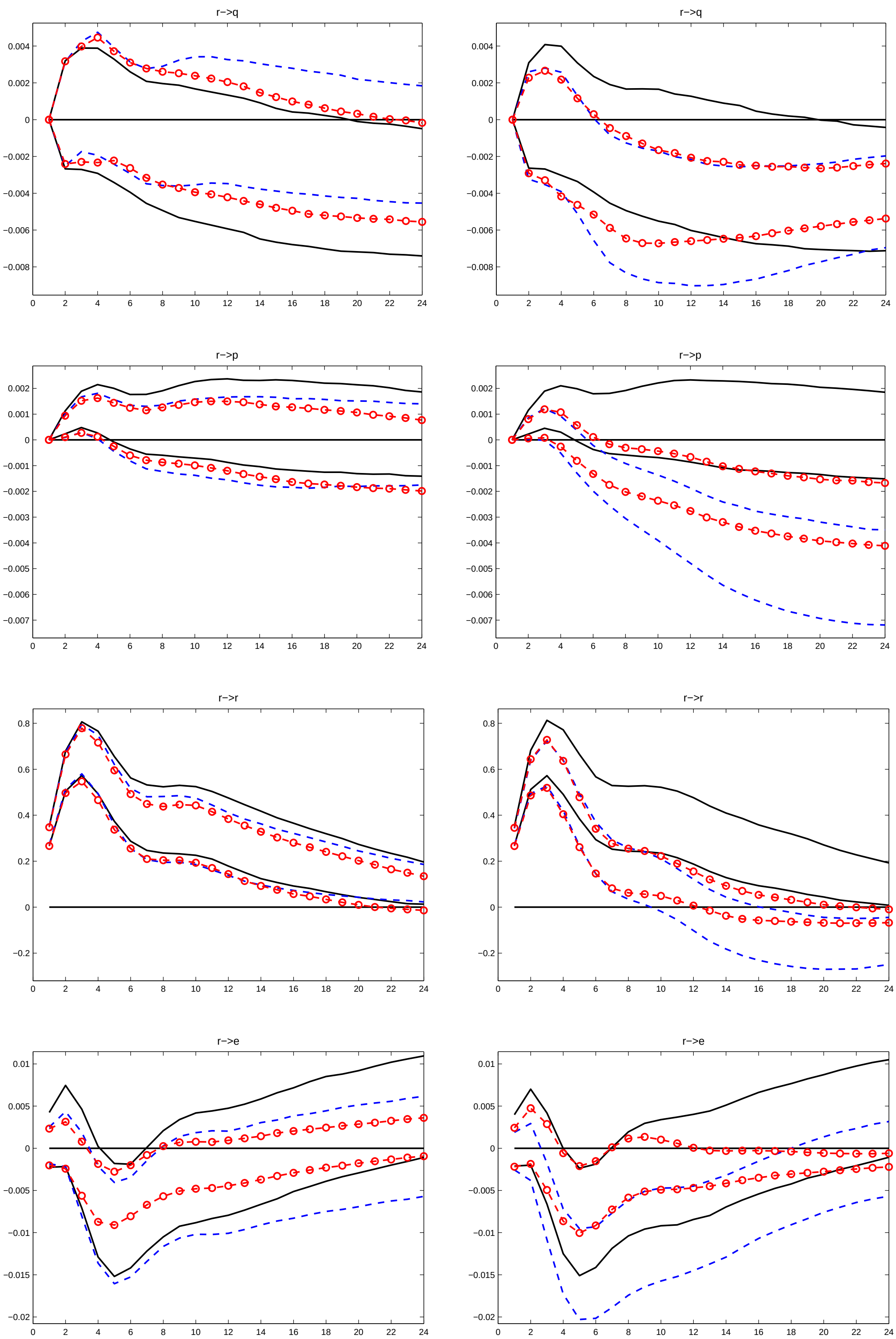

Figure 2.7: Czech Republic: 90% confidence intervals of responses to a contractionary monetary policy shock in benchmark VAR(3) (solid lines), FAVAR(3) with endogenous factors (dashed lines), and FAVAR(3) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1995M01-2007M12.

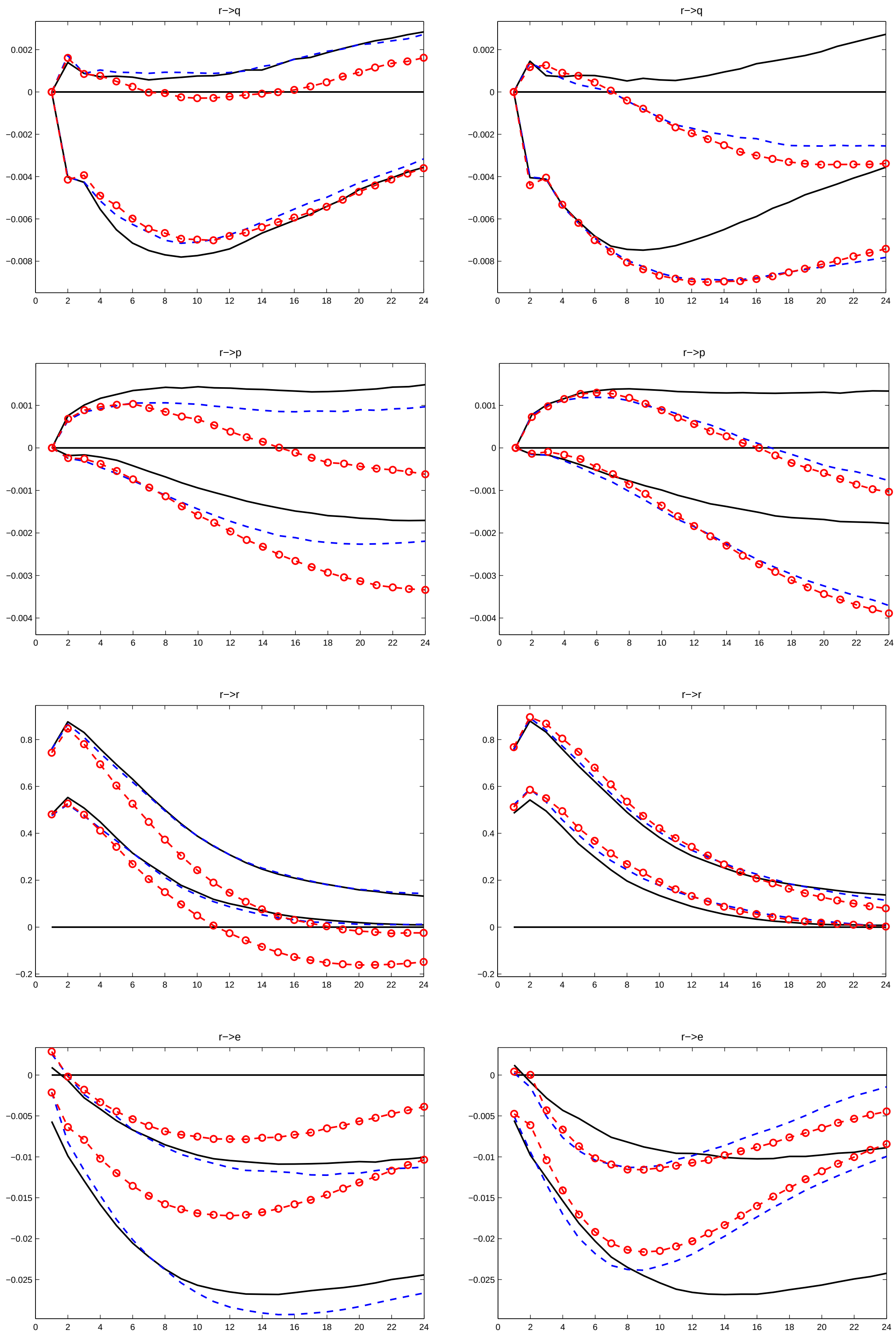

Figure 2.8: Hungary: 90% confidence intervals of responses to a contractionary monetary policy shock in benchmark VAR(2) (solid lines), FAVAR(2) with endogenous factors (dashed lines), and FAVAR(2) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1995M01-2007M12.

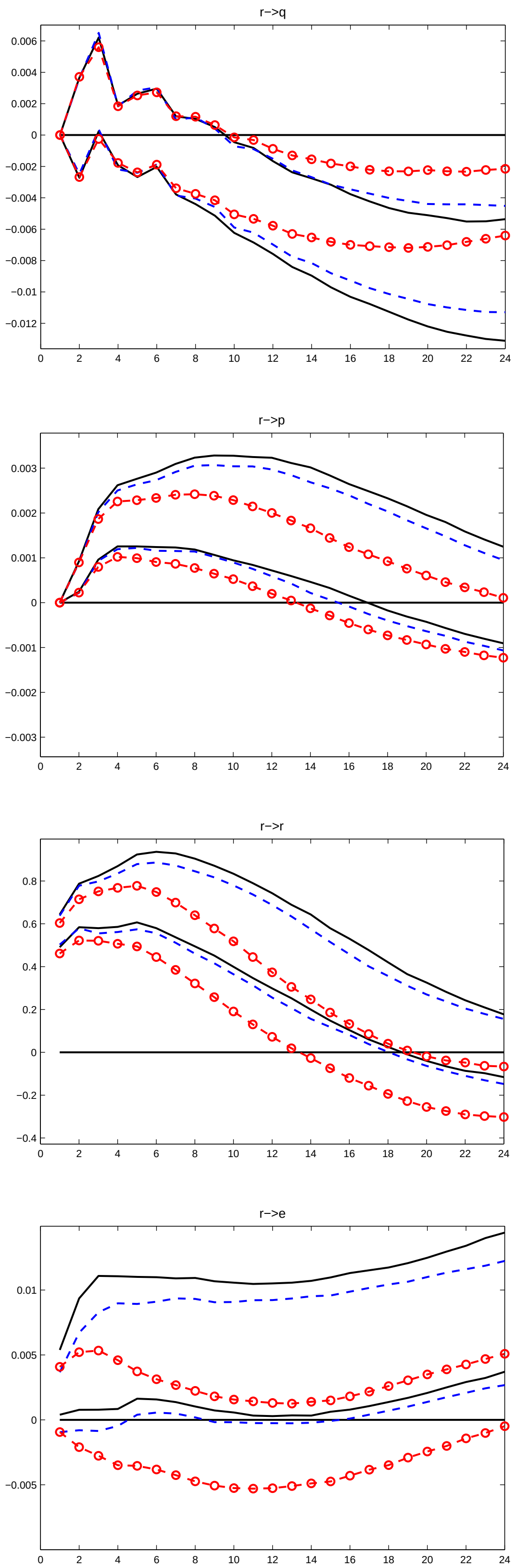

Figure 2.9: Poland: 90% confidence intervals of responses to a contractionary monetary policy shock in benchmark VAR(3) (solid lines), FAVAR(3) with endogenous factors (dashed lines), and FAVAR(3) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1995M01-2007M12.

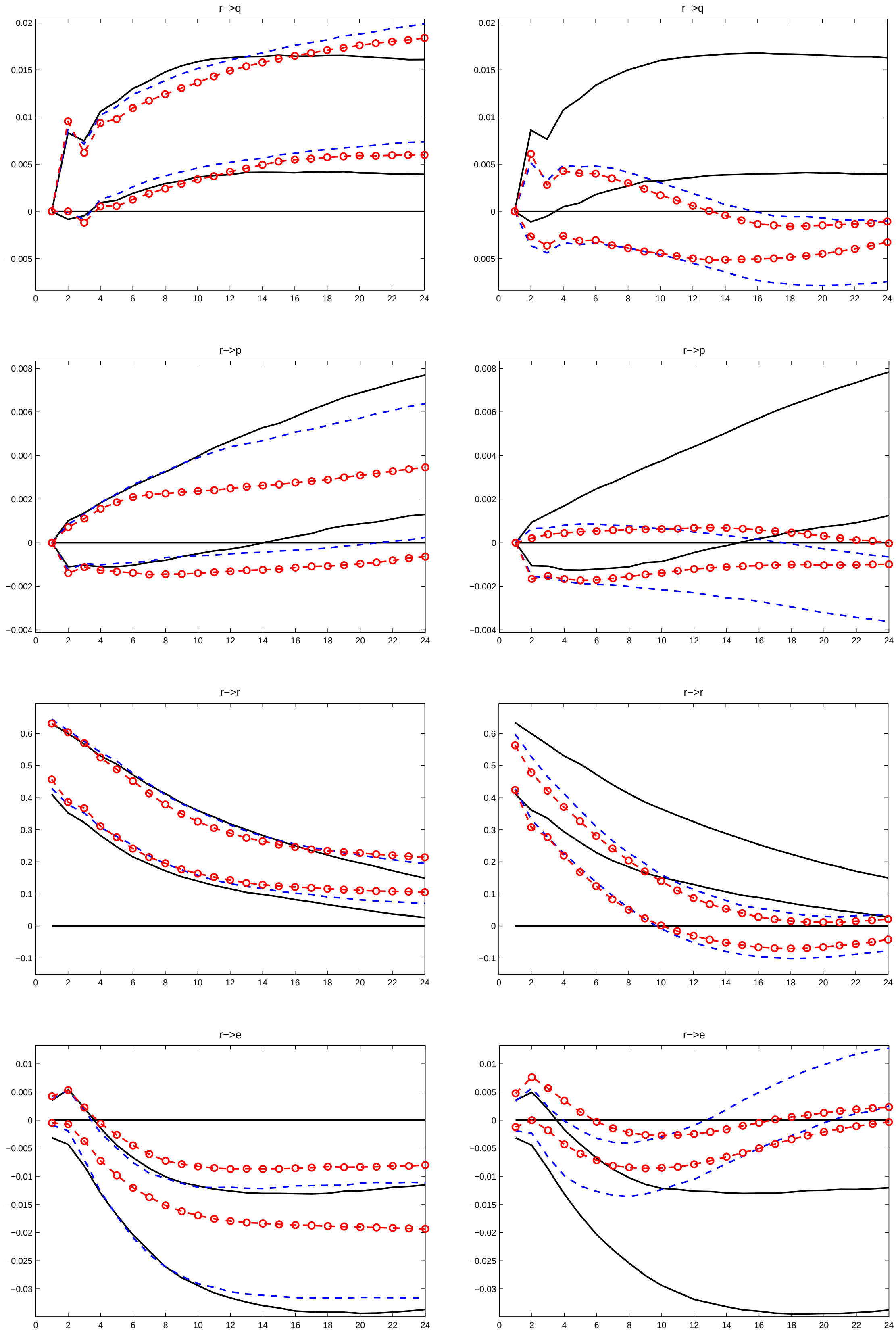

Figure 2.10: Slovakia: 90% confidence intervals of responses to a contractionary monetary policy shock in benchmark VAR(2) (solid lines), FAVAR(2) with endogenous factors (dashed lines), and FAVAR(2) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1999M01-2007M12.

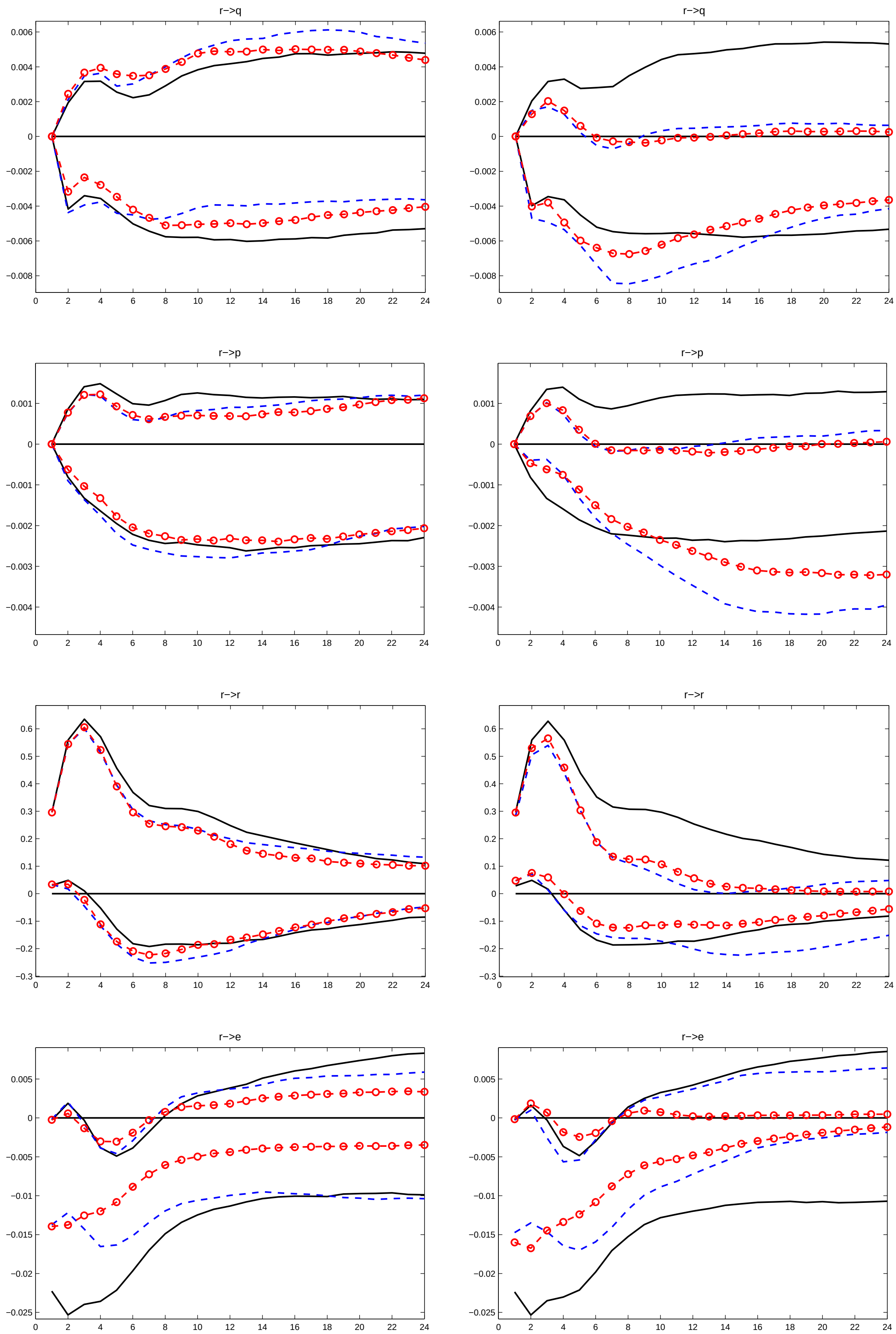

Figure 2.11: Czech Republic: 90% error bands of responses to a contractionary monetary policy shock using sign restrictions in benchmark VAR(3) (solid lines), FAVAR(3) with endogenous factors (dashed lines), and FAVAR(3) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1995M01-2007M12.

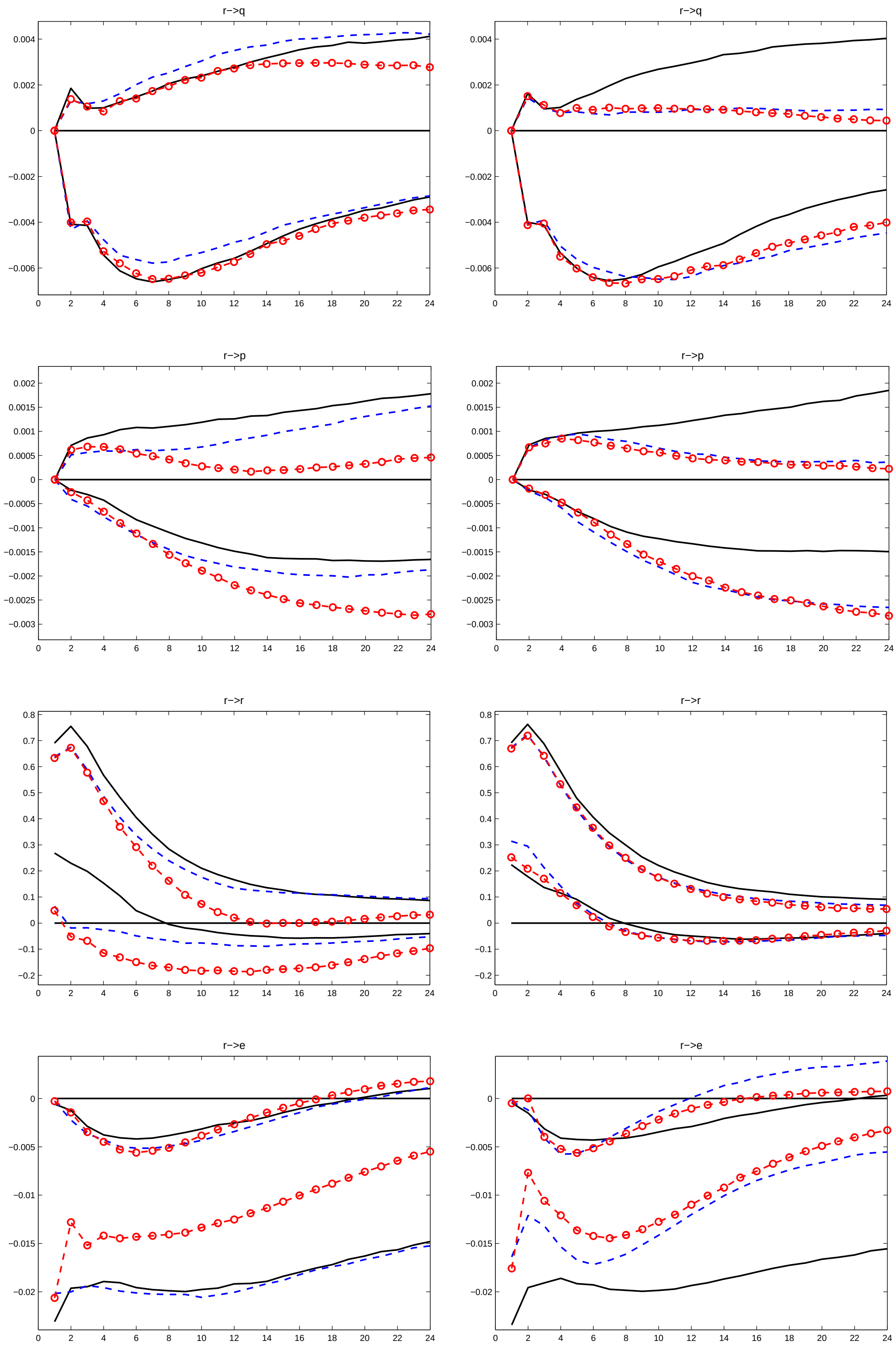

Figure 2.12: Hungary: 90% error bands of responses to a contractionary monetary policy shock using sign restrictions in benchmark VAR(3) (solid lines), FAVAR(3) with endogenous factors (dashed lines), and FAVAR(3) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1995M01-2007M12.

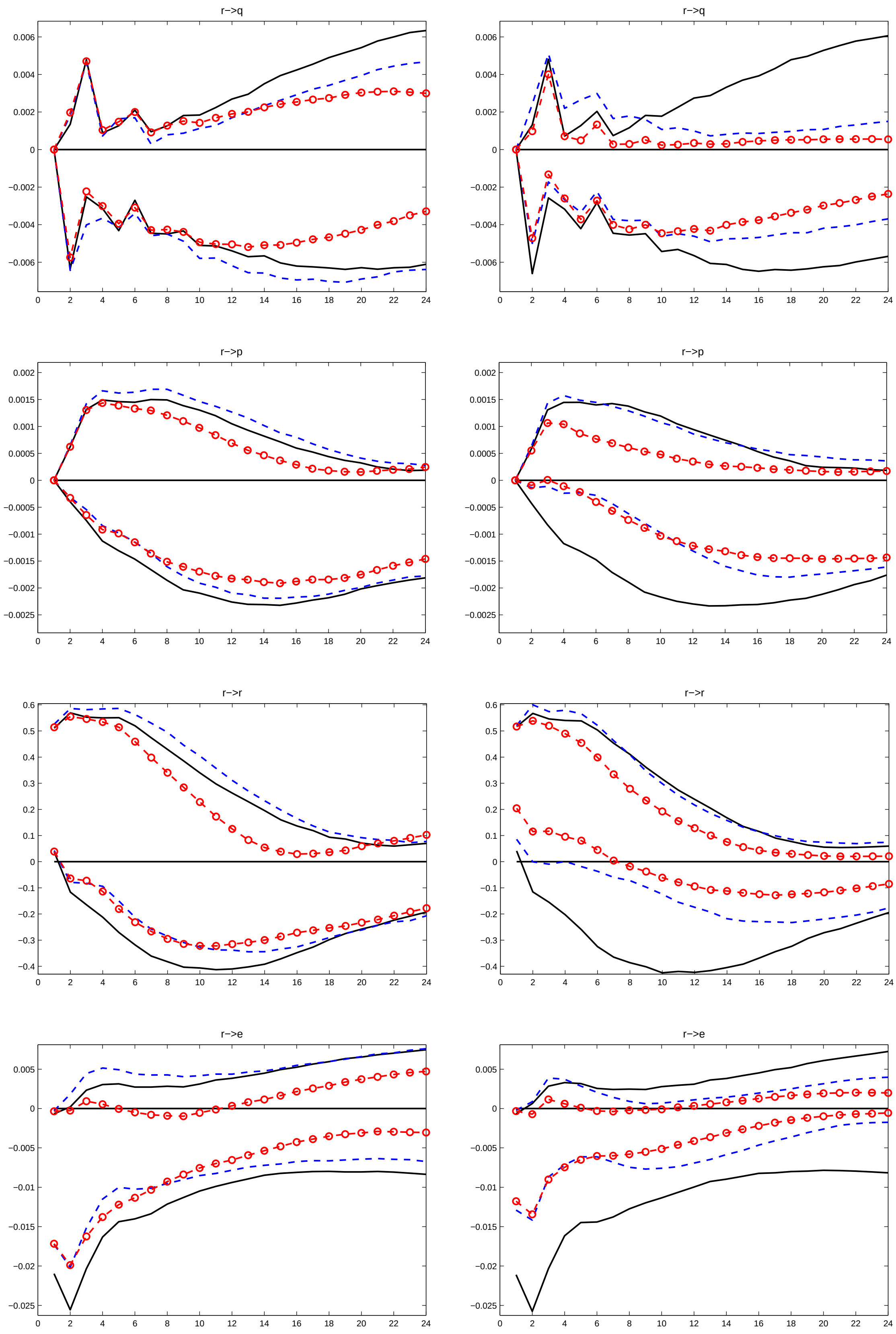

Figure 2.13: Poland: 90% error bands of responses to a contractionary monetary policy shock using sign restrictions in benchmark VAR(3) (solid lines), FAVAR(3) with endogenous factors (dashed lines), and FAVAR(3) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1995M01-2007M12.

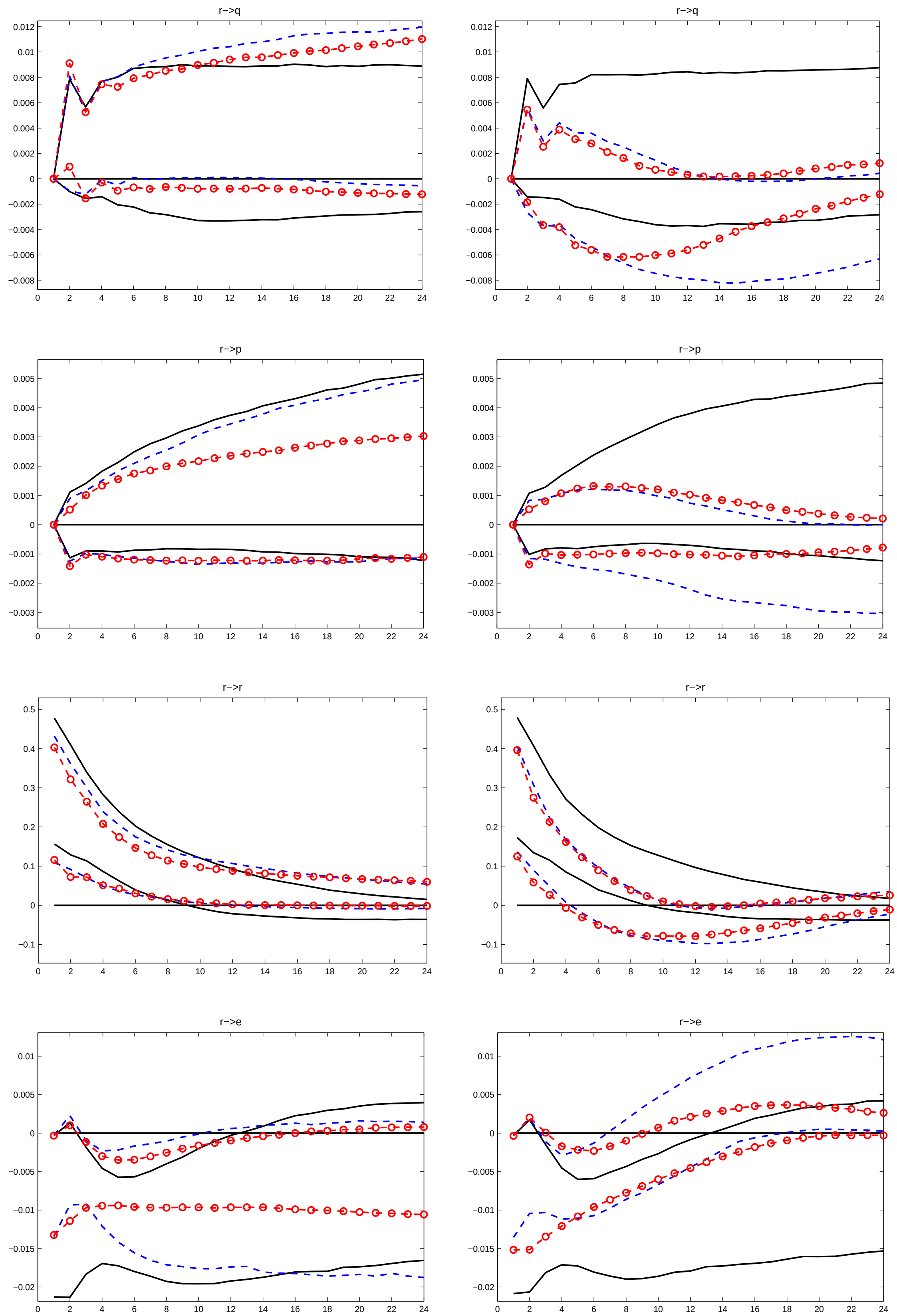

Figure 2.14: Slovakia: 90% error bands of responses to a contractionary monetary policy shock using sign restrictions in benchmark VAR(3) (solid lines), FAVAR(3) with endogenous factors (dashed lines), and FAVAR(3) with exogenous factors (lines w. circles). Right column: FAVARs using 1 EMU factor. Left column: FAVARs using 2 accession country factors. Sample period: 1999M01-2007M12.

Chapter 3

Wavelet-based Nowcasting of Euro Area Gross Domestic Product Growth

3.1 Introduction

This paper proposes a new model for the early estimation of quarterly gross domestic product (GDP) growth for the euro area using monthly data. The presented method uses wavelet based multi-resolution analysis of monthly time series to nowcast the quarterly GDP growth using bridge equations. The model outperforms the simple bridge equation benchmark model commonly used in the nowcasting literature.

The process of forecasting the very near future and recent past is usually referred to by economists as "nowcasting" (see Bańbura, Giannone and Reichlin, 2010), others do not differentiate it from the standard forecasting problem. In addition statistical institutes report "flash estimates" and usually central banks report it as "early estimates". Here we will use all of the terms above as synonyms to indicate the forecasting of missing end observations in economic indicators due to publication lags. In order to obtain timely estimates for indicators with publication lags additional available information should be considered. Often economists use indicators with higher frequency (usually on monthly frequency) that relate to the target variable (usually on quarterly frequency) in order to obtain early estimates. These models are often called mixed frequency models.

There are numerous mixed frequency models in the literature that are used to nowcast GDP growth. In one of the attempts to nowcast GDP growth, policy institutions use simple models like "bridge equations". Bridge equations are regression equations which use aggregated monthly indicators to forecast the quarterly GDP (see Diron, 2008; Rünstler, Barhoumi, Benk, Cristadoro, Reijer, Jakaitiene, Jelonek, Rua, Ruth and Nieuwenhuyze, 2009; Kitchen and Monaco, 2003; Ferrara, Guégan and Rakotomarolahy, 2010). Alternatively Mittnik and Zadrozny (2005) use state space vector autoregressive integrated moving average model (VARIMA) over an autoregressive benchmark model to forecast German GDP using the Ifo Business Climate Index. The idea of the model is to convert the low frequency series into high frequency indicators by assuming that some observations are periodically missing. On the other hand Clements and Galvão (2008) use the MIDAS (MIxed DAta Sampling) model, introduced by Ghysels, Santa-Clara and Valkanov (2004), to nowcast US GDP and compare its performance to alternative forecast methods. The MIDAS models usually regress the extra lags of the higher frequency variables on the lower frequency indicator. In order to avoid problems connected to the rapidly increasing number of regressors a weighting function is used. Kuzin, Marcellino and Schumacher

(2011) nowcast euro area GDP growth using MIDAS and compares it to a mixed frequency VAR model. All of the listed examples use a limited number of high frequency variables to nowcast GDP. Marcellino and Schumacher (2010) show that combining factor models with MIDAS can outperform the standard MIDAS model by including a large number of additional indicators. They apply the factor MIDAS model to nowcast German GDP.

This paper concentrates on the bridge equations models that are used in numerous central banks for the nowcast of GDP growth. The main idea behind this model is that a combination of different regression equations is used to forecast the dependent variable, which is GDP growth in our application. The explanatory variables are aggregated monthly economic indicators that relate to GDP. The single forecasts of each of these regression equations is combined (bridged) to create the final GDP growth nowcast. Our main goal will be to improve the current quarter nowcast of GDP growth as new high frequency indicators become available within the quarter. Wohlrabe (2009) groups the bridge equations into two types of models. He calls the first group of models the "supply-side" bridge equations, where GDP enters as dependent variable in all of bridge equations considered. The second group of models form the "demand-side" bridge equations where GDP is decomposed into its components for which regression equations are fitted (see Baffigi, Golinelli and Parigi, 2004; Parigi and Golinelli, 2007). Here we consider a "supply-side" type of model as in Angelini, Camba-Mendez, Giannone, Reichlin and Rünstler (2011). The important difference is that we improve the nowcast precision of the model by better nowcast of the ragged edges of the monthly variables. This is done with the help of the wavelet analysis.

Wavelet analysis has been employed extensively in fields like signal processing, physics, computer science and engineering, but was just recently introduced in economics and finance. It has been acknowledged that wavelets as time scale decomposition can be applied in economic forecast models and enhance their performance. In this paper we show that combining wavelet analysis with the bridge equations models improves the early estimate for euro area GDP growth. The main advantage of the wavelet analysis is that with its help each time series can be decomposed into different time scale components. Once these components are obtained different models can be fitted so that each frequency can be analysed separately or be compared across variables.

Ramsey and Lampart (1998b,a) first use wavelets to analyse the dynamics of different macroeconomic variables. They studied the relationship of money supply and output as well as income and consumption. In the same spirit Kim and In (2005) study the dynamics of inflation and stock returns. There are several studies that analyse the Capital Asset Pricing Model for different frequencies, among them are Gencay, Selcuk and Whitcher (2005) and Fernandez (2006). Wavelets are also used for business cycle analysis, for example in Yogo (2008) and Gallegati, Palestrini and Petrini (2008). Although the results of using wavelets in forecasting are promising not so many economists are using them. Among the few examples are Arino (1995) on forecasts car sales, Wong, Ip, Xie and Lui (2003) with an application to exchange rates, Conejo, Contreras, Espinola and Plazas (2005) use wavelets to forecast electricity prices and Fernandez (2007) with a similar analysis to forecast US manufacture shipments. All of these examples use wavelets in univariate models. Rua (2011) uses wavelets in a multivariate set to forecast GDP growth in major euro area countries.

In this paper we propose a novel approach that uses wavelet analysis and bridge equations to nowcast quarterly euro area GDP growth. Namely we forecast the ragged edge monthly variables that are included in the bridge equation on multiresolustion levels that were obtained with the help of the wavelet decomposition. Using the wavelet reconstruction techniques the forecasted levels are transformed to build forecasts of the monthly series. Next the full monthly series are transformed into quarterly and included in the bridge equations that nowcast GDP growth. The proposed model is used to nowcast euro area GDP growth and uses macroeconomic data spanning over the last 16 years. We evaluate the out-of-sample performance of the proposed model and compare it to the bridge equations forecasts used at the European Central Bank (ECB). In addition the nowcast is compared to a simple univariate autoregressive (AR) model. As robustness checks the nowcasting is applied using three different wavelet functions.

We find that the wavelet based nowcasting model outperforms the bridge equations model in the short run. In particular the one-step-ahead forecast shows that the wavelet based nowcasting with bridge equations is performing better regardless of the wavelet function considered. The gains of the forecast are homogeneous across the different wavelet functions. When the forecast horizon is increased to two quarters the best results are still obtained with the wavelet based nowcast using the Haar wavelet function. The results show that wavelet analysis aids short term forecasts of euro area real GDP growth and should be considered in combination with standard nowcasting algorithms. The results are confirmed by the forecast encompassing test that was performed.

This paper is structured as follows. Section 3.2 discusses the problems related with nowcasting GDP growth. Section 3.3 presents the empirical framework. The wavelet-based nowcasting model that uses bridge equations is presented in Section 3.4. The same section presents the data, the setup of the empirical exercise and the results from the out-of-sample forecasts. Section 3.5 concludes.

3.2 The Problem of Nowcasting GDP Growth

Before introducing the econometric framework of the proposed model an overview of the main challenges to nowcast GDP growth will be given. As discussed by Ferrara et al. (2010) there are three main problems that economists face when nowcasting GDP. These are the timeliness of the indicators, the need to use mixed frequency models and the choice of optimal information set. These challenges were discussed already in the introduction, whereas in this section a more practical example will be given that addresses the mentioned shortcomings and proposes solutions.

Euro area GDP data is published with a big delay by Eurostat. Delay in publication is usually observed for time series with lower frequencies (in this case GDP growth is measured on quarterly basis). The timeliness of the GDP series is six weeks after the end of the reference quarter q (that is 65 days after the end of quarter q)[1]. The consequences of such hindrance affect policy decisions that rely on timely data in order to identify possible acceleration or slowdown in the economy. Timely data is especially important in the context of business cycles where peaks and troughs develop within weeks. In such situations economists try to forecast the delayed lags of the quarterly GDP growth using data with higher frequency, usually monthly series.

The timely high frequency data used in forecasting GDP growth can be separated into three groups. The first group of variables is composed of "hard" indicators and include monthly variables like industrial production and construction that are released around six weeks after a reference month m. The second group of variables are called "soft" indicators and they include survey data that is available at the end of the reference month. This type of indicators are not revised, they are noisy and less precise but have the benefits of

[1] The reported period (month/quarter/year) will be called reference period.

being very timely. The last group of monthly variables are released with a publication lag of one month and they include labour market data and monetary aggregates.

The timeliness of the quarterly GDP and the monthly indicators used in this study is included in Figure 3.1 in the appendix. Suppose that we are at the beginning of month June of some current year y, then the last available GDP data for the euro area covers the last quarter of the previous year $y-1$. In the mean time we have timely monthly financial variables and survey data up to May of the current year, which are good proxies for economic activity and could be used in the nowcasting of GDP growth. The monthly production data has timeliness of one month and a half but still the delay is much shorter than the one for GDP. This data is very valuable for the early estimates of GDP since it measures some of its components. Monthly monetary aggregates and labour market data are published with approximately one month delay and are also informative regarding the short-term economic developments. As shown by Angelini et al. (2011), Diron (2008) and Baffigi et al. (2004) the groups of variables in Figure 3.1 compose the optimal information set for the nowcast of GDP growth.

As it was explained in the introduction, there are several alternative models in the literature that are used for the nowcast of GDP growth. All of these models address the challenges of the mixed frequencies of the variables composing the optimal information set and their asynchronous release time. Here the bridge equation method is considered. The reason why one of the simplest mixed frequency models is used is because this study is not concentrating on the mixed frequency modelling itself but would like to show the benefits of integrating multi-resolution analysis into nowcasting. The proposed decomposition could be integrated to any other nowcasting model, but for the sake of simplicity the bridge equation model is chosen. The only difference between the proposed wavelet-based bridge equation model and the model proposed by Angelini et al. (2011) is that the nowcast precision is improved by forecasting the "the ragged edges" of the monthly variables on different multi-resolution levels. This is done with the help of the wavelet analysis. The next section will introduce the discrete and the continuous wavelet transforms and will present in detail the wavelet-based bridge equation model for nowcasting GDP growth.

3.3 The Econometric Framework

With the help of the wavelet analysis one can decompose economic time series into multi-scale components. As Gencay et al. (2005) notice not all economic time series follow the same relationship as a function of time. Using spectral analysis one can decompose time series into different time horizons (scales) and in this way identify specific local and global dynamic properties of the time series like seasonalities, trends and structural breaks. Being able to forecast separately the different multi-scale components may improve the final forecast of the time series. In this section we will introduce the well-known Fourier transform and its extension, the wavelet transform, as examples of spectral analysis transformations. In addition the wavelet-based bridge equations model for nowcasting GDP growth will be presented at the end of the chapter.

3.3.1 Fourier Transform

In time series analysis we study the properties of an economic time series in the time-domain. In spectral analysis we study the properties of economic time series in the frequency domain. With the help of the spectral analysis like Fourier Transform (FT) economists can express $y(t)$ as a function of frequency. The FT approximates time series as a linear combination of sines and cosines at various frequencies. In this respect the Fourier transform can be seen as a frequency transform. FT is particularly valuable in the case of economic time series that exhibit seasonality or cyclical behaviour (as in the case of GDP growth). As Masset (2008) points out FT can be used to quantify the importance of the frequency components of economic variable under investigation.

Following Gencay, Selcuk and Whitcher (2002) the Fourier transform of the time series $y(t)$ can be written as a function of angular frequency ω

$$F_y(\omega) = \int_{-\infty}^{\infty} y(t)e^{-i\omega t}dt, \tag{3.1}$$

where $e^{-i\omega t} = \cos(\omega) - i\sin(\omega t)$ following from Euler's formula. $y(t)$ can be reconstructed from $F_y(\omega)$ by the inverse transform:

$$y(t) = \int_{-\infty}^{\infty} F_y(\omega)e^{i\omega t}\,\mathrm{d}\omega \tag{3.2}$$

The intuition behind (3.1) and (3.2) is that $F_y(\omega)$ shows how much of each frequency component is needed to synthetize the original time $y(t)$.

One of the main drawbacks of the FT is that it preserves information as a function of frequencies but not as a function of time. In other words the Fourier transform assumes that the frequency representation of a function is stationary over time. The times series that economists analyse are rarely stationary and usually have trends, seasonalities, or sudden changes in variability. Thus using FT to capture these dynamics is not appropriate. As noted by Crowley (2005), the Fourier series have infinite energy spectral density (because of the sinusoid representation they do not die out, in other words when $t \to \pm\infty$ time series is not converging to zero) and finite power spectral density (they cannot change over time thus require data to be stationary).

Gabor (1946) introduced the Short-Time Fourier Transform (STFT) in order to overcome some of the drawbacks listed above. The STFT applies the original FT to selected parts of the time series. The selection is done with the help of a sliding window that has a constant length. For the STFT the time resolution of the transform is missing for the window itself. This leads to fixed time-frequency decomposition within the window.

In contrast to the FT, wavelets capture features that are both localized in time and frequency. As it was noted above the FT and the STFT are functions of frequency, on the other hand with the help of the wavelets time series can be represented from both frequency and time perspective. In the case of FT a single shock affects all frequencies over the whole time span that is because the FT assumes that the signal is homogeneous across time. The wavelets on the contrary begin at some finite point of time and die out at some finite point of time. Wavelets can be literally stretched or squeezed in order to approximate locally the dynamics of the signal in space and time. Economic time series are usually finite and vary with time, thus they can be analysed using the wavelet transform.

Figure 3.5 shows the difference in the time-frequency plane between the above discussed transformations. In the case of a time series at each time point we have information based on all frequencies. On the contrary in case of Fourier transform for each frequency we have information for the whole time domain. In the case of the STFT the time domain is divided into windows with constant length and in case of the wavelet transform the length of the window changes with frequency. In other words wavelets can be seen as functions that split the time series into different components that evolve in time at particular frequency. This makes the wavelet transform suitable for the analysis of economic variables (like

GDP growth rate) that are driven through time by the interaction of different frequency components, including cyclical and trend components as well as non-standard components like shifts and structural breaks. In the next subsection the wavelet analysis will be introduced briefly.

3.3.2 Wavelet Analysis

Continuous Wavelet Transform

A wavelet $\psi(t)$ is a function of time t and has the following two properties:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{3.3}$$

and

$$\int_{-\infty}^{\infty} |\psi(t)|^2 \, dt = 1. \tag{3.4}$$

The original wavelet function $\psi(t)$ can be translated (shifted) or dilated (compressed/stretched). In this respect a translated by τ and dilated by s version of $\psi(t)$ can be presented as

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right),$$

where s defines the scale and should be positive and τ defines the shift and should be a real number. The term $\frac{1}{\sqrt{s}}$ ensures that the norm of $\psi_{\tau,s}(t)$ is unity. In the context of Figure 3.5 the translation of $\psi(t)$ relates to the location of the window along the time dimension. On the other side dilation relates to the scaling of the $\psi(t)$ along the frequency dimension.

Suppose that we have a time series $y(t)$ that we would like to analyse. The continuous wavelet transform of $y(t)$ is obtained by projecting $y(t)$ onto $\psi(t)$

$$W(\tau, s) = \int_{-\infty}^{\infty} y(t)\psi_{\tau,s}(t)dt. \tag{3.5}$$

$W(\tau, s)$ are the resulting coefficients which are no longer functions of time but functions of scale and location. We can decompose the series $y(t)$ into smaller detailed components using different dilations and translations of $\psi(t)$. For example if we would like to analyse $y(t)$ at small scale (i.e. at high frequency) then we have to choose small values for s. We can do this at different locations (i.e. time points) by changing τ.

From a computational point of view using a continuous wavelet transform to analyse time series is burdening. It is impossible to analyse the series using all continuous wavelet coefficients (our integrals have infinite limits thus the continuous wavelet coefficients are infinite). That is why usually a discrete number of wavelet coefficients are selected for the analysis of the series.

Discrete Wavelet Transform

As noted by Gencay et al. (2005) the Discrete Wavelet Transform (DWT) can be interpreted as a critical sampling of the continuous wavelet transform. The sampling is called critical because we need a minimum number of coefficients sampled from the continuous wavelet transform in order to be able to retain all of the information in the time series. The idea is that one can use a reduced number of translations and dilations for the analysis of a time series. We need to select τ and s such that the time series can be represented with a minimum number of wavelet coefficients.

The critical sampling is obtained from letting $\tau = k\tau_0 s_0^j$ and $s = s_0^j$, where $s_0 > 1$ and $\tau_0 > 0$ and j and k are integers that control the wavelet dilation and translation. In this context the wavelet function can be written as

$$\psi_{j,k}(t) = \frac{1}{\sqrt{s_0^j}}\psi\left(\frac{t - k\tau_0 s_0^j}{s_0^j}\right).$$

Usually $s_0 = 2$ and $\tau_0 = 1$ which infers dyadic sampling of both dimensions (frequency and time). This means that the wavelet transform is calculated for 2^j scales which are limited to the total number of observations T. The fact that $2^j \in [1, \ldots, T]$ implies that $j \in \left[0, \ldots, \frac{\log(T)}{\log(2)}\right]$[2]. The term *translation* represented by k is strictly related to time, in this respect $k \in [1, ..., T]$. Then the wavelet function $\psi_{j,k}$ can be expressed as

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t - k2^j}{2^j}\right).$$

In this respect in the discrete wavelet transform equation (3.5) can be written as

$$W^*(j,k) = \sum_k y(t)\psi_{j,k},$$

where $W^*(j,k)$ are the discrete wavelet coefficient of $y(t)$.

[2]When $2^j = T$, then $j = log_2 T = \frac{\log(T)}{\log(2)}$

The discrete wavelets are orthogonal to their dilated and translated versions. This means that the wavelet function is selected such that the orthonormal properties of the discrete wavelets holds (that is orthogonality and unity as indicated in (3.3) and (3.4).

Multiresolution decomposition

The wavelet function $\psi(t)$ (also called the mother wavelet) can be interpreted as band-pass filter. As can be seen from Figure 3.5 with each shrinking of the time domain with factor 2 the frequency domain increases with factor 2. This implies that we need a large number of wavelets in order to cover the whole spectrum band. To overcome this, a scaling function $\phi(t)$ is introduced. In this respect every wavelet function $\psi(t)$ has an orthogonal scaling function $\phi(t)$ (also called father wavelet). In order to be able to decompose and then reconstruct a time series using wavelet analysis we need a mother wavelet $\psi(t)$ (wavelet function) and an orthogonal father wavelet $\phi(t)$ (scaling function). The father wavelet function can be interpreted as a scaling function that captures the low frequencies of the time series, on the other side the mother function locates the high frequencies of the time series. Each orthogonal wavelet (the father wavelet) is completely defined by a scaling low-pass filter. Analogically each wavelet function (the mother wavelet) can be represented as a high pass filter. The mother and the father wavelet functions are orthogonal functions that have the following properties

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{3.6}$$

and

$$\int_{-\infty}^{\infty} \phi(t)dt = 1. \tag{3.7}$$

With the help of the wavelet analysis each time series can be decomposed into basic multiresolution components. The multiresolution decomposition of the time series $y(t)$ is given by

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{3.8}$$

where J is the number of multiresolution scales or levels and k is the number of coefficients in each level. If the total number of observations for $y(t)$ are T, where T is a dyadic number, then there are $T/2^j$ of $d_{j,k}$ coefficients at scale $j = 1 \ldots J-1$. For scale J

there are $T/2^J$ number of $d_{J,k}$ coefficients and $T/2^J$ number of $s_{J,k}$ coefficients. The scale j is always limited to the number of observations T so that $T \geq 2^j$ is always fulfilled. For the time series $y(t)$ with length T there is a total of T wavelet coefficients $T = T/2^1 + T/2^2 + \ldots + T/2^{J-1} + T/2^J + T/2^J$. For $j = 1, 2, \ldots, J$ the wavelet transform coefficients are given by

$$d_{j,k} = \sum_k y(t)\psi_{j,k}(t) \tag{3.9}$$

and

$$s_{J,k} = \sum_k y(t)\phi_{J,k}(t). \tag{3.10}$$

The coefficients $d_{j,k}$ are the detail coefficients of the time series for $j = 1, 2, \ldots, J$, and $s_{J,k}$ represent the smooth coefficients of $y(t)$. If we denote with $S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t)$ the approximation components of $y(t)$ and with $D_j(t) = \sum_k d_{j,k}\psi_{j,k}(t)$ the detail coefficients of $y(t)$ then equation (3.8) can be written as

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_1(t). \tag{3.11}$$

Equation (3.11) represents the multiresolution decomposition of the signal $y(t)$ into orthogonal components $S_J(t), D_J(t), D_{J-1}(t), \ldots, D_1(t)$. For example if we have a multiresolution decomposition that consists of J levels then the details of the time series at level J will be represented by $D_J(t), D_{J-1}(t), \ldots, D_1(t)$ and the approximation of the series will be represented by $S_J(t)$. Once the multiresolution decomposition is obtained, one can reconstruct the original time series $y(t)$ without loss of information using the estimated wavelet coefficients in (3.9) and (3.10) and the wavelet functions $\phi(t)$ and $\psi(t)$.

Figure 3.3, Figure 3.4, and Figure 3.5 in the appendix give examples of three different wavelets with their corresponding decomposition and reconstruction low and high pass filters. The specific wavelet and scaling functions for these wavelets are included also in the appendix.

3.3.3 Wavelet-based Nowcasting with Bridge Equations

Bridge equations are used by several policy institutions to obtain early estimates of quarterly GDP growth. In this respect we will follow Angelini et al. (2011) and introduce the bridge equation framework used by the ECB. The main idea behind the approach lies in "bridging" of information from timely monthly data to quarterly data (in our case

GDP growth) in order to obtain better forecasts for the quarterly series. One should note that usually the timeliness of the monthly data is much smaller than the timeliness of the quarterly data.

Let us denote the quarterly GDP growth series to be nowcasted with y_t^Q[3]. In addition the l monthly time series available are $x_t^M = (x_{1t}^M, \ldots, x_{lt}^M)'$ for $t = 1, \ldots, T$. Our main goal is to nowcast y_t^Q using x_t^M. In order to avoid the mixed frequency problem of the quarterly and monthly series, the monthly series x_t^M are aggregated to form quarterly series x_t^Q. The bridge equations link the forecast variable y_t^Q with different variables from x_t^Q. The bridge equations used to forecast GDP growth are presented in detail in appendix 3.B (the same bridge equations as in Diron (2008) and Ferrara et al. (2010) are considered). Note that in each bridge equation certain set of variables from x_t^Q is used.

As it was discussed earlier usually monthly variables have different timelines. In order to calculate x_t^Q from x_t^M we have to assure that all monthly variables cover the whole period $t = 1, \ldots, T$. For the monthly variables for which there are missing end observations a wavelet based multi-resolution forecast is performed. This is done by decomposing the monthly variables into different resolution levels (we decompose the time series into detail and approximation parts as shown in equation (3.8)). Once the multi-resolution levels are obtained an $AR(p)$ model is used to forecast each of these levels for the variables with ragged edges. The number of lags p is calculated using the Schwarz information criterion (see Schwarz, 1978). In addition the $AR(p)$ model includes a constant term and the non-stationary resolution levels are transformed using first differences. Using equation (3.8) the forecasted multi-resolution levels are reconstructed back to form the forecast of the original series. As a result we have all $x_t^M = (x_{1t}^M, \ldots, x_{lt}^M)'$ for all $t = 1, \ldots, T$ and we can aggregate the monthly variables to construct the quarterly indicators x_t^Q.

As a second step the forecast for y_t^Q is obtained by estimating every bridge equation j (here we will use eight bridge equations so $j = 1, \ldots, 8$)

$$y_t^{jQ} = \alpha_0^j + \sum_{i=1}^{l} \alpha_i^j(L) x_{it}^{jQ} + \epsilon_t^j, \tag{3.12}$$

where α_0^j is an intercept and $\alpha_i^j(L)$ is lag polynomial. Note that for each equation j, $x_{it}^{jQ} \subseteq x_t^Q$. Once the j forecasts of GDP growth are obtained a single forecast aggregate $\hat{y}_t^Q$ is calculated as an arithmetic mean of the forcasts of each of the j bridge equations.

[3]In order to simplify the notation form this point on we will abbreviate the time series $y(t)$ with y_t.

$$\hat{y}_t^Q = \frac{1}{8}\sum_{j=1}^{8} \hat{y}_t^{jQ}, \tag{3.13}$$

The specific bridge equations considered for the nowcast of euro area GDP growth will be discussed in the next section.

3.4 Nowcasting euro area GDP Growth: the Model at Work

In this section a wavelet-based nowcasting of euro area real GDP growth with bridge equations is evaluated. In particular we will estimate a recursive pseudo out-of-sample one and two quarters ahead forecast for euro area real GDP growth. First an overview of the data will be given. Next the setup of the model will be presented followed by the empirical results.

3.4.1 Data and Model Setup

The data that will be used in this paper can be divided into two groups depending on data frequency. The first group is composed of the quarterly euro area GDP growth rate and the second group includes the monthly euro area variables. The euro area real GDP growth rate is defined as indicated in equation (3.14) in the appendix. The GDP growth rate series are taken from Eurostat's website and are displayed in Figure 3.6 in the appendix. The drop in GDP growth in 2009 is due to the financial crisis. Apart from this, mostly positive growth rates have been observed for the rest of the period. The data set starts in January 1996 and it ends in September 2011.

Table 3.1 in the appendix includes the list of variables that compose the second group of time series: the monthly explanatory variables that enter the bridge equations. There is a total of thirteen monthly variables that are entering the eight bridge equations. The monthly data set is composed from data taken from four data sources. The confidence indicators based on survey data are taken from the European Commission. The production indices along with retail sales, new car registration and the EURO STOXX 50 index are taken from Eurostat. The effective exchange rate along with the EuroCoin indicator are taken from the ECB data warehouse. The OECD composite leading indicator is extracted from OECD statistics.

As it was discussed earlier the presented model consists of eight bridge equations.

Each of the eight bridge equations are defined and included in part B of the appendix. The explanatory variables and their allocation in the bridge equations are also listed in Table 3.2 in the appendix. For each of the equations the euro area GDP growth enters as dependent variable. In the first bridge equation GDP growth is linked with production indicators from three different activity sectors. The second equation takes into account private consumption. The third, the fourth and the fifth equations link the dependent variable to different confidence indexes. Financial monthly variables are considered in the sixth equation. In equation seven and eight the euro area GDP growth is linked with the OECD leading indicator and the EuroCoin. As it was noted previously this paper directly adopts the bridge equation methodology used in Ferrara et al. (2010) and Diron (2008). Here we will not concentrate on the definition and possible alternatives of the bridge equations but we will used them as a base model that is adapted for the multi-resolution nowcasting.[4]

Let us sketch the wavelet nowcasting algorithm in more detail. First a wavelet multi-resolution decomposition is done for all of the monthly series with lagged publication. Having in mind the length of the time series a wavelet scale level equal to one was chosen. The wavelet functions that were used are Haar, Symmlets 4 and Daubechie 4.[5] Thus, for each of the incomplete monthly series a wavelet detail D_1 and wavelet smooth S_1 is calculated. The frequency interpretation of the D_1 is associated with the dynamics with periodicity between the second to fourth month of the series. S_1 corresponds to fluctuations beyond the fourth month. In Figures 3.7, 3.8, 3.9 in the appendix all of the 13 monthly time series are plotted along with their detail and approximation coefficients. As one can notice the detail coefficients capture the high-frequency dynamics of the time series and the smooth coefficients capture the low frequencies.

Once the wavelet decomposition is done for each of the details and smooth components of the monthly series an $AR(p)$ model is fitted and a h-months ahead forecast for the particular multi-resolution level is performed. The number of lags p is calculated using the Schwarz information criterion. In addition the $AR(p)$ model includes a constant term. In case the multiresolution components are non-stationary stationarity is induced by taking

[4] The estimated coefficients of each of the eight bridge can be retrieved upon request from the author.

[5] As discussed by Crowley (2005) and Rua (2011) the Symmlet wavelet family with length four is commonly used when analysing economic time series. In addition we considered other wavelet families among which the Haar and Daubechies with lengths varying between one and four. The results appear to be stable regardless of the wavelet family and the chosen length. Due to the short period of the data the forecast from wavelets with length greater than four were not stable thus not considered.

first differences. The parameter h depends on the publication lag of the monthly series. Due to the orthogonality of the detail and smooth coefficients it is possible to reconstruct each of the decomposed series at every point of time t. This is done taking into account the different publication lags of the considered monthly variables. As a result a forecasted version of each of the ragged edged monthly series is constructed with no missing values.

After obtaining full coverage of the monthly variables, without missing values, the bridge equations described in the appendix are estimated. Since euro area real GDP growth is observed on quarterly frequency all of the monthly variables are transformed to form quarters.[6] The resulting quarterly variables enter as explanatory variables in the equations and GDP growth enters as dependent variable. Each of the eight bridge equations are estimated and a recursive pseudo out-of-sample one and two periods ahead forecast of GDP growth was calculated. As in Diron (2008), Ferrara et al. (2010), and Rünstler et al. (2009) the arithmetic mean of the eight real GDP growth rate forecasts build the final forecast.

The model is estimated for the period starting from quarter one in 1996 to quarter three in 2011. The recursive out-of-sample forecast covers the period starting from 2007:Q4 until 2011:Q3. For each time point from this interval one and two periods ahead forecast is done. The nowcasting exercise is challenging since the pseudo out-of-sample forecast is performed for the volatile period covering the global financial crisis and the European sovereign debt crisis. The next section will present the results from the wavelet-based nowcasting model. The proposed model will be compared with a traditional $AR(p)$ model and the simple bridge equation model as defined in (3.12) and (3.13), but without multi-resolution decomposition for the forecast of the monthly variables.

3.4.2 Empirical Results

The proposed nowcasting model is compared with two benchmark models: a bridge equations model and an $AR(p)$ model. The bridge equations benchmark model follows Diron (2008) where the bridge equations presented in the previous sections are used to forecast GDP growth. In the paper of Diron (2008) the ragged edged monthly series are forecasted using a simple $AR(p)$ model with a constant term. The number of lags p is calculated us-

[6] Depending on the accounting unit of the variables (stocks or flows) an appropriate transformation is applied. For the quarterly flows cumulative sum of the monthly values between each quarter was used. For the quarterly stocks the exact monthly value at the end-of-quarter date was used.

ing the Schwarz information criterion. The separate forecasts are estimated using each of the eight bridge equations that were introduced earlier. The final forecast of GDP growth is an arithmetic average of the single forecasts. The second benchmark model, the $AR(p)$ model for the quarterly growth rate of GDP, contains a constant deterministic term and the number of lags p is calculated again using the Schwarz information criterion.

The performance of the wavelet-based nowcast of GDP growth with bridge equations will be evaluated over the whole sample. The out-of-sample period runs from the last quarter of 2007 until the third quarter of 2011. As it was noted earlier recursive estimation is performed. Starting from the initial estimation sample (1996:Q1 to 2007:Q3), in each round a new observation is added to the sample and a h-step-ahead forecast is computed. Since we focus on the early estimates of GDP growth a short-time horizon is considered. One, two and three quarter ahead forecasts are estimated, they correspond to GDP growth at periods $t-1$, t and $t+1$[7]. Since the reported GDP growth has one and a half quarter delay, the nowcast of the current quarter will be presented by the two quarter ahead forecast and the forecast of the next quarter will be the three quarter ahead forecast. In order to simplify the notation the nowcast for each current quarter and the following quarter will be denoted as h-step-ahead forecasts with $h = 1, 2$. Only the nowcast for t and the forecast for $t+1$ will be reported and compared. In order to check the robustness of the wavelet nowcast model three different wavelet functions were considered.

Table 3.3 in the appendix present the results from the forecast comparison. The table reports the results using the bridge equation model as a base model. The Root Mean Squared Errors (RMSE) are reported for $h = 1, 2$[8]. The nowcast is performed using three different wavelet families: Haar, Symmlets and Daubechies.

The results from the one-step-ahead recursive forecast can be seen in the first row of Table 3.3. Several conclusions can be drawn. One can see that the wavelet bridge equation model outperforms the nowcast of both benchmark models for all three wavelet functions. Note that there is homogeneity in the magnitude of the gains for all wavelet functions. Looking at Table 3.3 for the one-step-ahead forecasts ($h = 1$, thus nowcasting current quarter t) the reduction of the relative RMSE is 13.6% when using the Haar wavelet, 13.8% with the Symmlet wavelet and 12.1% for the Daubechies wavelet.[9] The

[7]We denote the current nowcasted quarter with t.

[8]The RMSE is calculated as $RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t^Q - \hat{y}_t^Q)^2}{n}}$

[9]Both the Symmlet and the Daubechies wavelets have length of four.

best nowcast is obtained with the Symmlet wavelet (although differences are small), which is the most popular wavelet family among economists (see Crowley, 2005).

Additionally the two-step-ahead forecasts results ($h = 2$, thus forecasting the forthcoming quarter $t+1$) are reported in both tables. First we will compare the results of the wavelet-based model with the bridge equation model shown in the second row of Table 3.3. The relative RMSE is reduced just for the Haar wavelet family (reduction of 2.7%). The reduction in RMSE for $h = 2$ is much smaller compared with the nowcast when $h = 1$. For the rest of the wavelet families there is slight increase in RMSE. The results are in tune with other studies which also find that with the increase of the forecast horizon the gains from the multiresolution analysis diminish (see Rua, 2011; Yousefi, Weinreich and Reinarz, 2005). A potential reason why the wavelet-based bridge equation model performs worse than the simple bridge equation model with the increase of the forecast horizon lies in the fact that due to the short sample the wavelet decomposition levels are limited. In this way long term dynamics are not captured by the wavelet analysis.

It can be concluded that the wavelet-based bridge equation nowcast model outperforms both the $AR(p)$ and the bridge equation model for the one-step-ahead forecast. As it was discussed earlier, the only difference between the bridge equation model and the wavelet-based model is the forecast of the ragged edged monthly variables. The variables which had to be forecasted due to missing last observations are the industrial production index, the construction production index, retail sales and the registration of new passenger cars. Table 3.4 gives more insights from where the forecast gains are coming. The table reports the one and two-steps-ahead forecasts using the multi-resolution decomposition as presented in the wavelet-based bridge equation model versus the $AR(p)$ forecast used in the simple bridge equation model. The recursive out-of-sample forecast covers the period starting from 2007:Q4 until 2011:Q3. The reported results in Table 3.4 are based on forecast using the Haar wavelet[10]. For all of the four variables the wavelet-based forecast for $h = 2$ outperforms the univariate forecast. For the one-step-ahead forecast the wavelet method worked better for retail sales and new passenger car registration. The one-step-ahead wavelet forecasts for the industrial production index and the construction production index have slightly higher RMSE than the $AR(p)$ forecasts. In addition to the information that Tables 3.3 and 3.4 give, the recursive nowcast from the wavelet-based

[10] The calculations using the Symmlets and the Daubechies wavelets give very similar results and are therefore not reported here.

bridge equation, the simple bridge equations along with the observed series are plotted on Figure 3.10. As it can be seen the wavelet-based nowcast moves closer to the observed series than the nowcast from the bridge equation model.

In order to assess the gains from the wavelet-based nowcast we perform a forecast encompassing test as in Rua (2011). Here we would like to compare the two predictions: the bridge equation nowcast with the wavelet-based nowcast. The encompassing test simply regresses the observed series on the h-step-forecasts from the two models. In this context we have the following regression equation

$$y_{t+h} = \alpha_1 \hat{y}^1_{t+h} + \alpha_2 \hat{y}^2_{t+h} + u_{t+h},$$

where $\hat{y}^1_{t+h}$ is the h-step-forecast obtained from the bridge equation nowcast and $\hat{y}^2_{t+h}$ is the h-step-forecast obtained from the wavelet-based nowcast. If both $\alpha_1 = 0$ and $\alpha_2 = 0$ then the two forecasts contain independent information, so no relation between them can be established. If $\alpha_1 = 0$ and $\alpha_2 \neq 0$ then the second model (that is the wavelet base nowcasting) encompasses the first model (the simple bridge equation model). In the case when $\alpha_2 = 0$ and $\alpha_1 \neq 0$ the bridge equation model encompasses the wavelet-based nowcasting model.

Table 3.5 in the appendix displays the test statistics from the encompassing test under the null hypothesis that $\alpha_i = 0$ for $i = 1, 2$. When $h = 1$ the wavelet-based nowcasting is significantly relevant for all of the three wavelet functions and it encompasses the simple bridge equation model at the 5% significance level. For $h = 2$ the encompassing test gives uncertain results. The test confirms the applicability of the wavelet-based model just for the Symmlets at the 10% significance level. For the rest of the wavelet functions both of the forecast contain independent information and no clear cut conclusion can be made regarding the encompassing power of the models.

A future enhancement of the proposed model lays in the specification of the wavelet functions. The wavelet functions can be defined so that they correspond to the time series that they are applied to. In the current model the same type of wavelet functions are applied to each of the monthly series that are forecasted. A more enhanced model could choose the wavelet function depending on the time series to be forecasted. Another improvement of the model would be to use different forecast combinations of the bridge equations outcomes. In this paper an arithmetic mean of the forecasts from the eight bridge equations was used to form the final nowcast. Table 3.6 shows the RMSE of the nowcasts from each of the eight bridge equations relative to the RMSE of the arithmetic mean nowcast which is used in the paper. The results in the table are coming from recursive out-of-sample forecast that covers the period starting from 2007:Q4 until 2011:Q3. The RMSE refers to one- and two- step-ahead forecast. The results show that there are equations that provide better forecast than the arithmetic mean forecast. In addition there are equations which perform worse than the benchmark combination. Based on these results a weighting scheme could be developed in order to improve further the nowcast of the euro area real GDP growth.

3.5 Conclusion

In this paper we introduce a new method for nowcasting euro area GDP growth. In particular we use the wavelet analysis to aid the bridge equation nowcast model used by the ECB for their early estimates of GDP. Our results show that the wavelet-based nowcasting model outperforms the bridge equation nowcast for the short term forecasts of euro area GDP growth.

In order to obtain better nowcast of GDP growth it is crucial to use the most recent available data. Since economic time series have different frequencies and timeliness it is very difficult to fit nowcasting models to the most recent available data. Usually economic data has ragged edges where the last observations of the series are missing due to lags in measurement. Economists use univariate forecasting techniques like $AR(p)$ models to estimate the missing data and then fit it to the nowcasting models. In this paper we use the non-parametric wavelet analysis to aid the nowcasting bridge equations.

Here we introduce a multi-resolution approach that outperforms the usual single resolution forecast framework. In this respect we use a wavelet multi-resolution analysis with the help of which each time series can be decomposed into time scale components. Once this is done we forecast the ragged edges of the time series for each resolution levels and then use the properties of the wavelet transformation to reconstruct the forecast of the original time series. Eight bridge equations are used to obtain the final nowcasts for the euro area GDP growth. To assess the performance of the wavelet-based nowcasting method an out-of-sample forecasting exercise is performed. We use three different wavelet functions to analyse the sensitivity of the wavelet model. The results show the wavelet multi-resolution nowcasting model performs better than the standard single resolution nowcasting method for short run forecasts. The outcomes are supported by an encompassing test comparing the two types of forecasts.

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3.A Appendix - Figures and Tables

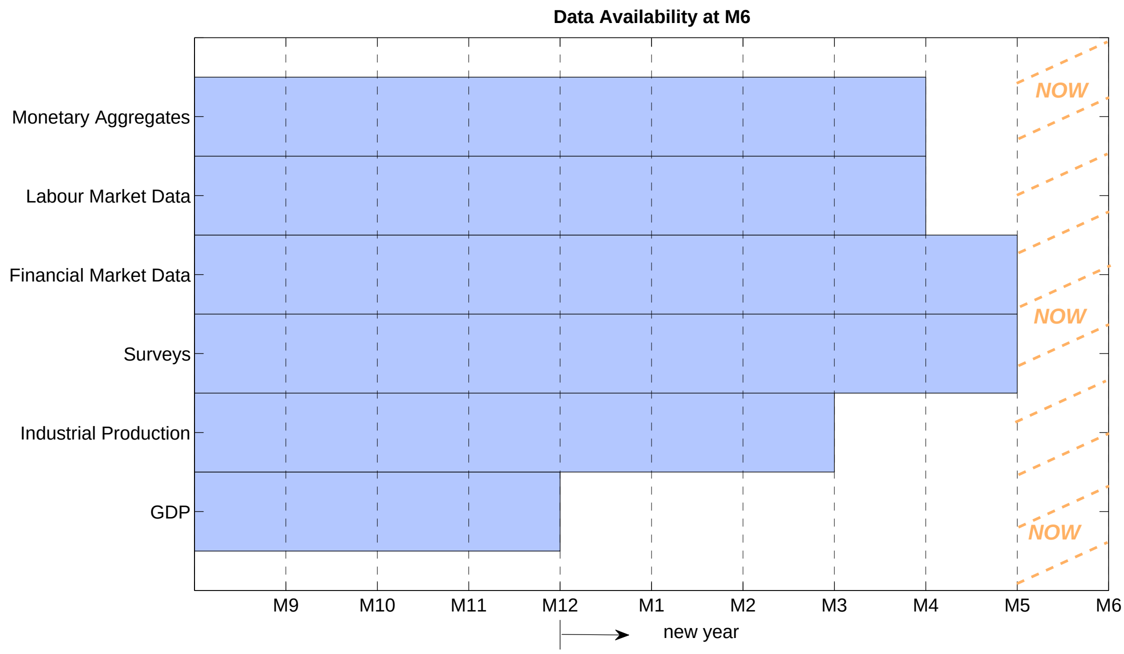

Figure 3.1: Timeliness of euro area economic variables. The graphic shows June (M6) as being the current month and the blue bars indicate data availability.

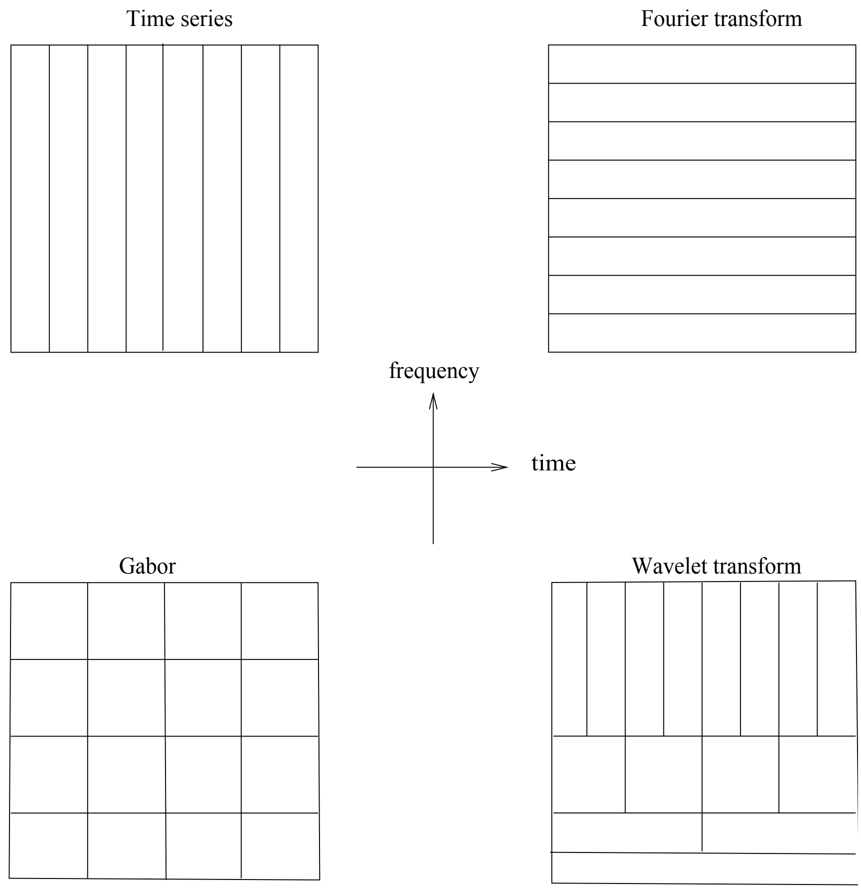

Figure 3.2: Time-frequency comparison between a time series, its Fourier transform, Gabor's short-term Fourier transform and wavelet transform. The graphic is an own replication of similar figure in Crowley (2005).

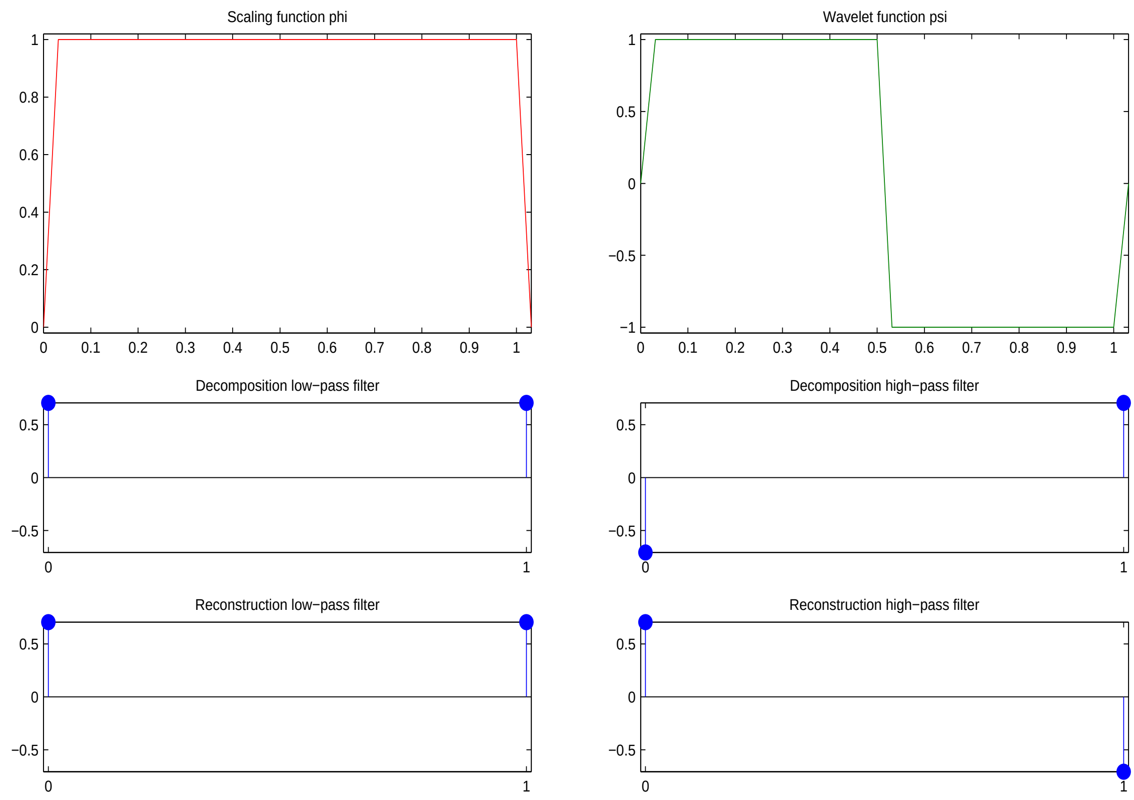

Figure 3.3: Haar wavelet. The wavelet and the scaling function are defined in the following way. $\phi(x) = 1$ for $x \in [0, 1]$ and $\phi(x) = 0$ for $x \notin [0, 1]$. $\psi = 1$ if $x \in [0, 0.5)$ and $\psi = -1$ if $x \in [0.5, 1)$ and $\psi = 0$ if $x \notin [0, 1)$

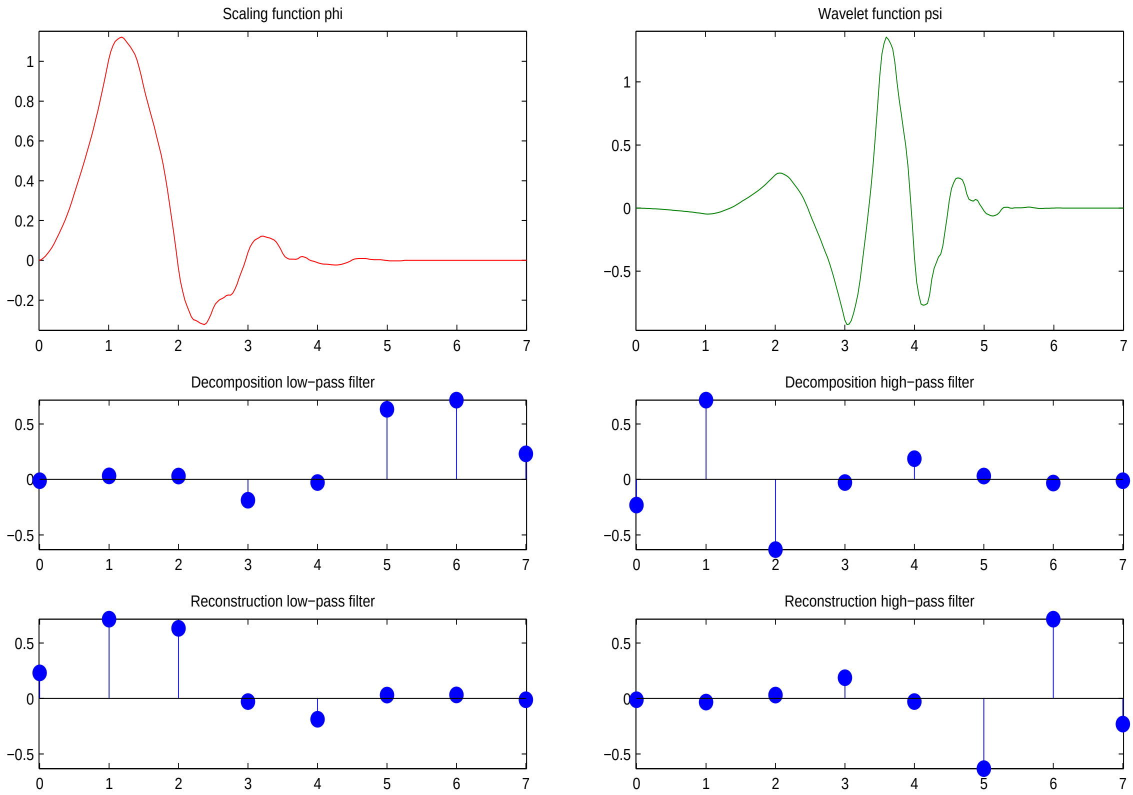

Figure 3.4: Daubechies 4 wavelet and scaling functions. This wavelet can be explicitly defined by the low and high band-pass filters.

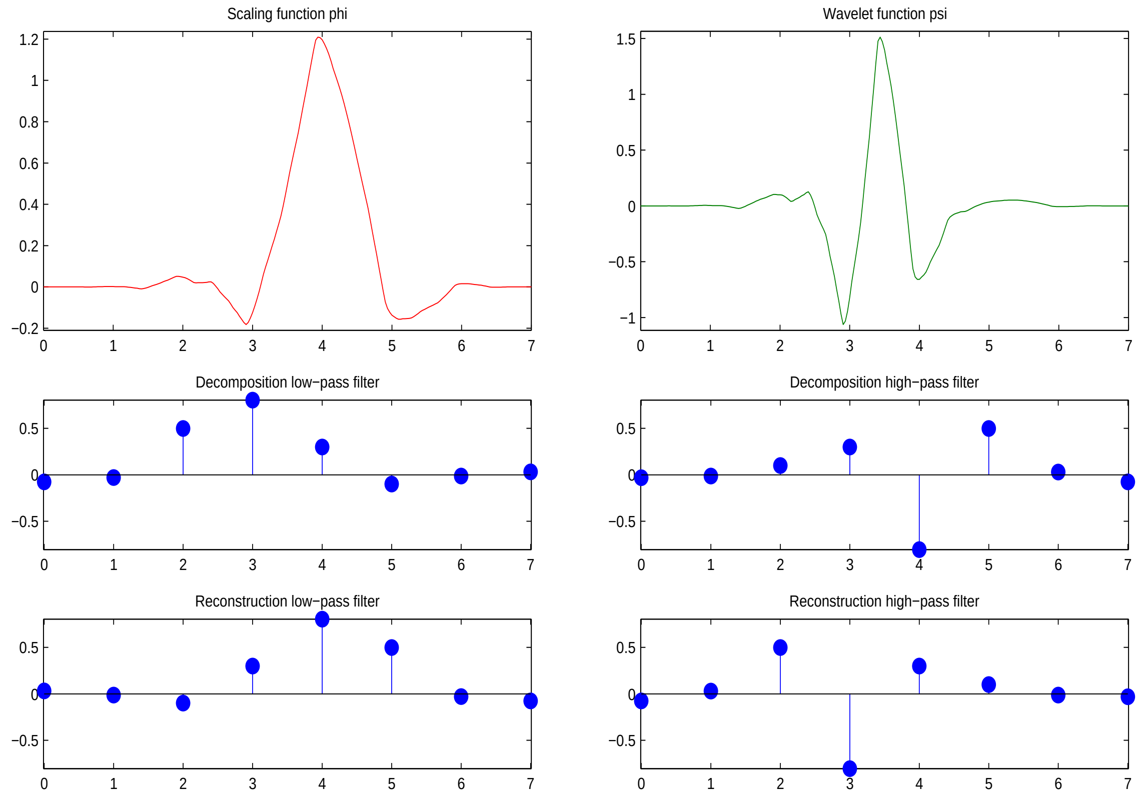

Figure 3.5: Symmlets 4 wavelet and scaling functions. This wavelet can be explicitly defined by the low and high band-pass filters.

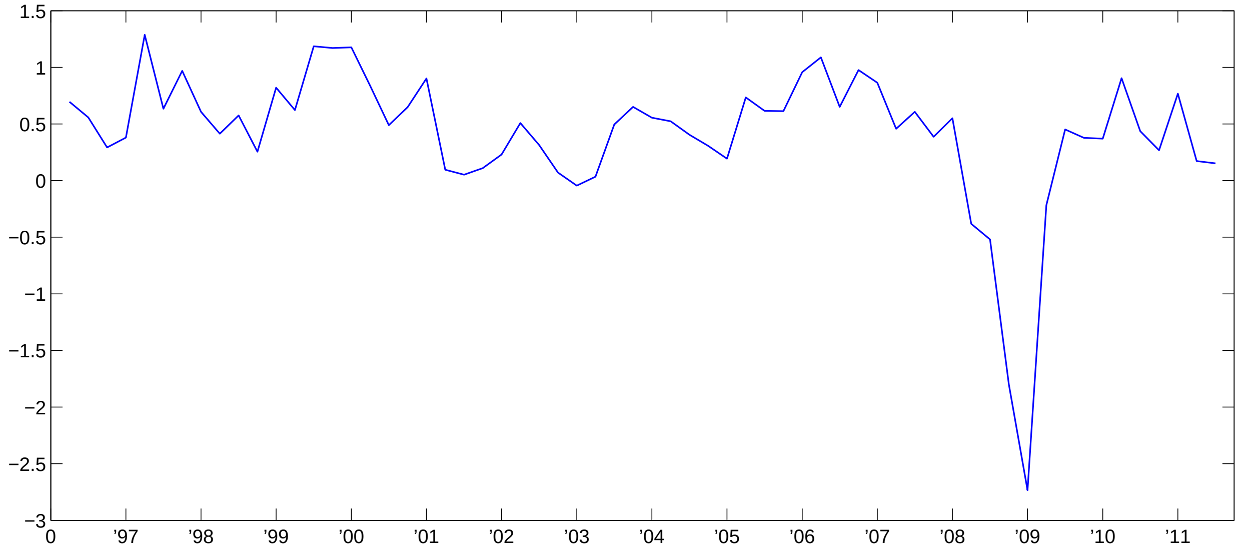

Figure 3.6: Quarterly euro area real GDP growth series defined as $y_t = 100(\log g_t - \log g_{t-1})$, were g_t is real GDP. Sample period: 1996Q1 to 2011Q3.

Table 3.1: Monthly economic indicators entering the eight bridge equations.

Explanatory variables	Source
Industrial production index	Eurostat
Construction production index	Eurostat
Confidence index in the services	European Commission
Retail sales	Eurostat
New passenger car registration	Eurostat
Confidence indicator in industry	European Commission
European economic sentiment index	European Commission
Consumers' confidence indicator	European Commission
Confidence indicator in retail trade	European Commission
Effective exchange rate	ECB
Deflated EURO STOXX 50 index	Eurostat
OECD composite leading indicator	OECD
EuroCoin Indicator	ECB

Table 3.2: Bridge equations with explanatory variables for real GDP growth nowcast.

Explanatory variables	eq1	eq2	eq3	eq4	eq5	eq6	eq7	eq8
Industrial Production Index	*	*						
Construction Production Index	*	*						
Confidence Index in the Services	*			*				
Retail sales		*						
New passenger car registration		*						
Confidence Indicator in Industry				*	*			
European Economic Sentiment Index			*					
Consumers' Confidence Indicator					*			
Confidence Indicator in Retail Trade					*			
Effective exchange Rate						*		
Deflated EURO STOXX 50 Index						*		
OECD Composite Leading Indicator							*	
EuroCoin Indicator								*

Note: Asterisk denotes that the corresponding variable is included in the denoted bridge equation.

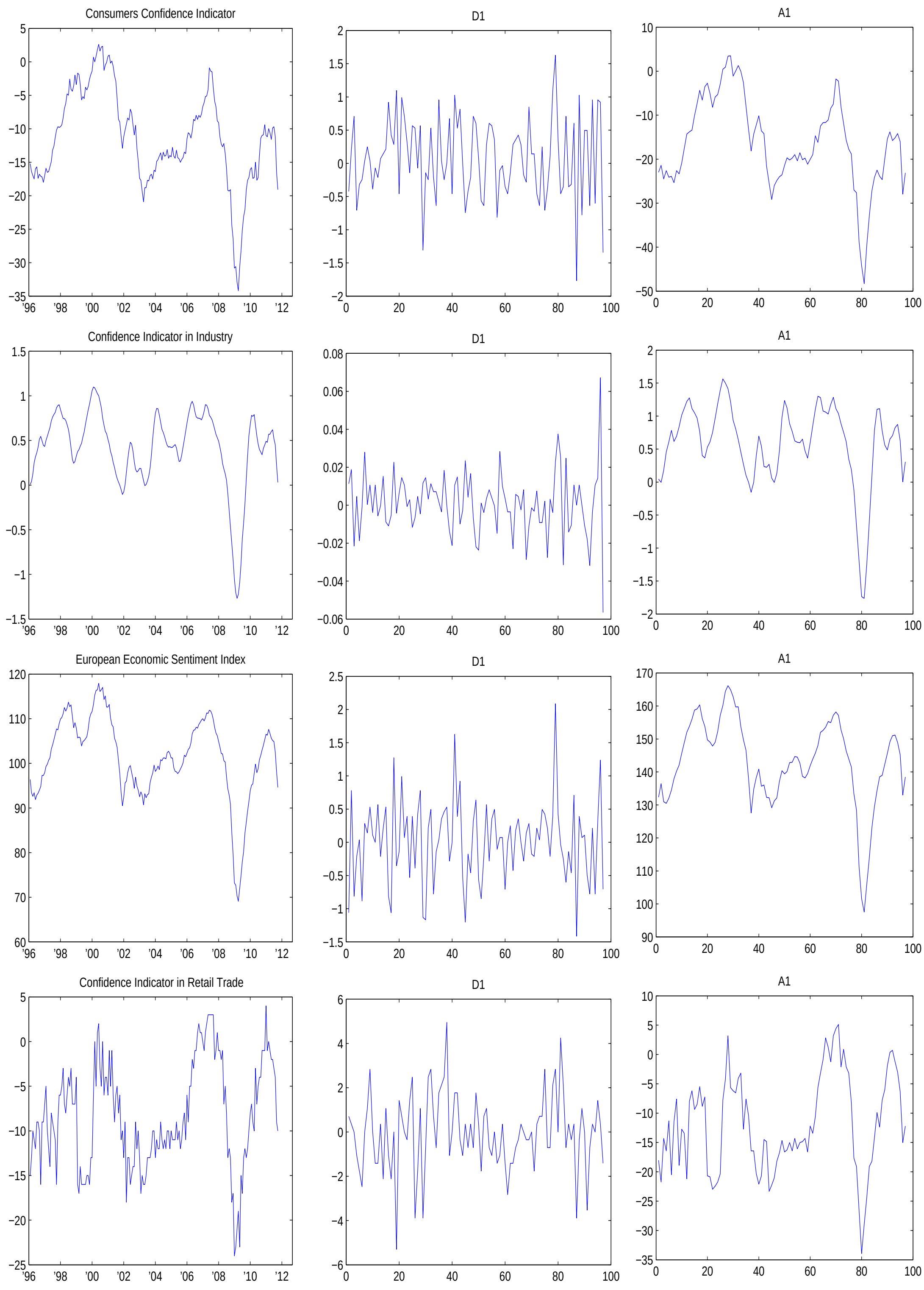

Figure 3.7: Wavelet multi-resolution decomposition. Consumer confidence indicator, confidence indicator in industry, European economic sentiment index and retail trade confidence indicator are plotted in the left panel, the middle panel plots the wavelet detail coefficients $D1$. On the left are the smooth coefficients $S1$.

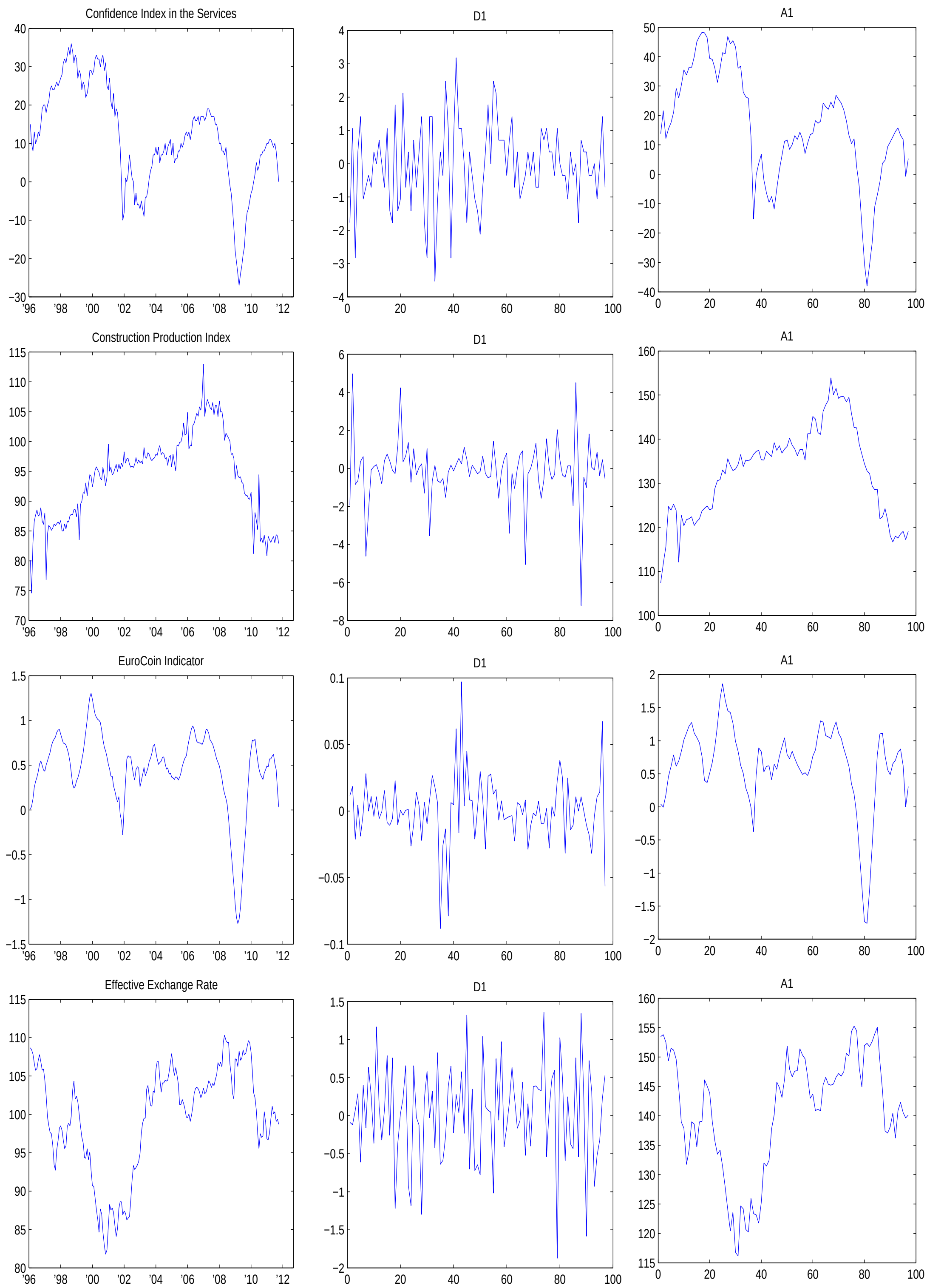

Figure 3.8: Wavelet multi-resolution decomposition. Confidence index in services, construction production index, EuroCoin indicator and effective exchange rate are plotted in the left panel, the middle panel plots the wavelet detail coefficients $D1$. On the left are the smooth coefficients $S1$.

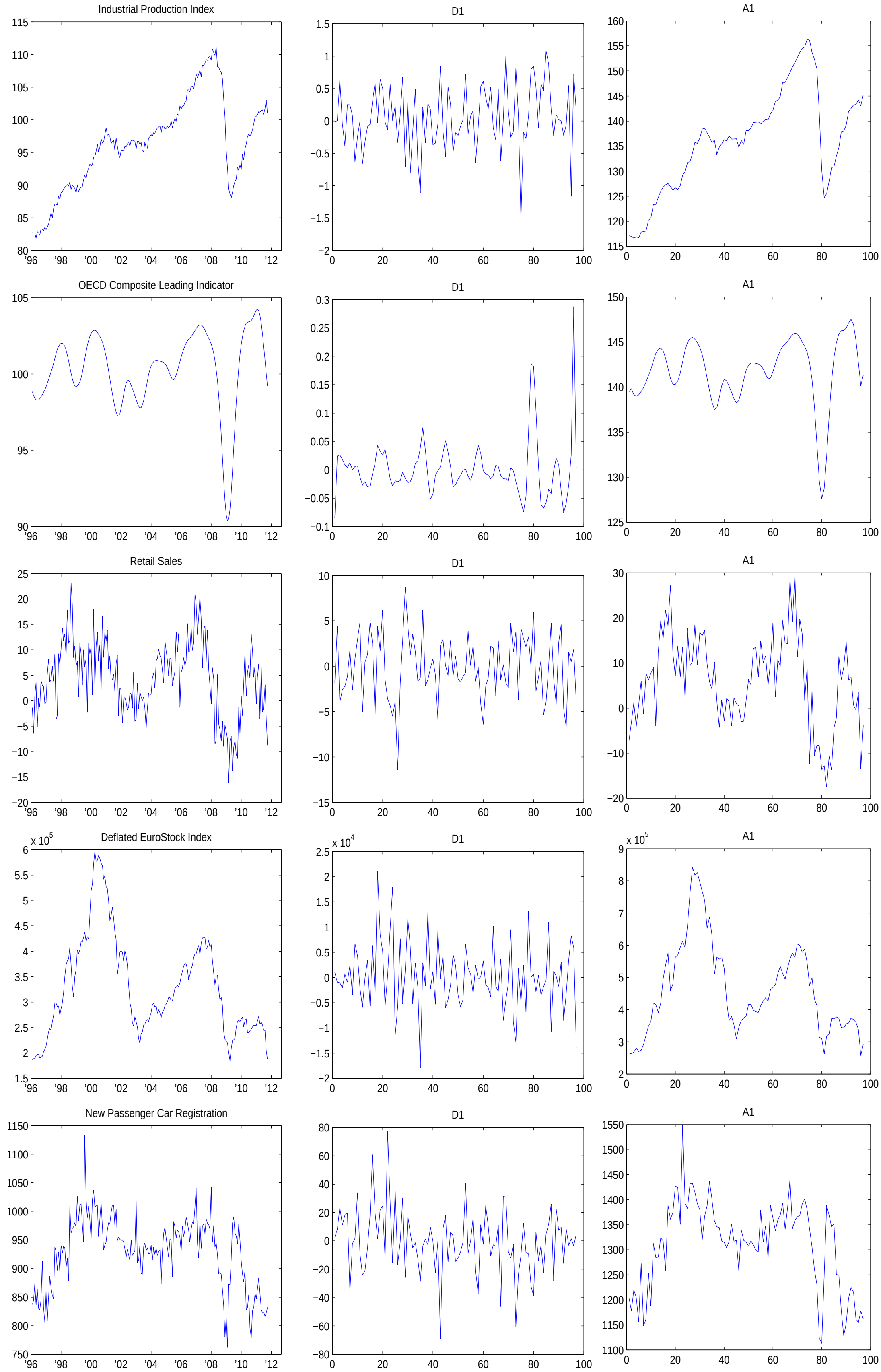

Figure 3.9: Wavelet multi-resolution decomposition. Industrial production index, OECD composite leading indicator, retail sales, deflated EURO STOXX 50 index and new passenger cars registrations are plotted in the left panel, the middle panel plots the wavelet detail coefficients $D1$. On the left are the smooth coefficients $S1$.

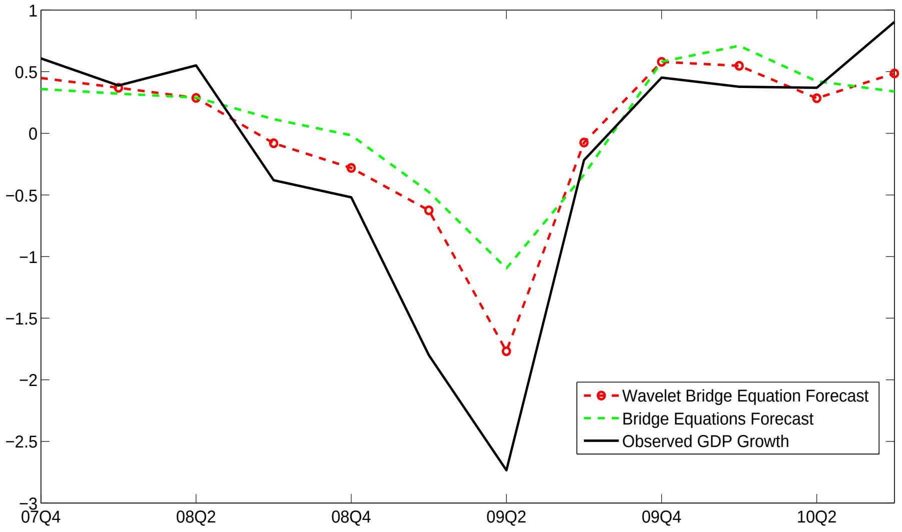

Figure 3.10: Euro area GDP growth real series along with the results of 1-step-ahead recursive forecasts from the bridge equation model and the wavelet-based bridge equation model.

Table 3.3: RMSE relative to the RMSE of the bridge equations model.

	Haar	Symmlets 4	Daubechies 4
h=1			
AR model	1.537	1.537	1.537
Bridge Equations	1.000	1.000	1.000
Wavelet Bridge Equations	0.864	0.862	0.879
h=2			
AR model	1.588	1.588	1.588
Bridge Equations	1.000	1.000	1.000
Wavelet Bridge Equations	0.973	1.094	1.052

Note: The results are based on recursive out-of-sample forecast covering the period from 2007:Q4 until 2011:Q3.

Table 3.4: RMSE of wavelet-based AR relative to the RMSE of the benchmark $AR(p)$ model.

	h=1	h=2
Industrial production index	1.03	0.63
Construction production index	1.09	0.99
Retail sales	0.79	0.98
New passenger car registration	0.83	0.65

Note: The results are based on recursive out-of-sample forecast covering the period from 2007:Q4 until 2011:Q3.

Table 3.5: Forecast encompassing test.

	Haar		Symmlets 4		Daubechies 4	
	α_1	α_2	α_1	α_2	α_1	α_2
h=1	-0.76	2.12**	-1.59	2.37**	-1.33	2.74**
h=2	1.65	-0.35	1.51	2.04*	1.71	0.73

Note: Asterisks denote rejection of the null hypothesis that $\alpha_i = 0$ for $i = 1, 2$ at $^*10\%$ and $^{**}5\%$ significance level, respectively.

Table 3.6: RMSE of each of the separate wavelet-based bridge equations relative to the RMSE of the arithmetic mean wavelet-based bridge equation model.

	Haar	Symmlets 4	Daubechies 4
h=1			
Wavelet BEq#1	1.235	1.222	1.270
Wavelet BEq#2	1.113	1.064	1.171
Wavelet BEq#3	1.146	1.133	1.125
Wavelet BEq#4	0.974	0.971	0.953
Wavelet BEq#5	1.390	1.390	1.367
Wavelet BEq#6	1.185	1.187	1.164
Wavelet BEq#7	1.024	1.061	1.027
Wavelet BEq#8	1.105	1.113	1.085
h=2			
Wavelet BEq#1	1.433	1.106	1.645
Wavelet BEq#2	1.403	1.263	1.735
Wavelet BEq#3	1.201	1.194	1.102
Wavelet BEq#4	1.071	1.237	0.974
Wavelet BEq#5	1.201	1.111	1.100
Wavelet BEq#6	0.993	0.883	0.919
Wavelet BEq#7	0.779	0.826	0.705
Wavelet BEq#8	1.121	1.105	1.038

Note: The arithmetic mean of the wavelet-based bridge equation forecast is defined in 3.13

3.B Appendix - Regression Bridge Equations

Let us define euro area real GDP with g_t. The real GDP is evaluated at market prices of the base year 2005. Euro area real GDP growth is defined as

$$y_t = 100(\log g_t - \log g_{t-1}) \tag{3.14}$$

The eight bridge equations to nowcast y_t will be presented below.

Equation 1: In this equation real GDP growth is linked with industrial production index ($x_{1,t}$), construction production index ($x_{2,t}$) and the confidence index in the services ($x_{3,t}$).

$$y_t = \alpha_0^1 + \alpha_1^1(x_{1,t} - x_{1,t-1}) + \alpha_2^1(x_{2,t} - x_{2,t-1}) + \alpha_3^1 x_{3,t} + \epsilon_t^1$$

Equation 2: The explanatory variables in the second equations are retail sales ($x_{4,t}$), new passenger car registration ($x_{5,t}$) as well as industrial production index ($x_{1,t}$) and construction production index ($x_{2,t}$)

$$y_t = \alpha_0^2 + \alpha_1^2(x_{1,t} - x_{1,t-1}) + \alpha_2^2(x_{2,t} - x_{2,t-1}) + \alpha_3^2(x_{4,t} - x_{4,t-1}) + \alpha_4^2(x_{5,t} - x_{5,t-1}) + \epsilon_t^2$$

Equation 3: In the third equation the European Sentiment Index ($x_{6,t}$) is used as explanatory variable.

$$y_t = \alpha_0^3 + \alpha_1^3 x_{6,t} + \alpha_2^3 x_{6,t-1} + \epsilon_t^3$$

Equation 4: In the fourth bridge equation the industry confidence index ($x_{7,t}$) along with services confidence index ($x_{3,t}$) is used

$$y_t = \alpha_0^4 + \alpha_1^4(x_{7,t} - x_{7,t-1}) + \alpha_2^4 x_{3,t} + \epsilon_t^4$$

Equation 5: GDP growth is forecasted with consumer confidence index ($x_{8,t}$), industry confidence index ($x_{7,t}$) and retail trade confidence index ($x_{9,t}$).

$$y_t = \alpha_0^5 + \alpha_1^5(x_{7,t} - x_{7,t-1}) + \alpha_2^5 x_{9,t} + \alpha_3^5 x_{8,t} + \epsilon_t^5$$

Equation 6: The sixth equation uses the effective exchange rate ($x_{10,t}$) and deflated

EURO STOXX 50 index ($x_{11,t}$)

$$y_t = \alpha_0^6 + \alpha_1^6(x_{10,t-2} - x_{10,t-3}) + \alpha_2^6(x_{11,t-1} - x_{11,t-2}) + \epsilon_t^6$$

Equation 7: The following variables enter as explanatory variables in the seventh equation: the OECD leading indicator ($x_{12,t}$) and the EuroCoin ($x_{13,t}$)

$$y_t = \alpha_0^7 + \alpha_1^7(x_{12,t} - x_{12,t-1}) + \alpha_2^7(x_{13,t-2} - x_{13,t-3}) + \alpha_3^7 y_{t-1} + \epsilon_t^7$$

Equation 8: In the last equation real GDP growth is bridged with the EuroCoin index ($x_{13,t}$)

$$y_t = \alpha_0^8 + \alpha_1^8 x_{13,t} + \epsilon_t^8$$

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Erklärung

Ich versichere hiermit, dass ich die vorliegende Arbeit mit dem Thema:

Three Essays on Applied Time Series Econometrics

ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Weitere Personen, insbesondere Promotionsberater, waren an der inhaltlich materiellen Erstellung dieser Arbeit nicht beteiligt.[1] Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Konstanz, den 18.12.2012

(Zlatina Balabanova)

[1]Siehe hierzu die Abgrenzung auf der folgenden Seite.

Abgrenzung

Ich versichere hiermit, dass ich Kapitel 1 und 3 der vorliegenden Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe.

Kapitel 2 entstammt aus einer gemeinsamen Arbeit mit Prof. Ralf Brüggemann (Universität Konstanz). Die Idee stammt von beiden Autoren. Ich habe die empirischen Analysen selbstständig durchgeführt. Die Ergebnisse wurden von beiden Autoren gemeinsam interpretiert.

Konstanz, den 18.12.2012

(Zlatina Balabanova)