JAN-ERIK ANTIPIN

Bayesian Applications in Empirical Monetary Policy Analysis

ACADEMIC DISSERTATION
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Tel. +358 40 190 9800
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In Stockholm, August 2012

Jan-Erik Antipin

Abstract

Jan-Erik Antipin
Bayesian Applications in Empirical Monetary Policy Analysis

This thesis investigates effects of sudden movement in monetary policy stance in the euro area and assesses forecasting performance of estimated structural dynamic equilibrium model for the United States data. In the first three essays the focus is on an inspection of the dynamic effects of sudden changes in the monetary policy conduct of the European Central Bank (ECB) in EMU member countries. We propose that asymmetric monetary policy responses would imply that domestic monetary policy transmission mechanisms have not necessarily integrated even if EMU convergence criteria were met on time, and it would be at odds that the euro area constitutes an optimum currency area. The fourth essay assesses the forecasting performance of a modern macro model for U.S. data. The statistical inference of the thesis is Bayesian.

In the first essay, we describe the dynamics of year-on-year consumer price inflation responses to an unanticipated expansionary monetary policy shock in the euro area with a vector autoregressive model (VAR) model. The variables and statistically testable short run restriction schemes ensuring identification are derivable from a new Keynesian macro model. A rather surprising finding is that traditional Cholesky identification is only weakly supported by the data. Impulse responses of year-on-year consumer price inflation to an expansionary monetary policy shock are calculated for a VAR model identified by the most probable identification scheme. In this identification scheme we let EMU member country information to affect simultaneously monetary policy instrument. Obtained results suggest asymmetric year-on-year price inflation responses to monetary policy conducted by the ECB.

In the second essay, we first survey, with help of a variant of the Taylor rule, six information sets on which the ECB most likely bases its monetary policy decisions. Assessment of information sets is an obvious accretion to the literature on the conduct of monetary policy by the ECB. In the analysis we approximate euro area's monetary conditions with an estimated VAR model for the suggested information set and calculate identified impulse responses of the difference in year-on-year producer price inflations in the euro area and few peripheral EMU member countries. According to results an unexpected variation in the monetary policy instrument conditioned on the information pertaining to the three

largest EMU member countries (Germany, France and Italy) will have asymmetric effects in year-on-year producer price inflation across the EMU member countries.

In the third essay, we apply a new Keynesian open economy macro model in setting identifying restrictions for impulse response analysis of consumer price inflation in the euro area. The relevance of the implied simultaneous parameter cross-equation restrictions is assessed by posterior estimation of the hyperparameter that measures prior beliefs on identifying restrictions. The posterior evidence suggests that prior beliefs on simultaneous effects of model variables are of relevance while identifying the VAR model with an open economy new Keynesian macro model for the euro area. Contrary to outcome of the first essay, the drawn impulse responses support the claim that an expansionary monetary policy shock would not cause evident asymmetric price inflation responses in EMU member countries. However, the impulse responses from recursively identified VAR-model are in line with the ones reported in the first essay.

The fourth essay evaluates a closed economy, log-linearized 3-variable new Keynesian model with an easily implementable method for the Bayesian analysis. It becomes evident that a small-scale modern macro model can rival commonly used forecasting tools, such as Bayesian VARs and forecasts based on random walks. According to the posterior evidence, the model manages to capture evolutions of U.S. macroeconomic variables, price inflation, short-term nominal interest rate and measure of output gap, fairly well.

Keywords: Monetary policy, new Keynesian macro model, Vector autoregressive model, impulse response function, forecasting, Bayesian inference.

Tiivistelmä

Jan-Erik Antipin
Bayesian Applications in Empirical Monetary Policy Analysis

Väitöskirjan kolmessa ensimmäisessä esseessä tutkitaan Euroopan Keskuspankin (EKP) yllätyksellisen rahapolitiikkatoimenpiteen vaikutuksia rahaliiton jäsenmaissa. Työn neljännessä esseessä tarkastellaan Keynesiläisen dynaamisen stokastisen yleisen tasapainomallin ennustekykyä Yhdysvaltojen aineistolla. Kolmen ensimmäisen esseen analyysin kantavana hypoteesina on olettamus, jonka mukaan rahaliiton jäsenmaiden rahapolitiikan välittymiskanavat ovat erilaiset. Tämä on mahdollista huolimatta siitä, että jäsenmaat olisivat täyttäneet EMU-lähentymiskriteerit ajallaan. Evidenssi rahaliiton jäsenmaiden epäsymmetrisistä reagoinneista EKP:n harjoittamaan yllätykselliseen rahapolitiikkaan tukisi väittämää, että euroalue ei olisi optimaalinen valuutta-alue. Väitöskirjan tilastollinen päätäntä on bayesiläistä.

Väitöskirjan ensimmäisessä esseessä kartoitetaan yllätyksellisen rahapolitiikkashokin aiheuttamia vuosimuutoksia rahaliiton jäsenmaiden kuluttajahintaindeksisarjoissa. Empiirinen tarkastelu toteutetaan vektoriautoregressiivisen aikasarjamallin identifioitujen impulssivastefunktioiden avulla. Analyysin muuttujajoukko on johdettavissa modernista makromallista. Esseessä lasketaan kilpaileville impulssivastefunktion identifioiville lyhyen aikavälin parametrirajoitteille posterioritodennäköisyydet. Esseen yllättävä tulos on, että havaintoaineisto tukee heikosti perinteistä rekursiivista (Cholesky) identifiointirakennetta. Sitä vastoin havaintoaineisto tukee identifiointirakennetta, joka sallii kansallisen kuluttajahintainflaation vaikuttaa EKP:n rahapolitiikkainstrumentin arvoon. Estimoidut kuluttajahintamuutokset yllätykselliselle rahapolitiikkatoimenpiteelle ovat tilastollisesti epäsymmetrisiä ja tukevat täten olettamusta, että rahapolitiikan välittymiskanavat rahaliiton jäsenmaissa ovat erilaiset.

Toisessa esseessä tutkitaan informaatiojoukkoja, joiden oletetaan vaikuttavan EKP:n rahapoliittiseen päätöksentekoon. Esseessä oletetaan, että EKP:n käyttämää rahapolitiikkainstrumenttia voidaan kuvata Taylor-säännön mukaisella rahapolitiikkasäännöllä. Esseessä lasketaan posterioritodennäköisyydet kuudelle informaatiojoukolle, joiden uskotaan vaikuttavan rahapolitiikkainstrumentin arvoon. Posterioritodennäköisyydet osoittavat, että Saksan, Ranskan ja Italian yhdistetty kansallinen aineisto selittää merkittävissä määrin EKP:n rahapolitiikkainstrumentin vaihtelua. Lisäksi esseessä tarkastellaan kuinka tuottajahintaindeksiai-

kasarjojen vuosimuutoksille estimoidut vektoriautoregressiivisen mallin impulssivastefunktiot käyttäytyvät ehdollistettuna eri informaatiojoukoille. Lasketuista impulssivastefunktioista nähdään, että EKP:n yllätyksellisen rahapolitiikkatoimeen vaikutus tuottajahintaindeksin vuosimuutoksiin on epäsymmetrinen rahaliiton jäsenmaissa.

Väitöskirjan kolmannessa esseessä käytetään uuskeynesiläistä avoimen talouden makromallia kuvastamaan rahapolitiikan virittämistä ja vaikutusten välittymistä euroalueella ja yksittäisessä rahaliiton jäsenmaassa. Toisin kuin toisessa esseessä, kansallisen informaation ei anneta vaikuttaa EKP:n käyttämän rahapolitiikkainstrumentin arvoon. Analyysissä oletetaankin, että EKP ehdollistaa rahapolitiikkatoimenpiteensä euroalueen aggregaatti-informaatiolle. Tuloksista käy ilmi, että makromallin implikoimat lyhyen aikavälin parametrirajoitteet ovat tilastollisesti merkittäviä. Estimoitujen rakennemuodon impulssivastefunktioiden perusteella voidaan todeta, että kuluttajahintainflaation reagointi yllätykselliselle rahapolitiikkainstrumentin muutokselle on, vastoin väitöskirjan ensimmäisen esseen tulosta, tilastollisesti symmetrinen rahaliiton jäsenmaissa. Huomionarvoista on toisaalta todeta, että esseen Cholesky-identifioidut impulssivastefunktiot ovat linjassa ensimmäisen esseen tulosten kanssa.

Neljännessä esseessä estimoidaan reaaliaikaisen havaintoaineiston avulla suljetun talouden Keynesiläinen dynaaminen stokastinen yleisen tasapainon malli helposti sovellettavissa olevalla estimointitavalla. Estimoidun tasapainomallin kykyä ennustaa Yhdysvaltojen korkoa, inflaatiota ja tuotantoa verrataan perinteisten, yleisesti käytettyjen aikasarjamallien ennustekykyyn. Tulokset osoittavat, että estimoidun makromallin ennustekyky on hyvä. Tulos on erittäin mielenkiintoinen, sillä alan kirjallisuudessa uskotaan, että vastaavaan ennustekykyyn päädytään kasvattamalla mallikokoa.

Avainsanat: Rahapolitiikka, uuskeynesiläinen makromalli, vektoriautoregressiivinen malli, impulssivastefunktio, ennustaminen, bayesiläinen päättely.

Author's address Jan-Erik Antipin
Macroeconomic Research and Simulations
P.O. Box 3116, SE-103 62 Stockholm, Sweden
National Institute of Economic Research (NIER)

Supervisor Ph.D. Jouko Vilmunen
Research Unit
Bank of Finland

Reviewers Professor Heikki Kauppi
University of Turku
Department of Economics

Professor Antti Ripatti
University of Helsinki
Department of Economics

Opponent Professor Juha Junttila
University of Jyväskylä
Department of Economics

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1 Introduction

This thesis empirically investigates the effects of common monetary policy in the euro area and presents forecast comparisons between estimated structural dynamic equilibrium model and traditional vector autoregressive models for the United States data.

In the analysis of common monetary policy the focus is on inspection of the dynamic effects of sudden changes in the monetary policy conduct of the European Central Bank (ECB) in the euro area. The motivation pours partly from Clausen and Hayo (2002, 2006), Huchet-Bourdon (2003) and Durand *et al.* (2008) reporting that responses to a common monetary policy shock can expected to be seen asymmetric in the euro area. In addition, the analysis of Gros and Hefeker (2002, 2007) shows that monetary policy that minimizes the sum of national utility lossess will lead to a higher average utility in the euro area thus allowing leeway for inspecting a possibility that the monetary policy for the euro area might not be conditioned on euro area aggregates. Furthermore, De Grauwe (2000) and De Grauwe and Sénégas (2004, 2006) conclude that national information should be used in design of common euro area monetary policy. Moons and Van Poeck (2008) question the appropriateness of ECB's monetary policy and argue that monetary policy exercised by the ECB does not fit individual EMU member countries equally well. In the spirit of these results we inspect information sets on which the ECB conditions its monetary policy and track down EMU member countries' price inflation dynamics to a shock in monetary policy instrument. As far as the forecasting performance is concerned we motivate it by referring to Sungbae and Schorfheide (2007) who focus on development of new Keynesian model suitable for forecasting and quantitative policy analysis. We will be measuring the forecasting performance of a modern macro model estimated for U.S. data. In the introduction part of the thesis we lay grounds for the essays by briefly discussing theoretical developments of macro models and empirics within with monetary policy motivation. We also cast a quick glance at Bayesian econometrics.

The thesis takes a positive viewpoint on model specification issues and estimation problems in monetary policy econometrics. It covers topics such as model uncertainty, forecasting performance and information sets used by modern central banks in conducting monetary policy. These topics are seen to be crucial for an applied economist developing and estimating economic models for policy analysis and forecasting purposes. The outcome of analysis of common monetary policy is that EMU member countries can be expected to face asymmetric price inflation responses to monetary policy shocks. The contribution of forecasting analysis is that a small-scale modern macro model can rival traditional forecasting models in forecasting performance. The statistical inference of empirics in the thesis is Bayesian, as is the current practice in the field.

The focus of the analysis is built on multivariate, dynamic time series models with identification restrictions derivable from economic theory. We apply both modern closed and open economy macro models in attaining these restrictions. Due to the dynamic nature of the phenomenon described in the essays, the statistical analysis is based on vector autoregressive (VAR) models, whose properties are widely known and the models are frequently applied to approximating the effects of unforeseen movements in the monetary policy instrument. The new Keynesian macro models provide theoretical motivations and help in drawing guidelines for identifying restrictions for simultaneous effects of the model variables.

Particularly, we seek evidence on the potential asymmetric national price inflation responses in the EMU member countries to an unanticipated common monetary policy shock. These asymmetric inflation responses can give rise to asymmetric, undesirable real effects. Asymmetric real effects could reflect persistent underlying structural differences even in the case where EMU member country has fulfilled EMU convergence criteria on time. Evidence on real asymmetric responses would be at odds with the paradigm initially designating the euro area as a common currency, and throw doubt on claims that the EMU would constitute an optimum currency area (Mundell, 1961). For a more thorough treatment of important aspects of monetary integration in the economic context see De Grauwe (2003).

One of the intensively debated topics in recent macroeconomic literature is forecasting performance of the new Keynesian dynamic stochastic general equilibrium (DSGE) models. Many recent studies have shown that the forecasting performance of new Keynesian DSGE models can be improved by specifying relatively complex DSGE model mechanisms. Our contribution in this thesis is to use quarterly U.S. data to evaluate forecasting performance of small-scale DSGE model in relation to traditional time series forecasting models. We use estimated model parameters to generate forecasts and to compare forecasting performance with abovementioned models.

Empirical analysis relies heavily on Bayesian methods which has become a common practice in macroeconometrics. In Bayesian statistics the inference is conditioned on information emanating from the observed data, and on prior knowledge. The rationale for using Bayesian statistics stems from the following: Bayesian methods allow data-consistent statistical inference of model parameters and statistical model comparison can be conducted in a transparent manner.

In the following subsections we describe shortly advances in macroeconomic modeling and the past evolution of econometric methods linking real-life observations and macro models together in the monetary economics literature. Here we also justify the selection of model framework and estimation methods. A short introduction to Bayesian econometrics helps reader to understand Bayesian methods applied in thesis. Then summaries of the essays are presented. The latter part of the thesis comprises the original essays.

1.1 Theoretical and Empirical Advances in Monetary Macro Models

1.1.1 General Discussion

Before we lay our hands on the thesis topics it is worthwhile to describe shortly how macroeconomic theory and empirical applications therein have developed over time. One can state that past advances in macroeconomic theory have accrued, roughly speaking, with respect to two aspects. The advances have taken place in building models as theoretical descriptions for a closed or open economy, or whether the models are meant to be dynamic or static descriptions of economy. In current economic theory it has come to be accepted that the state of an economy is dependent on previous states. This means that we expect that the current level of consumption depends on its level in future periods, since economic agents prefer a constant course of life-time consumption. For this reason, in dynamic macro models the Euler equation captures the evolution of an optimal consumption path of an economic agent. In similar vein, producers are aware that prices they set depend (among other things) on the level of demand, which is in turn dependent on the future path of consumption. Concurrently the model estimation methods have taken a giant leap. This can be seen enabled by increased low cost computational power required in the analysis of expectations augmented stochastic multivariate macro models.

A crucial topic in macromodelling is the model specification. Given the set of observations of reality, how should the estimating macro model look like? Empirical research provides one way to answer to this question via model selection methods that are based on the empirical fits of rivaling models for given observations of reality. It is commonly agreed that theoretical considerations and consistent statistical comparison of competing models facilitate model selection and development but some level of uncertainty about the true model specification will always remain. The Bayesian statistical methods enable consistent model comparison methods for model developers contemplating different model specifications. For instance, Rabanal and Rubio-Ramirez (2005), Lubik and Schorfheide (2005) and Del Negro (2003) use marginal likelihoods in evaluating the specifications of macro models. We, for instance, apply marginal likelihoods and fractional marginal likelihoods in deciding upon identification schemes for identification and lag structure of a vector autoregressive model and most probable information driving monetary policy decision in the euro area.

The current mainstream macroeconomic modeling, the new Keynesian model framework, combines the favorable aspects and properties of macro models developed in the past decades. For new Keynesian macro models major efforts have been made to attain both empirically and theoretically feasible macro modeling framework. In these models short-run nominal frictions, based on Keynesian assumptions[1], are combined with Real Business Cycle (RBC) models[2], which were introduced by Kydland and Prescott (1982). The synthesis emphasizes the stochastic behavior of macroeconomic variables and acknowledges the Lucas critique[3].

1.1.2 The new Keynesian Framework

Theoretical motivations for the analysis of monetary policy effects (the three first essays) pour from the new Keynesian approach that manifests that in the short-run monetary policy may have non-neutral effects on

[1] See Keynes (1936).

[2] Typically in RBC models flexible prices are assumed. With these models one may study how real shocks hitting economy could cause observed business fluctuations. Many RBC models also assume perfect competition, which is to imply that business cycle dynamics are Pareto efficient. Cooley (1995), for instance, provides a survey on RBC models.

[3] In his 1976 paper Lucas points out that we should be interested in deep parameters instead of reduced-form model parameters in understanding policy effects. He bases his reasoning on the claim that the estimated parameters of reduced-form models are not structural and are not policy-invariant. That is, if say monetary policy rule was changed then the estimates of parameters would be altered and lead to potentially misleading conclusions.

the real exchange rate, output and aggregate demand due to sticky prices and/or wages. Benigno (2004) writes that in the new Keynesian DSGE models for monetary union an asymmetry between different countries' price rigidity leads to asymmetric effects of monetary policy. Then on the other hand, economic models built on assumptions of Classical Theory imply that, for example, money is neutral[4] also in the short-run and that prices and wages will immediately adjust to keep the economy in equilibrium. In particular, Classical Theory thus suggests in particular that unforeseen movements in monetary policy would not cause asymmetric real effects. The working hypothesis in this thesis is that common monetary policy has asymmetric short-run real effects on EMU member countries.

Why should one use new Keynesian macro models in policy analysis and in forecasting? The answer is two-fold. First, these models are constructed to ensure internal consistency of the model framework[5]. Second, new Keynesian DSGE models are dynamic in nature. Traditional IS-LM macro models, on the other hand, impose no dynamic restrictions on the model variables, so the theoretical link between the static-in-nature IS-LM macro models and dynamic statistical modeling framework is evidently artificial.

A closed economy new Keynesian macro model for monetary policy analysis consists of equations for aggregate demand, aggregate supply (inflation adjustment equation or new Keynesian Phillips curve) and monetary policy[6]. One of the implications of the new Keynesian Phillips curve is that nominal rigidities cause actual output deviate from fully efficient output in the short-run.

As Clarida *et al.* (1999) we also believe that Keynesian nominal rigidities are the driving forces motivating the estimation of impulse responses to monetary policy shock. In the context of analysis of common monetary policy this implies that nominal rigidities can account for short-run real effects of an unanticipated monetary policy shock in the euro area. Evidently, EMU member countries will probably face real (output, unemployment etc.) monetary effects if national price inflation differentials do not remain constant after monetary policy shock.

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[4] A change in the rate of growth of the money supply, it will proportionally change the rate of inflation and the nominal interest rate but has no effects on a real facets of an economy.
[5] One could consider e.g. Gordon (1990), Mankiw and Romer (1990), Woodford (2003) and Walsh (2003) for a textbook on new Keynesian macro models in a dynamic stochastic general equilibrium (DSGE) setting.
[6] In addition, recent empirical studies by María-Dolores and Vázquez (2006), Sooreea (2007) and Nason and Smith (2008) shed light on Taylor rule specification in new Keynesian macro models.

1.1.3 Monetary Policy in new Keynesian Models

More often than not in modern monetary policy models the interest rate is a key policy instrument. This seems to be in line with actual practice of modern central banks. A frequent specification for monetary policy in the literature is to presume that a modern central banker commits to adopting a policy instrument rule according to which central bank's policy instrument responses to information available to the central banker. For example, according to the Taylor rule (Taylor, 1993) the nominal interest rate is a linear function of current economic activity and inflation. Authors such as Clarida *et al.* (1998, 2000), Judd and Rudebush (1998), Gerlach and Schnabel (2000) and Martins *et al.* (2004) present evidence that different variants[7] of the Taylor rule closely track the short-run interest rate in the United States and in the euro area.

The information set on which the central bank conditions its monetary policy is actively debated topic. The empirical evidence for the way price inflation and economic activity terms should be specified in the Taylor rule is conflicting; for instance Canova (2006) specifies a variant of the Taylor rule with lagged inflation and output gap[8] together with an interest rate smoothing term for the United States and argues that his specification for monetary policy is consistent with the idea that the central banker observes lagged values of economic activity and inflation. In contrast, Lindé (2005) assumes that in addition to interest rate smoothing term the nominal interest rate responds to contemporaneous output and inflation while Clarida *et al*. (2000) estimate the Taylor rule with forward-looking inflation and output terms for the U.S. data. Kahn *et al.* (2007) provide an easy-to-follow discussion of the way the Taylor rule has influenced macroeconomic research and the Federal Reserve's conduct of monetary policy. Given the mixed evidence on Taylor rule specifications, we see that in the near future empirical macroeconomic work will extend to comparison of new Keynesian macro models with different monetary policy rules.

[7] Lindé (2005) specify the Taylor rule with an interest rate smoothing term to gain better empirical fit. Rotemberg and Woodford (1997) and Woodford (1999) analyzed variants of the Taylor rule from the point of view of transparency of monetary policy.
[8] Output gap, introduced by Okun (1962) into the macroeconomic analysis, is a broad measure of inflationary pressure in the economy. Theoretically, it is defined as the difference between actual output and its frictionless level. In new Keynesian models with Calvo pricing it proxies deviations of marginal cost from its frictionless level. Thus, positive values of the output gap imply that current marginal costs are on a higher level than they would be for the natural level of economic activity. Billmeyer (2004) discusses ways of measuring the output gap and evaluates their relative performance. In all papers here the one-sided HP filter is applied in estimating the potential output level.

Generally, the Taylor rule or its variants specified and estimated from data should possess a property that fulfils the Taylor principle. The Taylor principle is an essential and important part of the discussion of interest rate rules followed by central banks. According to the principle, interest rate should response more than one-to-one to an increase in inflation rate.

The robustness of variants of the Taylor rule in different macro models has been examined, for instance by Levin *et al.* (1999). Rudebusch (2002), on the other hand, reports that variants of the Taylor rule can be seen to be robust especially to different model specifications of a closed economy. Svensson (2003) discusses the existence of instrumental rules and stresses that instrumental monetary policy rules should not be seen as mechanical rules but merely as guidelines for monetary policy conduct, leaving some room for judgment, as Taylor (1993, 2000) put it.

1.1.4 Overview of the Empirical Monetary Policy Analysis: Calibration vs. Estimation

In the 80's and still in the 90's general equilibrium models were frequently calibrated. The major issue with the calibration is that the economic model and the outcome of calibration need to be seen as highly sample-specific. Furthermore model comparison is obscured for calibrated models, since for calibration purposes one needs to assume ex-ante that the calibrated model is the true model leaving no room for model uncertainty. For a reader interested Hansen and Heckman (1996) provide a fruitful discussion of calibration methods in economics and give calibration examples for the RBC model of Kydland and Prescott (1982). We claim that the robust likelihood-based parameter estimation fills the gap of econometric inference of large-scale economic models. We argue that by likelihood-based estimation of parameters we achieve consistent statistical analysis of parameters and may execute tractable model selection.

1.1.4.1 Vector Autoregressive Monetary Models

During recent decades VAR models are the most widely applied statistical models to analyze dynamic properties of macro models and form forecast for their variables. In the literature the VAR models are acknowledged to come with robust properties to analyze the dynamics of a set of variables which together form an endogenous system of equations. VAR models are considered as empirical reduced-form approximations of underlying structural macro models, i.e. an approximation of underlying macro models, such as new Keynesian macro models. VAR models also allow empirical analysis of monetary policy abstaining from over-reliance on specific model structure. However, despite their robust properties as forecasting model the current literature questions the forecast performance of VAR models and suggests that theoretically tractable DSGE models can form an option.

In a structural VAR (SVAR) model, for instance, we allow simultaneity of model variables (and their shocks) derived from underlying economic theory. Definitions of reduced and structural-form models were first presented by Haavelmo (1943), who addressed the identification problems in simultaneous equations. We see that a reduced-form model provides reduced representation of the model variables, whereas a structural-form model is a reformulation of the reduced form imposing a view suggested by the underlying economic theory.

Dynamic effects of changes in monetary policy stance can be analyzed through identified unanticipated movements in the monetary policy instrument specified in VAR models. For analysis of the effects of monetary policy in the United States, the Federal Funds Rate (FFR) is taken as the monetary policy instrument describing the stance of policy. Researchers have adopted the view that in the euro area the Eonia[9] interest rate has the same role as the FFR. Unforeseen movements in the FFR or Eonia interest rates are assumed to provide good estimates of monetary policy shocks.

Sims (1980) in his well-known article proposes that the underlying economic model is a good starting-point to derive identifying restrictions for VAR model parameters. Sims and Zha (1999) suggest that Bayesian statistics should be favored in structural SVAR models, especially in the case of an overidentified VAR model. The lag length of Bayesian VAR models is obtained by marginal likelihood-based inference or by calculating average discrepancy measures.

Identification of a VAR model is required to inspect the dynamic effects of a *structural* shock in other model variables. Hence, orthogonal structural shocks are assumed and cross-equation restrictions are set in a matrix presenting the contemporaneous effects of VAR model variables. Bernanke (1986) holds that structural shocks are ´primitive´ exogenous forces not observed by an econometrician. The reason for regarding

[9] Eonia (Euro overnight index average) is the weighted average of overnight Euro Interbank Offer Rates for inter-bank loans.

shocks as orthogonal is that they are primitive in nature and therefore do not have common causes and hence are uncorrelated. A closer, textbook inspection of VAR models can, for instance, be found in Hamilton (1994). Lütkepohl (2005) gives an exhaustive introduction to VAR models, while Sims and Zha (1999) deepen the discussion on identification issues and provide posterior-based confidence intervals for impulse responses. Giannini and Amisano (1997) elaborate the concept of rank identification of VAR models in the econometric context. A more philosophical discussion of usefulness and identification of economic measurements for policy and predictions is given in Marschak (1953). The bearing point in Marschak's writings is that the policy maker does not necessarily need to know exactly the structure of an economy in order to make good policy decisions and limited knowledge of the economic structure might be sufficient. The message here is that statistical descriptions of reality can be enough for a policy maker and this is what it is all about in SVAR models.

There is a large body of VAR literature on policy effects in the euro area. The most relevant are Clausen and Hayo (2006), Mojon and Peersman (2001), Peersman (2004) and Angeloni and Ehrmann (2004). A general message of these studies is that heterogeneous inflation persistencies and structural divergences across EMU member countries are to cause asymmetric responses to an unanticipated shock in monetary policy instrument. Bernanke *et al.* (2005) suggest a very promising direction of future research to measure monetary policy effects. They apply a factor-augmented VAR (FAVAR) model that combines factor analysis of large data sets and traditional structural VAR modeling to have a comprehensive picture of the effect of monetary policy on economy. In similar vein, Milani (2008) assumes that decision makers have an access to wider information set on economic indicators than a mainstream economic model assumes and presents promising results by capturing the actual interest rate path smoothly.

In the monetary policy analysis (three first essays) we describe dynamics of monetary policy shock transmission in the euro area relying on VAR model framework. We discuss uncertainty how to identify shocks in a VAR model for euro area inflation, output gap, monetary policy instrument and EMU member country inflation. We also show in Bayesian VAR model that the year-on-year producer price inflation's reaction to monetary shock is asymmetric if the monetary policy is tuned and exercised conditional on Germany, France and Italy. We then estimate a Bayesian SVAR model for an open economy new Keynesian model between the euro area and EMU member country. Our SVAR model is then identified using parameter restrictions of the underlying model.

1.1.4.2 Generalized Method of Moments and Likelihood-Based Estimation Methods

Instead of estimating a VAR model to approximate the likelihood function of the new Keynesian DSGE model, underlying dynamic equations can be estimated by the GMM (generalized method of moments, see e.g. Hayashi, 2000) method or by a full information likelihood approach. In GMM or likelihood-based parameter estimation the economic model is estimated as it is in its structural form, whereas in VAR modeling the economic model is rather in a role *suggesting* identification restrictions to attain identified impulse responses. Hence, VAR models are more suitable for descriptive data analysis.

Recent empirical studies of contemporary macroeconomic models apply full-information likelihood estimation methods. A major drawback in GMM parameter estimation is its vulnerability to use of instrumental variables, which often weakens the transparency of estimation results. Furthermore, Lindé (2005) reports that GMM estimation evidence on the new Keynesian Phillips curve is mixed, and the GMM estimation results of Galí and Gertler (1999), Roberts (2005) and Fuhrer (1997) suggest different specifications for the new Keynesian Phillips curve, indicating possible problems with instrumental variables.

The role of VAR models as superior forecasters of macroeconomic variables has recently been rivaled. Before the studies by Smets and Wouters (2003), Del Negro *et al.* (2007) and Dib *et al.* (2008), it was common among new Keynesian macro model practitioners to relax cross-equation restrictions in a VAR model to gain an increase in model fit and obtain efficient forecasts. However, for instance, Del Negro *et al.* (2007) investigate the forecasting performance of the new Keynesian DSGE model and obtain evidence that the forecasting performance of large-scale new Keynesian DSGE models can be comparable to that of Bayesian VAR models. Antipin and Luoto (2008) (the fourth essay) come to the same conclusion for a small-scale new Keynesian DSGE model. These findings would suggest that new Keynesian DSGE models can be useful tools in forecasting and quantitative policy analysis.

Recent empirical macro-economic studies have been made mostly in the Bayesian framework. This is because the classical theory of inference is seen to limp, for instance, in analysis of VAR models with overidentifying restrictions and small sample sizes. In addition, impulse response functions are (highly) non-linear functions of VAR model parameters and for finite sample sizes (their properties are tricky to attain). In classical statistics the empirical impulse responses can also be seen only approximative, since they are based on asymptotic results of estimators. This evidently reduces the advisability of applying classical statistical methods to VAR models and increases the attractiveness of Bayesian econometrics; see e.g. Hamilton (1994), Sims and Zha (1999) and Ni and Sun (2005).

The likelihood-based estimation of the new Keynesian DSGE models may also involve problems. For example, the DSGE models come typically with multimodal likelihood function leading to challenges in maximum likelihood parameter estimation[10]. From the economic point of view a multimodal likelihood function suggests that the likelihood peaks in regions of parameter space on which the parameter values can be economically infeasible. This issue can be circumvented in Bayesian econometrics with informative prior distributions for structural parameters, so that the probability of parameter values at odds with those economically feasible is down-weighted. Similarly, informative priors will add curvature to the likelihood function to ease numerical maximization, as Sungbae and Schorfheide (2007) report. Limiting bounds for regions of feasible parameter values of DSGE models can be obtained, for instance, from microeconometric evidence while eliciting prior distribution of model parameters.

The trade-off from using informative prior distributions is increased subjectivism in posterior analysis, which has been criticized in the literature. On the other hand, however, Fernández-Villaverde and Rubio-Ramírez (2004) argue that informative prior distributions may turn out to be useful in avoiding potential misspecification and can be eminently helpful in parameter identification. Furthermore, Bayesian analysis based on informative prior distributions allows tractable model selection, comparison and development methods through marginal likelihood values.

A current and prominent area for future research is to evaluate the likelihood of a macro model solution for instance with Sequential Monte Carlo (SMC) methods. Here one needs not to linearize the underlying macro model and assume Gaussanity of model errors but instead approximate the likelihood implied by the approximated linear solution

[10] See for instance Hamilton (1994) as a text book reference for maximum likelihood estimation of log-linearized DSGE model based on the Kalman filtering technique.

of the model, see Fernández-Villaverde and Rubio-Ramírez (2005, 2006 and 2007) and Fernández-Villaverde (2009).

1.2 A Short Introduction to Bayesian Econometrics

In this chapter we have an introduction to Bayesian statistics in context of statistical topics we have in the thesis essays. The chapter also comments major differences between the Classical and Bayesian schools of statistical inference.

In Bayesian econometrics one collects a sample of observations, i.e. data (y), for some model M_i. The information content of the sample is then used in updating prior beliefs of unknown parameter θ described in $p(\theta \mid M_i)$ via the density of observations $L(y \mid \theta, M_i)$ (the likelihood function). Eventually, the statistical inference is based on the properties of the conditional distribution $p(\theta \mid y, M_i)$, called posterior distribution. In contrast, in non-Bayesian econometrics one starts with a blank mind regarding the parameter value, θ.

In particular, a posterior distribution for θ of given data y and model M_i may be written as

$$p(\theta \mid y, M_i) = \frac{p(\theta, y \mid M_i)}{p(y \mid M_i)} = \frac{L(y \mid \theta, M_i)p(\theta \mid M_i)}{\int p(\theta \mid M_i)L(y \mid \theta, M_i)d\theta}, \; i = 1, \ldots, k. \qquad (1)$$

Equation (1) is an updated version of the prior distribution. If the data come with high information content as to the location and the shape of the parameters' distribution, and the prior knowledge is not analogous, we can expect the posterior distribution to differ from the prior distribution. The denominator in Equation (1) is the normalizing constant ensuring that the distribution integrates to one, and this is called the marginal likelihood. The marginal likelihood is a basic Bayesian measure of model fit and it is a key quantity for measuring posterior model probabilities, which have an important role in Bayesian decision-making (Andersson and Karlsson, 2007).

1.2.1 Classical vs. Bayesian Statistics

Two practical differences between the classical (non-Bayesian) and the Bayesian theory of inference are evident. First, the classical school conditions on unknown parameter and apply a likelihood function to learn from it using the observed data points. Bayesians, on the other hand, base their inferences on the full density $p(\theta, y|M_i)$, having first specified the prior distribution of a parameter.

Furthermore, additionally to the way how the conditioning is implemented, there is a conceptual difference between the classical and the Bayesian schools regarding the interpretation of parameter estimates and confidence intervals. Specifically, the Bayesian posterior intervals give us a specified probability p that the value of parameter θ lies within a certain confidence interval conditional on the observed data. The corresponding classical statement would be that the confidence interval would cover the true parameter value in a certain percentage of cases if the random experiment was repeated infinitely. This implies that according to classical theorists, a confidence interval can be obtained if calculations are repeated many times or a really large dataset is available. Even then, however, there is no guarantee that the calculated confidence interval would contain the unknown parameter value θ. This is not the case in the Bayesian theory of inference, as explained above; See O'Hagan (1988), Zellner (1971), DeGroot (1970), Poirier (1988) or Koop (2003) for a detailed treatment of the Bayesian approach in statistics and econometrics. Especially Bauwens *et al.* (1999) concentrate on dynamic models and the Bayesian econometrics therein. Geweke (2005) covers many important aspects of modern computational Bayesian econometrics. Additionally, Zellner (2008) provides a comprehensive summary of advances in Bayesian econometrics and relates the discussion to comparing Bayesian to classical methods.

To sum up, with non-Bayesian statistics a sufficient number of observations is in most cases required to achieve eligible outcomes. As the name implies the asymptotic consistency of many relevant estimators of non-Bayesian econometrics is achieved only for high numbers of observations. Good examples are the frequently applied instrumental variable estimators, which attain their good properties specifically for large sample sizes. A statistician will run into problems in assessing the statistical significance of non-Bayesian parameter estimates of consistent estimators applied to low numbers of observations and such results should be seriously questioned. A low number of observations implies for Bayesians that the prior distribution will not be updated with an ample amount of information in the likelihood function. This is because the posterior distribution can be seen as a weighted average of the prior distribution and the likelihood function. The need to specify prior distributions suggests that one should be careful in eliciting prior distributions for small sample sizes in order to avoid overweighting the prior knowledge in parameter estimates.

1.2.2 Prior Distributions, VARs and Bayesian Model Comparison

The prior distributions form a vital element in Bayesian statistics, and Bayesian theory is often criticized in the context of priors. It would seem that an econometrician could *ex ante* alter the posterior results and design such a prior distribution which produces subjectively favorable outcome. This would of course immediately contaminate the objectivity of results. To avoid issues of wrongly elicited informative prior distributions, Bayesian econometricians may decide to proceed with non-informative prior distributions. In line with these aspects Bayesian econometrics has a long history of non-informative prior distributions. In Jeffreys (1939, 1961) one finds through presentation of improper and non-informative priors, and Zellner (1971), Koop (2003) and Gelman *et al.* (2004) present eminently useful textbook treatments of these priors in various econometrical contexts.

In lack of pre-knowledge of the parameter values of a VAR model, the posterior distribution is typically obtained by updating uninformative prior parameter distribution with sample information channeled through the likelihood function. Typically a constant prior for VAR model autoregressive parameters and Jeffreys-type[11] uninformative prior distribution for the model error covariance matrix is specified. Such a joint prior distribution allows streamlined posterior distribution simulation in small-scale VAR models (i.e. VAR models especially designed for small numbers of variables), like VAR models for a closed-economy setting. Phillips' (1991) suggestion of specifying a joint Jeffreys prior on both autoregressive parameters and elements of error covariance matrix for a VAR model should be rejected, since a joint Jeffreys prior in time series models is found to be computationally inconvenient and highly sample-size dependent. Additionally, Berger and Bernardo (1992) point out that the likelihood function of high-dimensional VAR model, i.e. a VAR model of many variables, should not be coupled with a Jeffreys prior, since this has been shown to produce undesirable results. In turn, in high-dimensional VAR models informative *Minnesota priors* á la Minnesota group (see more in Litterman, 1980, 1986, and Doan *et al.*, 1984) could be used. Alternatively, one could follow the lines of Berger and Bernardo (1992), Yang and Berger (1994) and Berger and Strawderman (1996) in designing priors for high-dimensional VAR models. A rather rigorous treatment of selection for VAR models is provided in Kadiyala and Karlsson (1997).

[11] Diffuse prior and Jeffrey's prior may be found interchangeably used as synonyms in the literature.

Non-informative prior distributions appear with high variance or they belong to improper distributions, that is, they are non-integrable. A high prior variance of the underlying parameter or model probability indicates unawareness of the econometrician as to the true location of a parameter or model likelihood. Other motivations to assign a non-informative prior distribution are cases where the econometrician has no idea as to the values the parameter might take or does not want his subjective prior knowledge to affect the posterior analysis. Generally seen, the choice of non-informative prior distribution rests on the notion that the econometrician lets the data speak for themselves as we do in the first three essays. Informative prior distributions will prove handy, especially in estimation of new Keynesian DSGE macro models, where the interesting posterior densities for parameters can be restricted with suitable informative prior distributions to regions which are feasible in the economic sense. Because of this reason we in essay 4 specify informative prior distributions for model parameters.

Choice of a proper or improper prior distribution will affect model comparison. This is because the Bayes factor is defined as the ratio of the marginal likelihoods of two competing models. In elicitation of prior distribution one needs to know whether the model comparisons will be based on marginal likelihoods. Thus, if the prior distribution is improper, then the model comparison based on marginal likelihoods is not possible (The Bayes factor becomes indeterminate), since we do not know the normalizing constants of improper prior distributions. As Hoeting *et al.* (1999) and Wasserman (2000) emphasize, marginal likelihoods have a vital role in Bayesian model selection, since marginal likelihoods enable consistent comparison of nested and non-nested models. This should be seen as one of the very attractive features of Bayesian compared to Classical statistics.

Model comparison can also been based on *approximate* marginal likelihoods, as O´Hagan (1995) suggests. Villani (2001), for example, invokes a fractional marginal likelihood approach in deciding the lag length for VAR models under improper parameter prior distribution. We also follow Villani (2001) and calculate fractional likelihood function values while deciding the lag length of a VAR model in the first three essays. Garratt *et al.* (2009) compare the approximate marginal likelihood values of competing models, relying on the asymptotic approximation to the marginal likelihood first presented in Schwarz (1978). In the second essay the most probable information set conditioning the ECB's monetary policy decisions is obtained by calculating approximate marginal likelihood values using the Taylor rule as ECB's monetary policy rule.

The posterior model odds calculated along these lines will favor the same model specification as would the Schwarz Bayesian Information Criterion (BIC). As an alternative to the marginal likelihood-based model comparison, Gelman *et al.* (2004) propose an average discrepancy measure which approximates the posterior expectation of the deviance between the data and the model. They advocate that the average discrepancy should be used in model comparison for improper prior distributions, since the estimated average discrepancy is not sensitive to the design of prior distribution. However, a number of questions should be dealt with before applying either average discrepancy or marginal likelihood approach in model comparison. Namely, the problem with average discrepancy is that it has no proper scale whereas model comparison based on marginal likelihood assumes that the list of rivaling models contains the true model.

The posterior distribution $p(\theta \mid y, M_i)$ could be of the form of an unknown distribution when non-conjugacy[12] prior distributions are used. To draw samples from the posterior distribution one then needs to apply numerical integration methods. Samples drawn from the posterior distribution are used in describing the statistical properties of the posterior distribution. A current practice is to use Markov Chan Monte Carlo (MCMC)-based methods in enabling the numerical evaluation of posterior distribution. The validity of Monte Carlo chains as representatives of samples drawn from the posterior must be checked with caution. This means that the convergence of the MCMC sampler to an ergodic distribution needs to be assessed with formal diagnostics. A textbook by Robert and Casella (2004) provides, with examples, an excellent updated discussion and a rigorous treatment of Monte Carlo statistics.

[12] A family of prior probability distributions $p(\theta \mid M_i)$ is conjugate to a family of likelihood functions $p(y \mid \theta, M_i)$ if the resulting posterior distributions $p(\theta \mid y, M_i)$ are in the same family as $p(\theta \mid M_i)$.

1.3 Summaries of Thesis Studies

1.3.1 Essay 1: Dynamics of Inflation Responses to Monetary Policy in the Euro Area

In this essay we capture the dynamics of year-on-year consumer price inflation responses to an unanticipated expansionary monetary policy shock in the euro area with a VAR model. The variables and potential restriction schemes ensuring identification of a VAR model are derived from variants of the new Keynesian closed economy macro model. Variables specified govern inflation dynamics in the euro area and member countries, economic activity and monetary policy. The demand side of the economy is described by the difference of total industrial production from its potential level, while the supply side is captured with help of the new Phillips curve and monetary policy is conducted according to a variant of the Taylor rule, and instrumented with the Eonia interest rate. The monthly data cover the period 1999.1 to 2007.10.

We motivate the research of this essay as follows. Before entering the EMU program an independent member country central bank could stimulate the domestic economy if deemed necessary. Now, in the EMU the independency of domestic central banks can be seen to be lost, the decision power invested in monetary policy tools being handed over to the ECB officials. The ECB declares that it will conduct a monetary policy feasible to all EMU member countries. Heuristically this means that the ECB should, with its monetary policy tools, provide and maintain fertile economic conditions in the euro area in such a way that no member country should suffer from its monetary policy actions. Past economic conditions in member countries imply that economic conditions have been and are heterogeneous *per se*, which means that common monetary policy actions based on euro area aggregate information will most likely cause asymmetric effects and the design of such monetary policy is suboptimal (De Grauwe (2000), De Grauwe *et al.* (2004, 2006)). Hence, we agree for instance with Clausen and Hayo (2002, 2006), Huchet-Bourdon (2003) and Durand *et al.* (2008) that the ECB should find itself confronted with challenges in tuning and conducting monetary policy.

A VAR model is a natural choice for a statistical model to capture the correlation structure of the variables specified. In this essay we suggest different short-run simultaneous restriction schemes ensuring the identification of the VAR model. The most probable short-run restriction scheme is found by calculating the posterior model probabilities for a

VAR model identified by a different scheme. This is the main contribution of the essay.

The data support an identification scheme in which the monetary policy rule is to have simultaneous effects on euro area and domestic price inflation. For the supported scheme the stance of the monetary policy in the euro area is also affected by domestic, EMU member country inflation. One important notion is that traditional Cholesky identification is weakly supported for variables specified. In the posterior estimation a Jeffreys-type prior distribution for short-run effects is assumed and the posterior distribution of the difference between impulse responses of euro area inflation and member country inflation to common monetary policy shock is simulated and compared with Cholesky identified VAR model impulse responses.

Monthly euro area data supports the conception that unanticipated monetary policy operations of the ECB will cause asymmetric inflation responses in the euro area. Specifically, the amplitude of contemporaneous inflation responses will be heterogeneous in the EMU member countries. An interesting finding is that the immediate inflation response of Germany, France and Italy is more sluggish to an expansionary monetary policy shock that on average in the euro area. Clausen and Hayo (2006) report similar finding.

1.3.2 Essay 2: Information Sets Used by the ECB in Determining Monetary Policy Operations and Dynamic Monetary Responses of Producer Price Inflation: A Quantitative Study

In this essay we empirically survey information sets on which the ECB most likely bases its monetary policy decisions and investigate how year-on-year producer price inflation responses to an identified shock in the monetary policy instrument in the euro area. Assessment of the posterior probabilities of information sets is an obvious accretion to the literature on the conduct of monetary policy by the ECB. The information conditional on which monetary policy decisions are made are evidently crucial while the ECB steers overnight interest rates to stabilize price inflation and maintain fertile economic conditions in the euro area.

We allow for information sets which only represent the subset of total information available. We do this by forming EMU member country coalitions and construct relevant variables to be used in the Taylor rule and impulse response analysis. In view of known differences between the economic structures among the member countries, conduct of monetary policy conditioned not on the whole euro area information but instead on some subset of it, might have more or less favorable effects in the EMU member countries. This is the working hypothesis of the essay. For instance Kool (2005) finds that German economic conditions have a crucial role while the ECB tunes its monetary policy operations. However, we do not find statistical evidence in our data to say that German conditions would be driving the monetary policy through the Taylor rule in the euro area.

In the analysis we assume that the variables specified in the Taylor rule constitute sufficient statistics to capture the monetary policy phenomenon in the euro area. We estimate a VAR model for the information set obtained and calculate impulse response function values for the difference in year-on-year producer price inflations in the euro area and a few peripheral EMU member countries. The estimation data comprise monthly data for period 1999.1 – 2006.4.

The marginal likelihood calculations show that the economic conditions of the three largest EMU member countries (Germany, France and Italy) are acceptable as presenting the information set conditional on which the ECB rests in deciding on monetary policy actions. This backs up Clausen and Hayo (2006) who find that Germany, France and Italy share similar monetary policy transmission mechanisms. We could not find evidence for the assertion that the Bundesbank was the predecessor to the ECB as Buiter (1999) suggests.

Drawn impulse responses of year-on-year producer price inflation suggest that unexpected variation in the monetary policy instrument conditioned on the information pertaining to the three largest EMU member countries has statistically asymmetric effects in year-on-year producer price inflation. The asymmetricity of the drawn impulse responses arises in two ways – the monthly euro area data supports both immediate and lagged asymmetric responses. In the case of Finland the asymmetric response is immediate and vanishes after 1 month. For Ireland and Portugal the asymmetric responses prevail for a month after an expansionary monetary policy shock, and die off in 5 months. These results give reason to expect that shocks to monetary policy instrument will cause changes in mutual demand for tradable sector goods produced in EMU member countries.

1.3.3 Essay 3: Are There Asymmetric Inflation Responses in the EMU?

In this essay we apply the new Keynesian open economy macro model of Galí and Monacelli (2005) in setting identifying restrictions for impulse response analysis of consumer price inflation in the euro area. The five-equation macro model captures the evolutions of the inflation and output gap for both the euro area (excluding the domestic EMU member country) and the domestic member country. The model specifies terms of trade between the two economies modeled. The economic model is closed by the assumption that monetary policy is operated through a variant of the Taylor rule.

The relevance of the implied parameter cross-equation simultaneous effect restrictions is assessed by posterior estimation of the hyperparameter that measures prior beliefs. In our VAR-analysis of monthly 1999.1-2006.4 euro area data the posterior evidence suggests that prior beliefs on simultaneous effects of model variables of the underlying new Keynesian open economy macro model are of relevance for these data.

The drawn impulse responses support the claim that an expansionary monetary policy shock in the euro area does not imply asymmetric price inflation responses in EMU member countries. This result is partly at odds with the outcome of the first essay. One explanation to different impulse response results is that in this essay the dynamics of annualized price inflation were analyzed in open economy model framework whereas in the first essay we focus on dynamics of year-on-year price inflation series in a closed economy model. However, one should note that the impulse responses attained from recursive identification are in line with the ones of the first essay.

1.3.4 Essay 4: Forecasting Performance of the Small-scale Hybrid new Keynesian Model

With this essay we provide a method for the Bayesian analysis of a simple closed economy new Keynesian DSGE macro model for U.S. data and compare the forecasting performance of the estimated model to that of naïve forecasts based on univariate random walks and Bayesian VAR models. In particular, the predictability of three key macroeconomic variables, inflation, short-term nominal interest rate and a measure of output gap, are studied. The analysis is conducted with both quarterly

US real-time and current vintage data from the period of 1953.2 to 2004.4. The source of the current vintage data is the FREDII databank of the Federal Reserve Bank of St. Louis and the source of the real-time data is the Federal Reserve Bank of Philadelphia. The new Keynesian DSGE macro model is similar to one discussed in Clarida *et al.* (1999) and maximum likelihood estimated in Lindé (2005).

The estimation method chosen, the Bayesian full-information method, proved to be more efficient than the method based on the Kalman filter, which has recently became current practice in the estimation of dynamic structural models. As did Lindé (2005), we also found that the full-information maximum likelihood (FIML) estimates were sensitive to the starting values of maximization due to the multimodality of likelihood. We noted that the estimator easily converged to the parameter region of more or less infeasible parameter values even if the algorithm was restricted to an economically feasible region. The Bayesian full-information estimation method managed to produce reliable parameter estimates. This is because it specifies an informative joint prior distribution for model parameters which both allows parameters to be estimated fairly freely and importantly, keeps the posterior distribution in economically feasible region. In closer detail, the marginal priors of the preference related and policy parameters are derived from micro-level studies, while the priors of the autoregressive parameters are based on a simple parameter transformation, which forces the posteriors of these parameters to be located in the interval (–1, 1). The standard deviations of structural shocks are assumed to follow an inverse-gamma distribution with the shape and scale parameters yielding fairly loose priors.

Forecasting performance evidence emanating from out-of-sample forecasts implies that in the entire forecast sample (period 1976.4-2004.4) the forecasts of the new Keynesian DSGE macro model outperform those of the Bayesian VARs. In the low inflation period (1990.1-2004.4) all the multivariate forecasting methods seem to produce equally accurate forecasts. Both the new Keynesian DSGE macro model and the Bayesian VAR models turned out to produce inflation forecasts which outperformed naïve forecasts for up to six quarters in all samples. The results presented in this essay are important, since Atkeson and Ohanian (2001) found that the one-year-ahead Federal Reserve's Greenbook inflation forecast has not been superior on average to the naïve forecast since 1984.

The results of this essay are particularly interesting, in that in the recent current literature various papers have suggested different ways to improve the forecast performance of new Keynesian DSGE macro models at the cost of increasing the complexity of model mechanisms and model uncertainty, thus reducing the practicability of suggested approaches in applied work.

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2 Essay 1: Dynamics of Inflation Responses to Monetary Policy in the Euro Area

Jan-Erik Antipin
University of Tampere,
Helsinki School of Economics
and UNU-WIDER

Abstract:

This paper analyses the effects of the European Central Bank's monetary policy on EMU member countries' year-on-year inflation rates in a Bayesian structural vector autoregressive framework. The choice of variables capturing monetary conditions in the euro area is guided by a simple closed-economy new Keynesian macro model in which the interest rate is the channel for monetary policy transmission. Drawn impulse responses suggest that year-on-year inflation rate responses to a common, expansionary monetary policy shock can be seen to be asymmetric in the euro area.

JEL Classification: C11, C52, E52, E31.

Keywords: European Central Bank, monetary policy, asymmetry, Bayesian structural vector autoregressive model, posterior model probabilities.

2.1 Introduction

At the beginning of 1999 11 European countries[1] were shifted into a monetary system with a common monetary policy. Before the European Monetary Union era central banks in member countries were able to conduct independent monetary policies. Policy operations could be implemented solely on the basis of domestic economy conditions – an independent central bank could for instance stimulate the domestic economy if deemed necessary. The independency of domestic central banks can be seen to be lost when countries joined the EMU and ever since monetary policy decisions have been made exclusively by the European Central Bank (ECB). An evident practical problem with this common monetary policy area is written in its history. De Grauwe (2000) and De Grauwe and Sénégas (2004, 2006) discuss that increase in degree of asymmetries in monetary transmission mechanism will reduce the effectiveness of monetary policy in the euro area. Looking at past economic conditions of EMU member countries immediately shows that conditions have been and are heterogeneous *per se*, which means that common monetary policy actions will most likely cause asymmetric effects in member countries. For this reason, the ECB inevitably finds itself confronted with challenges in tuning and conducting monetary policy. It may well be the diversity of economic and institutional structures across the EMU member countries which constitute the reason why common monetary policy shocks have impacts of different magnitudes in the economies in the euro area, especially in inflation. The essence of this is manifested in the year-on-year inflation figures of the various member countries, where in only few cases inflation series have converged to the 2 per cent inflation target, while the aggregate inflation has varied fairly closely around the target. Although it must conceded that the ECB's monetary policy can have a stabilizing role and might be optimal at aggregate level, monetary policy effects in individual member countries can nevertheless be crucially asymmetric.

The successful conduct of monetary policy in the euro area requires knowledge of the rate at which innovations in monetary policy are absorbed in member countries and of the actual magnitude of monetary policy effects. Then, for instance, it would be of interest to see how consumer price inflation in a given EMU member country responds to a common monetary policy shock in relation to aggregate euro area consumer price inflation. The monetary response dynamics of consumer price inflation in EMU member countries is important in that according

[1] Greece joined the group two years later, in 2001.

to the ECB the (euro area) consumer price inflation plays a major role in the ECB's monetary policy strategy and generally, relative price inflation among the member countries must also be seen to be important for welfare reasons.

The literature provides a wide range of studies concerned to depict monetary conditions and monetary policy effects in the euro area. For detailed surveys see for example Mojon and Peersman (2001) and Peersman (2004). Angeloni and Ehrmann (2004) use quarterly euro area panel data over the period 1998:1-2003:2 to track down the sources of inflation differences among the EMU member countries. They find that the magnitude of inflation persistence is the driving force generating inflation divergence among the EMU member countries. Clausen and Hayo (2006) provide a semi-structural VAR (vector autoregression) study of asymmetric effects of monetary policy in large EMU member countries and find that monetary transmission mechanisms in Germany, France and Italy are similar. Huchet-Bourdon (2003) in turn estimate monetary policy reaction functions for the euro area over the period 1980-1998 and report that some EMU member countries seem to be more sensitive to unanticipated monetary policy changes. Durand *et al.* (2008) VAR estimate sacrifice ratios with as an indicator for structural dispersion in the euro area using quarterly observations on real GDP and inflation rate for period 1972-2003. They conclude that data do not imply reduction in structural differences and this might imply asymmetric responses of EMU member country economies to common monetary policy shock. Antipin and Luoto (2005) construct a SVAR model in which short-run interaction restrictions are derived from a simple, small-scale closed-economy DSGE model. They report that the price inflation responses to an unanticipated monetary policy shock can be seen to be asymmetric on the euro area.

Recent papers have focused on highly structural macroeconomic models (new Keynesian models) specified for both forecasting and policy analysis purposes; see Sungbae and Schorfheide (2007) for a survey. The drawback in these studies models is that they are typically extremely complex and tedious to estimate; see for instance Smets and Wouters (2003, 2005 and 2007). Hence, a descriptive statistical modeling approach would seem preferable to enable us to better describe the dynamics of conditions affecting the stance of monetary policy in the euro area.

In this paper we capture the monetary policy effects in year-on-year price inflation dynamics with a statistical model which both allows empirical description of the dynamic responses of model variables and is sufficiently flexible in setting ex-ante restrictions on the contemporaneous effects of variables specified in a model. We find the structural vector autoregressive (SVAR) models to be best suited for our purposes, since we agree with Peersman (2004) that to make valid cross-country comparisons we need to construct a model wherein all member countries are exposed to the same monetary policy shock. Moreover, SVAR models are commonly applied in the monetary policy literature and the statistical properties of these models are widely reported and known. Batini (2006) and Batini and Nelson (2001) list and discuss three possible types of inflation persistence; 1) positive serial correlation in inflation, 2) lag between system monetary action and its effect of inflation and 3) lagged responses of inflation to shocks in monetary policy. With a SVAR model we can control for type 1 and type 3 inflation persistence.

This paper provides updated empirical evidence on monetary policy transmission in the euro area derived from the following contributions: first, we use updated euro area data and a common reaction function across the EMU member countries and explicitly allow the size of the monetary policy shock to be the same across the member countries. Secondly, we derive posterior model probabilities to test the validity of ex-ante knowledge on the set of contemporaneous effects of the variables assumed to capture the monetary conditions for the euro area. More specifically, in model specifications we allow for EMU member country information to have an immediate effect on the monetary policy instrument as suggested by De Grauwe (2000) and De Grauwe and Sénégas (2004, 2006). Thirdly, the variables used in our SVAR model are the same as the ones frequently used in the analysis of monetary policy in closed economies. The variables we use are motivated by a new Keynesian closed economy monetary policy model where the output gap measures general economic activity, the Phillips curve presents the supply side and the interest rate instruments for monetary policy. We rely on Bayesian inference in SVAR models due to Sims and Zha (1999).

The impulse response results obtained for an overidentified Bayesian SVAR model suggest that the euro area data lend support to the conception of short-run asymmetric price inflation responses to an unexpected expansionary monetary policy shock in the euro area.

The rest of this paper is organized as follows: Section 2 presents econometric methods, Section 3 presents the data and results and Section 4 comprises concluding remarks.

2.2 Econometric Methods

European policy-makers evince an awareness of the existence of a delay between monetary policy action and its effect on inflation and on economies in general. Due to these reasons the ECB's declaration of medium-term price stability is widely accepted to constitute the first pillar of monetary policy in the euro area. Furthermore it is publicly understood that today's monetary policy actions are likely to have an impact on the future values of important macroeconomic variables such as inflation and output level.

For the sake of dynamics, the monetary conditions in which the central bank needs to act should thus be seen as a dynamic process involving multiple endogenous macroeconomic variables. Evidently, for the aforesaid reasons we model monetary conditions for the euro area applying a statistical model which captures the dynamics of an endogenous system of variables. The analysis in this paper is based on a SVAR model framework. The model takes the form

$$\Gamma_0 y_t = \delta + \sum_{i=1}^{p} \Gamma_i y_{t-i} + v_t \,, \tag{1}$$

where δ is a vector of constants, a nonsingular parameter matrix Γ_0 indicates how the variables listed in y_t simultaneously interact, matrices Γ_i contain parameters of lagged values of y_t, and unobservable structural shocks in v_t are assumed to be normally distributed with zero means and the diagonal covariance matrix denoted as Λ. The orthogonality of structural shocks is typically assumed in the literature on SVAR models. The underlying idea of the SVAR approach is to impose theoretical restrictions[2] on the data to identify structural shocks and then calculate identified impulse responses. In this study we identify the structural shocks of a SVAR model by specifying alternative short-run restriction schemes.

The literature lists a number of studies where the monetary policy transmission mechanism is examined using SVARs. To name but a few, Bernanke and Blinder (1992) analyze the way unexpected changes in the Federal Funds Rate are transmitted to the U.S. economy, Sims (1992) explains the reasons for the price puzzle[3] obtained in many VAR studies, Angeloni *et al.* (2003) compare euro area and U.S. monetary transmission

[2] Short-run restrictions are set in the Γ_0 matrix and long-run restrictions in matrices Γ_i.
[3] A contradictory monetary policy action causes inflation to rise, whereas inflation is expected to drop.

mechanisms. Christiano *et al.* (1999) provide a survey of monetary policy SVAR models.

To capture the dynamics of the euro area monetary conditions we collect in y_t the series of euro area year-on-year consumer price inflation rate (π_t), the output gap (x_t) which measures euro area output deviations from steady-state levels[4], (r_t) to capture the status of monetary policy and ($\hat{\pi}_{t,j}$) to measure the year-on-year consumer price inflation rate in a member country *j*. We thus specify $y_t = (\pi_t \; x_t \; r_t \; \hat{\pi}_{t,j})'$ in a SVAR model for a EMU member country *j*.

The variables listed in y_t are in line with the models presented in an excellent survey of new Keynesian models by Clarida *et al.* (1999). Accordingly, we define year-on-year price inflation rate (π_t) to capture the supply side and the output gap (x_t) to depict demand in the euro area. As is common in the current monetary policy literature, the dynamics of monetary policy instrument (r_t) are modeled in the spirit of Taylor (1993); see also Hetzel (2000). As the monetary transmission channel is the interest rate the central bank is assumed to be able to influence economic conditions by adjusting the real interest rate and thus affect aggregate consumption decisions; see Walsh (2003). The orthogonal property of structural shocks implies that for instance the cost-push shock to inflation is independent of any monetary policy shock and vice versa.

The member country-specific output variable is excluded from the model, since the weight of a domestic output in the euro area aggregate is minor. Furthermore, the variation in member-country output and inflation series can be seen to be driven by the interest rate. This is because in the European Union both capital and labor force are both free to move frictionlessly across national borders. This paper comprises an analysis for twelve EMU member countries: Belgium, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal and Finland.

As in Sims and Zha (1999), the SVAR model in Equation (1) is reparameterized such that

[4] Galí and Gertler (1999) use the labor share of output as a proxy for marginal costs. However, Neiss and Nelson (2005), on the contrary, using data for the United States, the United Kingdom, and Australia, report that labor costs do not suffice to explain inflation dynamics as well as the output gap. Hence, we describe marginal costs with a measure of the output gap.

$$A_0 y_t = \delta + \sum_{i=1}^{p} A_i y_{t-i} + \eta_t \,, \qquad (2)$$

where $A_0 = \Lambda^{-1/2}\Gamma_0$ and $\eta_t = \Lambda^{-1/2}v_t$. Hence $\eta_t \sim N(0, \mathrm{I})$ due to standardization. Thus Var($A_0^{-1}\eta_t$) = Σ = $\left(A_0^{'}A_0\right)^{-1}$.

The likelihood function of a SVAR model in Equation (2) can be expressed as

$$\begin{aligned} L\left(Y \middle| X, \Sigma\right) &\propto \left|\Sigma\right|^{-0.5T} \exp\left\{-0.5tr\left(\Sigma^{-1}E^{'}E\right)\right\} \\ &= \left|\Sigma\right|^{-0.5T} \exp\left\{-0.5tr\left(\Sigma^{-1}S\right) - 0.5tr\left(\left(B-\hat{B}\right)^{'} X^{'} X\left(B-\hat{B}\right)\Sigma^{-1}\right)\right\}, \end{aligned} \qquad (3)$$

where $E = (Y\text{-}XB)'(Y\text{-}XB)$, $S = (Y\text{-}X\hat{B})'(Y\text{-}X\hat{B})$, and the tth rows of Y, X, E are given by y'_t, $(1, y'_{t-1},\ldots,y'_{t-p})$ and v_t', respectively. The matrix B is obtained by stacking the matrix product $(A_0^{-1}A_i)'$ and $\hat{B} = (X'X)^{-1}X'Y$ is a matrix of OLS parameter estimates.

As noted above, the matrix A_0 for the short-run effects of variables in y_t is the focal point of this study. We seek information on the way variables in vector y_t simultaneously interact and thereby identify the impulse response functions of an estimated SVAR model. The traditional mode of SVAR model identification is to assume recursive restrictions, i.e. Cholesky decomposition[5]. For given variable ordering in y_t the frequently used Cholesky decomposition does not let simultaneous EMU member country information affect the monetary policy instrument as De Grauwe (2000) and De Grauwe and Sénégas (2004, 2006) suggest. To allow for this we will go beyond the simple Cholesky restrictions and concentrate on different simultaneous effects among the variables in y_t. Especially we let EMU member country inflation have a simultaneous effect on the monetary policy instrument. In specifying restrictions other than recursive we need to ensure that the simultaneous restrictions do not lead to an underidentified SVAR model. To avoid underidentification issues we verify that simultaneous restrictions fulfill the rank condition[6] for identification. See Giannini and Amisano (1997) for a discussion of identification of SVAR models in econometrics.

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[5] The Cholesky decomposition leads to an exactly identified model. Setting underidentifying restrictions in matrix A_0 is of no interest, since in that case we cannot separate out the effects of a structural shock into model variables.

[6] See for instance Hamilton (1994). pp. 334, presenting a method to check the rank condition for identification.

We consider 7 different simultaneous effect schemes to identify the SVAR model in Equation (2). The Cholesky restrictions (${}_7A_0$) and the six other identification schemes for contemporaneous values of $y_t = (\pi_t \; x_t \; r_t \; \hat{\pi}_{t,j})'$ in a SVAR model are as follows:

$$ {}_1A_0 = \begin{pmatrix} a_1 & a_{12} & 0 & 0 \\ 0 & a_2 & 0 & 0 \\ a_{31} & a_{32} & a_3 & 0 \\ 0 & 0 & a_{43} & a_4 \end{pmatrix}, \qquad {}_2A_0 = \begin{pmatrix} a_1 & a_{12} & 0 & 0 \\ 0 & a_2 & 0 & 0 \\ a_{31} & a_{32} & a_3 & 0 \\ 0 & a_{42} & a_{43} & a_4 \end{pmatrix}, $$

$$ {}_3A_0 = \begin{pmatrix} a_1 & 0 & 0 & 0 \\ a_{21} & a_2 & 0 & a_{24} \\ a_{31} & a_{32} & a_3 & 0 \\ 0 & 0 & a_{43} & a_4 \end{pmatrix}, \qquad {}_4A_0 = \begin{pmatrix} a_1 & a_{12} & 0 & 0 \\ 0 & a_2 & 0 & 0 \\ a_{31} & a_{32} & a_3 & a_{34} \\ 0 & a_{42} & a_{43} & a_4 \end{pmatrix}, $$

$$ {}_5A_0 = \begin{pmatrix} a_1 & 0 & a_{13} & 0 \\ 0 & a_2 & 0 & 0 \\ a_{31} & a_{32} & a_3 & a_{34} \\ 0 & a_{42} & a_{43} & a_4 \end{pmatrix}, \qquad {}_6A_0 = \begin{pmatrix} a_1 & 0 & a_{13} & 0 \\ 0 & a_2 & 0 & 0 \\ a_{31} & a_{32} & a_3 & a_{34} \\ 0 & 0 & a_{43} & a_4 \end{pmatrix} $$

and the Cholesky identifying restrictions are

$$ {}_7A_0 = \begin{pmatrix} a_1 & 0 & 0 & 0 \\ a_{21} & a_2 & 0 & 0 \\ a_{31} & a_{32} & a_3 & 0 \\ a_{41} & a_{42} & a_{43} & a_4 \end{pmatrix}. $$

In the above matrices a_{kj}s denote the simultaneous effect of variable j on variable k. On a first row simultaneous effects of output gap (x_t), monetary policy instrument (r_t) and inflation in EMU member country ($\hat{\pi}_t$) on euro area inflation are measured. The second row indicates how variables are interacted with the output gap contemporaneously. The effects of variables on the monetary policy instrument are on the third row and finally, the fourth row contains the effects on member country inflation. The lower-triangular matrix ${}_7A_0$ is a Cholesky factor of the covariance matrix Σ. The restriction schemes ${}_4A_0$, ${}_5A_0$ and ${}_7A_0$ provide an exactly identified SVAR model, whereas other schemes constitute an over-identified model. All the matrices ${}_iA_0$ above fulfill the rank condition for SVAR model identification.

A closer inspection of the foregoing identification matrices reveals that besides the matrices ${}_4A_0$, ${}_5A_0$ and ${}_6A_0$, the monetary policy (instrumented by r_t) is allowed only simultaneously to be affected by euro area year-on-year inflation rate (π_t) and the output gap (x_t), which is in accordance with the declared ECB monetary policy targets. By specifying restrictions ${}_4A_0$, ${}_5A_0$ and ${}_6A_0$ we suggest that member country's year-on-year inflation rate can have weight in the ECB's monetary policy decision-making by allowing $\hat{\pi}_{t,j}$ to have a simultaneous effect on a monetary policy instrument (r_t) (nonzero a_{34}) together with euro area aggregates (π_t) and (x_t). The nonzero assumption of a_{34} is hence in accordance with De Grauwe (2000) and De Grauwe and Sénégas (2004, 2006). Their general conclusion is that common monetary policy would benefit from using national information when national monetary policy transmission mechanisms are asymmetric and thus the design of monetary policy that uses only euro area aggregates (π_t and x_t) needs to be seen suboptimal.

Furthermore, Benigno (2004) shows that for inflation targeting policy purposes it requires that a higher weight for inflation should be given to regions with higher degree of nominal rigidity. This means that in identification schemes where a_{34} is set to zero it is assumed that nominal rigidities share the same degree and the terms of trade is insulated from monetary policy.

The difference between the restrictions in ${}_1A_0$ and ${}_2A_0$ is that the euro area output gap is also allowed simultaneously to affect jth member country inflation dynamics (a_{42}). Matrix ${}_3A_0$ exhibits such restrictions that the euro area year-on-year inflation rate (π_t) cannot be seen to be contemporaneously affected by the euro area demand side (x_t) (a_{13} = 0), and monetary policy is assumed to have a simultaneous impact only on member country year-on-year inflation rate[7]. Restrictions driven in ${}_2A_0$ and ${}_4A_0$ are almost the same except that member country year-on-year inflation rate ($\hat{\pi}_{t,j}$) is allowed simultaneously to affect the value of the monetary policy instrument (r_t) in ${}_4A_0$. Restrictions in ${}_5A_0$ suggest that monetary policy simultaneously affects euro area and member country inflation rates. Restrictions in ${}_6A_0$ exhibit restrictions similar to ${}_5A_0$ but member country inflation rate is not allowed to be simultaneously affected by the euro area output gap (x_t).

There are seven different competing identification schemes constituting 7 models among which we should choose. We apply posterior model

[7] Since the euro area year-on-year inflation is a population- and GDP -weighted average of member country inflations and unanticipated movements in monetary policy instrument are diluted while averaging over member countries figures.

probabilities to find the most likely restrictions matrix for the SVAR model. Given the data Y and seven rivaling identification schemes, the posterior model probabilities in SVAR models identified with restrictions ${}_iA_0$, $i = 1, \ldots, 7$ can be expressed as

$$p(Model_k|Y) = \frac{p(Y|Model_k)p(Model_k)}{\sum_{i=1}^{7} p(Y|Model_i)p(Model_i)}, \tag{4}$$

where the marginal likelihood of model k is defined as

$$p(Y|Model_k) = \int p(Y|\theta_k, Model_k)p(\theta_k|Model_k)d\theta_k .$$

$Model_k$ and parameter vector θ_k refer to a SVAR model in Equation (2) identified with ${}_kA_0$ restrictions. $p(\theta_k|Model_k)$ is the prior density function of θ_k under model k and $p(Y|\theta_k, Model_k)$ is the likelihood function. We assume that the prior model probability of model k, $p(Model_k)$, is the same (one over seven, i.e. 1/7) for all seven SVAR models.

To the best of our knowledge this is the first paper that ranks the identification schemes for a SVAR model using posterior model probabilities. In line with Garratt *et al.* (2009) we base the analysis on Schwarz (1978), by presenting an asymptotic approximation to the marginal likelihood function of the form

$$\log p(Y \mid Model_i) \approx l - K \log(T)/2, \tag{5}$$

where l is the log of the likelihood function evaluated at maximum likelihood estimates, K is the number of parameters and T is the number of observations.

To measure posterior model probabilities in Equation (4) we specify a likelihood function of a SVAR model for given restrictions ${}_iA_0$ (i = 1, …, 7). For a Cholesky identified SVAR model (${}_7A_0$) the concentrated likelihood function evaluated at maximum likelihood estimates $\hat{B}$ and $\hat{\Sigma}$ takes the form

$$L\left(Y \middle| X,{}_7A_0\right) = (2\pi)^{-0.5Tm}\left|\frac{S^*}{T}\right|^{-0.5T} \exp\left\{-0.5trace\left(\left(\frac{S^*}{T}\right)^{-1} S^*\right)\right\} \quad (6)$$

$$= (2\pi)^{-0.5Tm}\left|\frac{S^*}{T}\right|^{-0.5T} \exp\{-0.5Tm\},$$

where S^* = $(Y\text{-}X\hat{B})'(Y\text{-}X\hat{B})$ under Cholesky restrictions and the maximum likelihood estimate of Σ is hence S = $(Y\text{-}X\hat{B})'(Y\text{-}X\hat{B})/T$, where $\hat{B}$ = $(X'X)^{-1}X'Y$. The trace of an identity matrix I_{mxm} is m, the number of diagonal elements and m is the number of variables.

The concentrated likelihood function evaluated at maximum likelihood estimates of B for SVAR models identified with other than Cholesky restrictions, i.e. ${}_iA_0$, i ≠ 7, is

$$L\left(Y \middle| X,\ {}_iA_0\right) = (2\pi)^{-0.5Tm}\left|\left({}_iA_0'\,{}_iA_0\right)^{-1}\right|^{-0.5T} \exp\left\{-0.5trace\left({}_iA_0 S\,{}_iA_0'\right)\right\} \qquad (7)$$

$$= (2\pi)^{-0.5Tm}\left|{}_iA_0\right|^{T} \exp\left\{-0.5trace\left({}_iA_0 S\,{}_iA_0'\right)\right\}.$$

To obtain a value for Equation (4) we calculate Equation (6) for a Cholesky identified SVAR model and maximize Equation (7) for SVAR models identified with restrictions ${}_iA_0$, i = 1,…, 6.

With a SVAR model with suitable simultaneous restrictions in matrix A_0 we will establish whether there exist member country-specific asymmetric price inflation responses to an unanticipated expansionary common monetary policy shock. Following Sims and Zha (1999) we update uninformative prior knowledge of the reduced-form parameter values of a VAR model with the information summarized by the likelihood function. Sims and Zha (1999) set uninformative and improper prior distributions for A_0 and B of a SVAR model identified with non-recursive restrictions (${}_iA_0$, $i \neq 7$). The full conditional and marginal posterior densities for the SVAR model specified with non-recursive restrictions in A_0 are

$$\beta \middle| X, Y, {}_iA_0 \sim N\left(\hat{\beta}, \left({}_iA_0'\,{}_iA_0\right)^{-1} \otimes \left(X'X\right)^{-1}\right) \qquad (8)$$

and

$$q\left({}_iA_0 \middle| X, Y\right) \propto \left|{}_iA_0\right|^{(T-k)} \exp\left\{-0.5trace\left({}_iA_0 S\,{}_iA_0\right)\right\}, \qquad (9)$$

where k = mp + 1. The full conditional posterior distribution in Equation (8) is the multivariate normal and the marginal posterior distribution in

Equation (9) is not in a form of standard distribution, which means that we must use numerical integration methods to draw samples from it.

Having an uninformative[8] joint prior probability density function (p.d.f.) for B and Σ in a Cholesky identified SVAR model gives the marginal posterior distribution of Σ the following form

$$\Sigma \mid X, Y \propto |\Sigma|^{\frac{-(T-(mp+1)+m+1)}{2}} \exp\left\{-0.5 trace\left(\Sigma^{-1} S\right)\right\}. \tag{10}$$

Equation (10) is the kernel of the inverse Wishart distribution for Σ, i.e. $\Sigma \sim iW_m(S, T\text{-}(pm+1))$. The parameters β in a Cholesky identified SVAR model follow the multivariate normal distribution of Equation (8).

Vectors β and $\hat{\beta}$ in Equations (8)–(10) are formed by stacking the columns of B and $\hat{B}$, respectively. The motivation for using the Jeffreys prior in a Cholesky identified SVAR model is that the posterior distributions for B and Σ are known and drawing samples from them is trivial. The information content of a Jeffreys prior is in practice the same as in a flat prior for B and ${}_iA_0$, i = 1,…, 6, which Sims and Zha (1999) suggest to be used in non-recursive identification schemes. For a good reference on the Bayesian statistics one might consider Zellner (1971).

To analyze the possibility of asymmetric price inflation responses to a common monetary policy shock we draw impulse responses for SVAR models identified with simultaneous restrictions which are supported by the data. For the impulse responses the size of a shock in the monetary policy instrument (r_t) is normalized to one standard deviation in a SVAR model in Equation (2). The properties of the standard impulse response function for linear models are well known and documented in the literature; see for example Hamilton (1994) and Sims and Zha (1999). For a general case we define the standard impulse response function by letting c_{lk} be the response of variable $y_{l,t+s}$ to shock $\eta_{k,t}$, i.e.,

$$c_{lk,s} = \frac{\partial y_{l,t+s}}{\partial \eta_{k,t}}. \tag{11}$$

The values of the response function depend only on the parameters of the structural model of Equation (2), and the values can be obtained using basic matrix operations.

[8] The joint prior distribution is constant in B and uses Jeffreys prior on Σ, as in Villani (2001).

2.3 Data and Results

The analysis is based on monthly euro area data covering the period from 1999.1 to 2007.10 (106 observations). The data are collected from the sources of the online data bank services of the EuroStat.

The series for the HICP (harmonized index of consumer prices) of EMU member countries and the euro area aggregate are neither work-day nor seasonally adjusted. Seasonally adjusted series of the index of industrial production[9] (IIP) (excluding construction) in the euro area are used in the formation of the output gap (x_t). The IIP series look back to the year 1980. Monthly values for Eonia are used as a proxy for the ECB's monetary policy instrument (r_t). The series for the Eonia interest rate is calculated using the day-to-day interest rates without seasonal adjustment. The reference year for all HICP series is 2005, and 2000 is the reference year for the euro area IIP series.

The monthly output gap (x_t) is measured as the logarithmic difference between the actual and the potential output level. The logarithm of the potential output is proxied by a one-sided Hodrick-Prescott (HP) (Hodrick and Prescott, 1997) trend estimate of the unobserved trend component τ_t in a model

$$g_t = \tau_t + \zeta_{1t}, \tag{12}$$

$$(1 - L)^2\tau_t = \zeta_{2t}, \tag{13}$$

where g_t is the logarithm of a measure of actual output, L is the lag operator and ζ_{1t} and ζ_{2t} are mutually uncorrelated white noise sequences with a relative variance of $q = \text{var}(\zeta_{1t})/\text{var}(\zeta_{2t})$. The value of $q = 0.67\text{x}10^{-3}$ is taken from Stock and Watson (1999).

The year-on-year price inflation rates, π_t and $\hat{\pi}_{t,j}$ are constructed[10] for both the euro area and individual EMU member countries, respectively.

Figures 1-5 in Appendix section A plot the series of year-on-year HICP inflation rates ($\hat{\pi}_{t,j}$) for EMU member countries together with the euro area year-on-year HICP inflation rate (π_t) and the Eonia interest rate (r_t).

[9] One could use aggregate GDP series instead of IIP series, but the problem is that there are no monthly data available for the GDP in the euro area. Furthermore, we could consider the IIP series to depict the manufacturing sector more accurately. Aksoy *et al.* (2002) use monthly industrial production series in their study tracking down the impact of economic and institutional asymmetries on the effectiveness of monetary policy in the euro zone with an explicit policy target rule.

[10] We use 1998 HICP values in calculating 1999 year-on-year inflation figures.

Figure 1 shows the year-on-year inflation rate in the euro area to be more or less an average of inflation figures for Germany, France and Italy. Additionally, the inflation rates plotted in Figure 1 all tend to converge to an overall 2 per cent inflation target. In Figure 2 the year-on-year inflation rates for the euro area, Belgium, Greece and Spain are plotted against time. The series for Spain and Greece vary similarly at higher levels than those for Belgium and the euro area. Convergence to the overall 2 per cent inflation target is not evident for these member countries.

Figure 3 implies that year-on-year inflation rate for Finland has been at lower levels than in any other EMU member country. The year-on-year inflation rates in Ireland and Portugal have been historically higher than on average in the euro area. Figure 4 shows that since the beginning of 2003 year-on-year inflation rates in the Netherlands and Austria have followed euro area inflation. Meanwhile, the year-on-year inflation rate in Luxembourg has been fluctuating relatively strongly, indicating no convergence to the overall 2 per cent annual target. Thus, a striking observation is that the aggregate euro area year-on-year inflation rate has varied closely around the declared inflation target, while inflation series for member countries have been fluctuating at different levels.

Finally, in Figure 5, the Eonia interest rate (r_t), output gap (x_t) and year-on-year euro area inflation rate (π_t) are plotted. The output gap, as a proxy variable for marginal costs, has not followed a constant pattern – it has fluctuated mainly on the negative side. Observations on consumer price year-on-year inflation rates and the output gap suggest that in the euro area inflation rate stabilization is allocated greater weight while the ECB decides the optimal value of the monetary policy instrument (r_t).

On the basis of Figures 1-4 we can hypothesize that asymmetric year-on-year price inflation responses to a monetary policy shock are to be expected due to the somewhat heterogeneous HICP inflation dynamics among the EMU member countries.

The posterior model probabilities in Equation (4) are calculated for seven SVAR models for each member country. Specifically, a SVAR model in Equation (2) with restrictions ${}_iA_0$ (i = 1, …, 7) and Equations (6) and (7) are maximized respectively conditional on the member country data.

The data we feed into Equations (6) and (7) are $y_t = (\pi_t\ x_t\ r_t\ \hat{\pi}_{t,j})'$, where π_t and $\hat{\pi}_{t,j}$ are the year-on-year HICP inflation rates in the euro area and in the jth member country, respectively. Variable x_t is the monthly output gap obtained using filtering methods presented in Equations (12) and (13) and r_t is the Eonia interest rate describing monetary policy instrument.

Allowing for 7 identification schemes means that for each member country we get 7 posterior model probabilities, one for each identification scheme. Posterior model probabilities are reported in Table 1 below. A lag length of five (5) was chosen, since it turned out to be the shortest lag length providing homoscedastic and autocorrelation-free model errors.

TABLE 1. Posterior model probabilities. Bolded figures indicate the most probable identification scheme for a member country.

SVAR(p), p=5	**POSTERIOR MODEL PROBABILITIES**						
COUNTRY	**IDENTIFICATION SCHEME**						
	${}_1A_0$	${}_2A_0$	${}_3A_0$	${}_4A_0$	${}_5A_0$	${}_6A_0$	${}_7A_0$
Belgium	0.000	0.000	**0.322**	0.220	0.024	0.197	0.237
Germany	0.000	0.000	0.232	0.179	0.018	**0.391**	0.179
Ireland	0.148	0.000	0.214	0.142	0.022	**0.253**	0.221
Greece	0.000	0.000	0.000	0.059	0.009	**0.843**	0.088
Spain	0.000	0.000	0.108	0.146	0.021	**0.517**	0.208
France	0.000	0.000	**0.611**	0.089	0.022	0.061	0.218
Italy	0.000	0.001	0.049	0.275	0.051	0.116	**0.509**
Luxembourg	0.000	0.000	0.129	0.179	0.018	**0.493**	0.179
Netherlands	**0.461**	0.056	0.007	0.057	0.007	0.339	0.072
Austria	0.000	0.000	0.000	0.168	0.017	**0.648**	0.168
Portugal	**0.836**	0.098	0.015	0.007	0.001	0.029	0.013
Finland	0.000	0.000	**0.687**	0.072	0.007	0.163	0.072

The highest posterior model probability of a member country is highlighted in bolded font in Table 1 (the probabilities do not sum to one due to rounding). The last column indicates that commonly used Cholesky restrictions (${}_7A_0$) are relatively weakly supported in the data. Only for Italy ${}_7A_0$-restrictions seem to produce the best model fit. For the rest of the member countries the model fit of Cholesky restrictions is more or less moderate. Results for the Cholesky restrictions imply that the ECB gives higher weight for inflation to countries having relatively greater nominal rigidities. This is in line with Benigno (2004).

The data support restrictions ${}_3A_0$ and ${}_6A_0$ and restrictions according to ${}_2A_0$ are in fact faintly supported. A somewhat striking finding is the posterior model probability of a SVAR model under ${}_5A_0$ restrictions is that low despite the restriction scheme being very similar to ${}_6A_0$ restrictions. The difference between ${}_5A_0$ and ${}_6A_0$ restrictions is that in ${}_5A_0$ the euro area output gap (x_t) is allowed simultaneously to affect member country year-on-year inflation rate ($\hat{\pi}_{t,j}$). It emerges from Table 1 that ${}_6A_0$ restrictions are best supported in the data, i.e. the restrictions which allow the euro area (π_t) and member country consumer price year-on-year inflation rate to be both simultaneously affected by monetary policy shock. ${}_6A_0$ restrictions let monetary policy to be conditioned also on member country inflation. Furthermore, comparing the posterior model probabilities for identification schemes ${}_2A_0$ and ${}_4A_0$ we see that almost in all cases the data lend support to the conception that the ECB takes into account the inflation rate of an individual member country. This finding is in line with De Grauwe and Sénégas (2004, 2006) and Benigno (2004).

To attain identified impulse responses we restrict the analysis to a SVAR model using ${}_6A_0$ and ${}_7A_0$ restrictions. The Cholesky restrictions (${}_7A_0$) are also taken into the impulse response analysis, since typically SVAR models are identified with a recursive identification scheme and they thus provide a good reference to which compare ${}_6A_0$ restricted VAR model impulse responses.

For a Cholesky identified (${}_7A_0$) SVAR model it is assumed that the contemporaneous effect of monetary policy (r_t) on euro area year-on-year inflation rate (π_t), i.e. contemporaneous interest rate elasticity, is by definition zero. This is not the case with ${}_6A_0$ restrictions, since monetary policy can have an immediate effect on both the euro area inflation rate (π_t) and member country inflation rate ($\hat{\pi}_{t,j}$) and EMU member country inflation is assumed to be partly targeted in monetary policy instrument ($a_{34} \neq 0$). In total we will be estimating 24 SVAR models, two for each member country – one SVAR model identified with Cholesky restrictions (${}_7A_0$) and one with ${}_6A_0$ restrictions.

One should note that the SVAR model with ${}_6A_0$ restrictions is such that the posterior p.d.f. in Equation (9) is not in the form of the standard p.d.f. To generate a Monte Carlo sample from the posterior of ${}_6A_0$ we use a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MMCMC). One could of course follow more sophisticated versions of the algorithm but the time and effort involved in refinements would not compensate the efficiency improvements.

The algorithm for the ${}_6A_0$-restricted VAR models uses multivariate normal distribution for the jump distribution on changes in parameters in ${}_6A_0$. We first simulate 15,000 draws using a diagonal covariance with diagonal entries 0.00001 in the jump distribution. These draws are then used to estimate the posterior covariance matrix of parameters in ${}_6A_0$ and scale it by the factor $2.4^2/9$ to obtain an optimal covariance matrix for the jump distribution; see Gelman *et al.* (2004). In estimating the SVAR models identified with ${}_6A_0$ restrictions, we use 100,000 draws, discarding the first 10,000 as a burn-in period. As a convergence check three chains with different starting values are simulated. For each chain we pick every 100th draw to achieve a nearly independent sample. The potential scale reduction factor of Gelman and Rubin (1992) is between 1 and 1.08 for each parameter in ${}_6A_0$. The multivariate version of Gelman and Rubin's diagnostic, proposed by Brooks and Gelman (1997), is between 1.00 and 1.05. Finally, the frequencies of accepted jumps are roughly 0.24. Eventually our results for ${}_6A_0$ restricted SVAR models are based on 2,700 draws for each member country. For a Cholesky identified (${}_7A_0$) SVAR model we generate 3000 draws from p.d.f.s given in Equations (8) and (10). The conditional posterior p.d.f. is multivariate normal and the marginal posterior p.d.f. of Σ is, as already noted, inverse Wishart distribution.

When computing the posterior of impulse responses we follow Sims and Zha (1999) and calculate Bayesian 68 per cent error bands. In Figures 6-17 in Appendix section B, for each member country in turn, the impulse responses drawn are

$$D_{s,j} = \frac{\partial \pi_{t+s}}{\partial \eta_{r,t}} - \frac{\partial \hat{\pi}_{j,t+s}}{\partial \eta_{r,t}} \text{ for } s = 0, \ldots, 12 \text{ and } j = 1, \ldots, 12. \quad (14)$$

The first term in Equation (14) is the annual euro area year-on-year inflation rate response to an unanticipated, one standard deviation expansionary monetary policy shock. The latter term in Equation (14) is the member country's year-on-year inflation rate response. Black lines in Figures 6-17 are for a SVAR model with ${}_6A_0$ restrictions and dotted lines a SVAR model identified with Cholesky restrictions, ${}_7A_0$. In both identification schemes the middle line is the median impulse response value. For both ${}_6A_0$- and ${}_7A_0$ -identified VAR models we calculate impulse responses up to 13 periods (the length of a period is 1 month), including the shock period denoted as time 0 in the figures. If 68 per cent error bands contain the value $D_{s,j} = 0$, then the year-on-year inflation rate responses are statistically the same in the euro area and in any given member country j at 68 per cent posterior probability.

Next we will first discuss the impulse responses drawn for Cholesky identified SVAR models and thereafter comment on impulse responses obtained from an overidentified SVAR model with restrictions in ${}_6A_0$. For Cholesky identified SVAR models, the monetary response of euro area inflation (π_t) is identically zero, i.e. $\partial\pi_{t+s}/\partial\eta_{r,t}$ = 0 for s = 0. This implies that the immediate (s = 0) impulse response value is dictated solely by the second term $\partial\hat{\pi}_{j,t+s}/\partial\eta_{r,t}$ in Equation (14). Thus, if the immediate response of jth member country year-on-year inflation rate ($\hat{\pi}_{j,t}$) to a shock in the monetary policy instrument ($\eta_{r,t}$) is positive, it will be shown in Figures 6-17 in that the $D_{0,j}$ assumes negative value.

Impulse responses drawn for a Cholesky identified SVAR model with $\hat{\pi}_{t,j}$ series for Belgium, Germany, Greece, France and Finland imply that the immediate year-on-year inflation rate responses are asymmetric with 68 per cent posterior probability for these countries. However, with the exception of Greece, inflation rate responses for later periods are statistically the same as the euro area inflation rate response. This means that the posterior intervals contain the zero level of $D_{s,j}$ for s > 0. Figure 9 for Greece shows that during the last 5 periods (i.e. s = 8, …, 12) drawn responses exhibit persistent asymmetric year-on-year inflation rate responses.

Drawn differences between the impulse response of the aggregate euro area and Luxembourg, Dutch, Portuguese and Italian year-on-year inflation rates convey asymmetric responses. Specifically, the Luxembourg inflation rate response is statistically more moderate than the euro area inflation rate response between 3 and 7 months after the initial monetary policy shock. Portuguese asymmetric inflation rate responses begin 5 months after the shock and have ever since remained different from those of euro area inflation. The Dutch responses are more aggressive /moderate than euro area inflation one/eleven months after the shock. Two months after the shock the inflation rate response in Italy is more moderate than the euro area response for 1 month. We see that the results from the Cholesky identified SVAR models suggest heterogeneous type 3 inflation persistence among the EMU member countries. Inflation rate responses in Ireland, Spain and Austria are statistically the same as the euro area responses.

Posterior distributions show that immediate inflation rate responses ($D_{0,j}$) are mixed for ${}_6A_0$-identified SVAR models. In the model for Germany, France, Italy and Finland the immediate year-on-year inflation rate response is statistically stronger than the euro area year-on-year inflation rate response. For Belgium, Ireland, Greece, Spain, Luxembourg and Austria the adjustment to a shock in the monetary policy instrument is not as rapid as it is on average in the euro area. The immediate year-on-year inflation rate response in the Netherlands and Portugal is statistically the same as in euro area on average, as shown in Figures 14 and 16.

The ${}_6A_0$-restricted SVAR model for the Belgian, Italian, Austrian and Finnish year-on-year inflation rate responses implies that it takes 1 month for Belgium to adapt and Italy waits for 3 months, whereas Austria and Finland need 2 months to adjust. The difference between the euro area and Greek inflation rate responses exhibit lagged response behavior (type 3 inflation persistence;) during the 3 and 6 months after the shock the difference in responses is statistically positive, indicating a more sluggish inflation rate adjustment process in Greece than in the euro area. Inspecting the impulse responses drawn for Germany, France and Italy we see that inflation rate responses are similar, suggesting a similarity in price transmission mechanisms for monetary policy shock[11]. This finding is in line with that of Clausen and Hayo (2006). Furthermore, for ${}_6A_0$ restrictions no persistent asymmetric inflation rate responses can be obtained for any member country.

Following important findings can be derived from the impulse response analysis. Firstly, there occur statistically significant asymmetric immediate (s = 0) year-on-year inflation rate responses for SVAR models specified with both ${}_6A_0$ and ${}_7A_0$ restrictions for Belgium, Germany and Greece. Secondly, the different adjustment speeds (compared to euro area year-on-year inflation rate) in response to a monetary policy shock indicate that in the euro area inflation persistence is heterogeneous among the member countries.

2.4 Conclusions

In this paper we provide empirical evidence of transmission of the ECB's monetary policy actions in year-on-year consumer price. The evidence is obtained using an actual monetary policy instrument and error bands for impulse responses which characterize the true shape of the likelihood, as Sims and Zha (1999) argue.

[11] Note that the total weight of Germany, Italy and France in constructing the EMU aggregate series is high.

We calculate posterior model probabilities for SVAR models identified with a set of plausible identification schemes. We find that the data weakly supports Cholesky restrictions, while the strongest posterior support goes to an identification scheme possessing overidentifying restrictions which also let the EMU member country year-on-year inflation rate simultaneously interact with the monetary policy instrument and allow the monetary policy shock to have an immediate effect on euro area and EMU member country year-on-year inflation rates. We found evidence that the ECB also exploits national information while tuning and conducting monetary policy.

Given the impulse response function calculations based on the posterior distributions we may state that the data bespeak short-run asymmetric consumer price year-on-year inflation rate responses to a monetary policy shock across the member countries in the euro area. This verifies also the hypothesis that the ECB's monetary policy conduct needs to be seen as a complicated task, because if the ECB conducts its monetary policy conditional on union-wide aggregates (where the target of aggregate euro area inflation has a substantial role), unforeseen shocks in the monetary policy have an asymmetric impact on consumer price inflation across the member countries. This result is in line with the findings, for instance, of Clausen and Hayo (2006) and Huchet-Bourdon (2003).

One possible way to understand the asymmetric inflation responses addressed is to allow nominal rigidity in firms' price-setting, i.e. assuming that firms in individual member countries follow Calvo (1983) pricing with different price adjustment probabilities. Under Calvo pricing firms may adjust their prices with some constant probability, and since the adjustment probabilities vary across the member countries, deviations from the optimal price level will occur when adjustments are needed. This will evidently show in asymmetric inflation responses to a common monetary policy shock. These asymmetric effects operate through the output gap in the new Keynesian model.

Finally, as a consequence of asymmetric inflation responses and a fixed exchange rate across the member countries, unanticipated monetary policy actions will influence relative prices in member countries, causing disturbances in mutual price competition and thereby indirectly altering consumption schemes, this will lead to changes in EMU member country welfare levels in the short-run.

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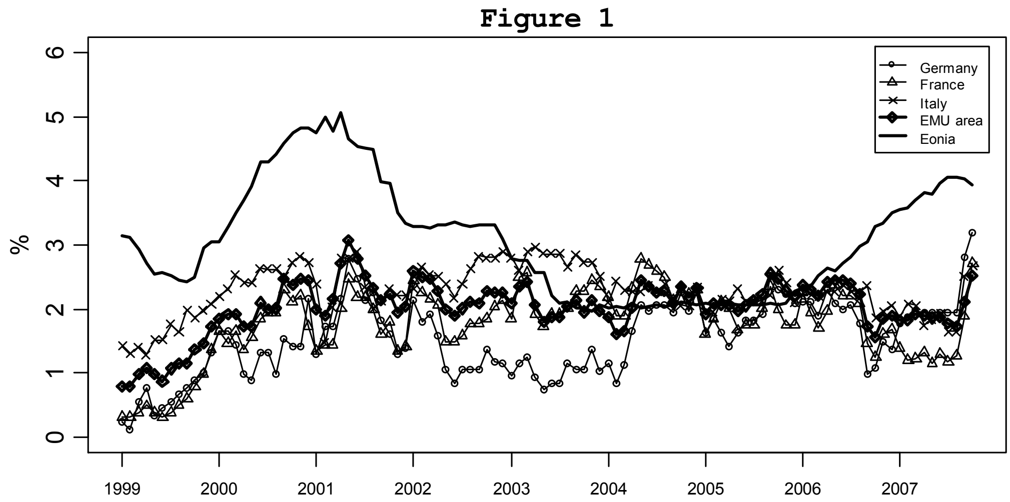
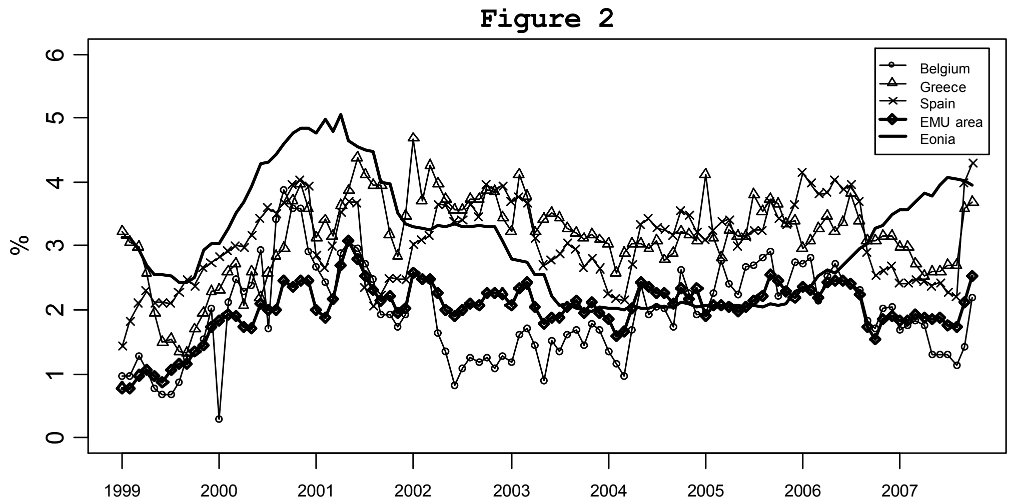
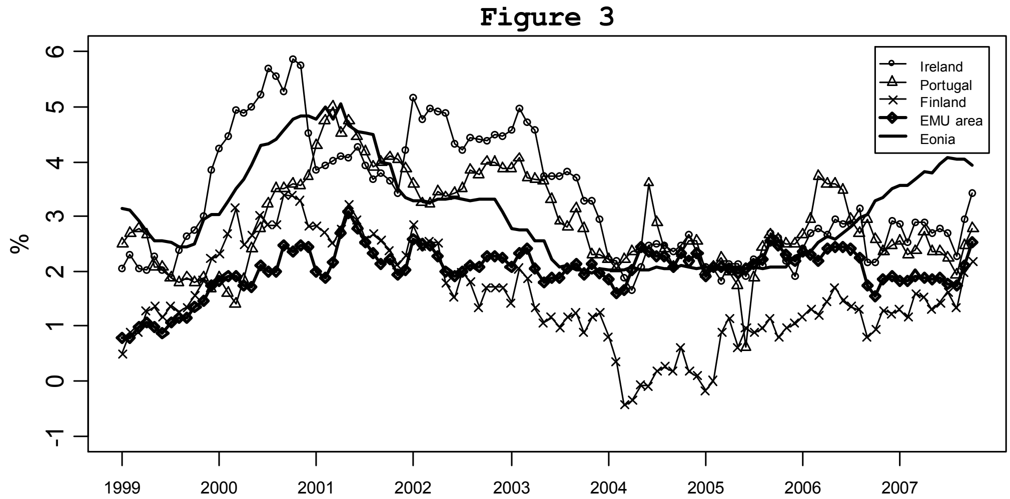
Appendix

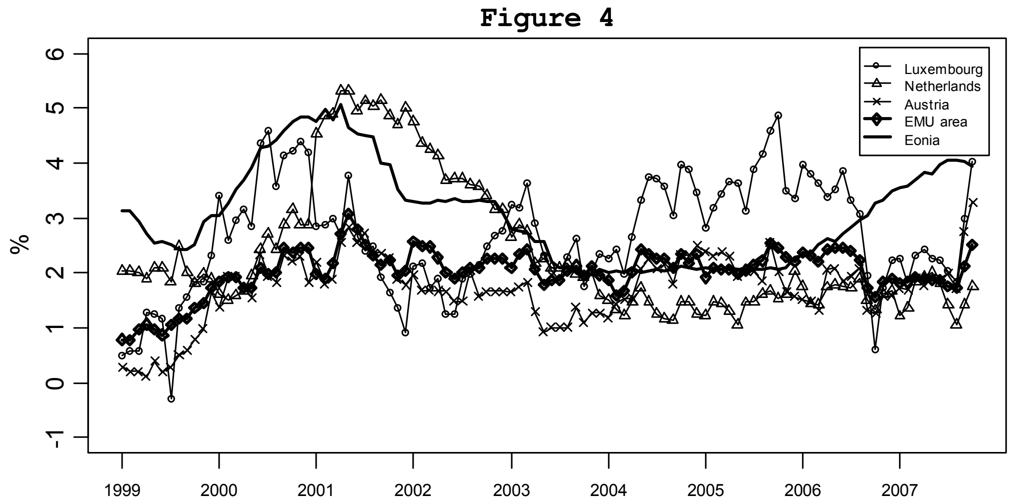
A. Figures





FIGURES 1-2. Year-on-year HICP inflation rates and the Eonia interest rate.
Sample period for monthly data is Jan 1999 – Oct 2007.





FIGURES 3-4. Year-on-year HICP inflation rates and the Eonia interest rate. Sample period for monthly data is Jan 1999 – Oct 2007.

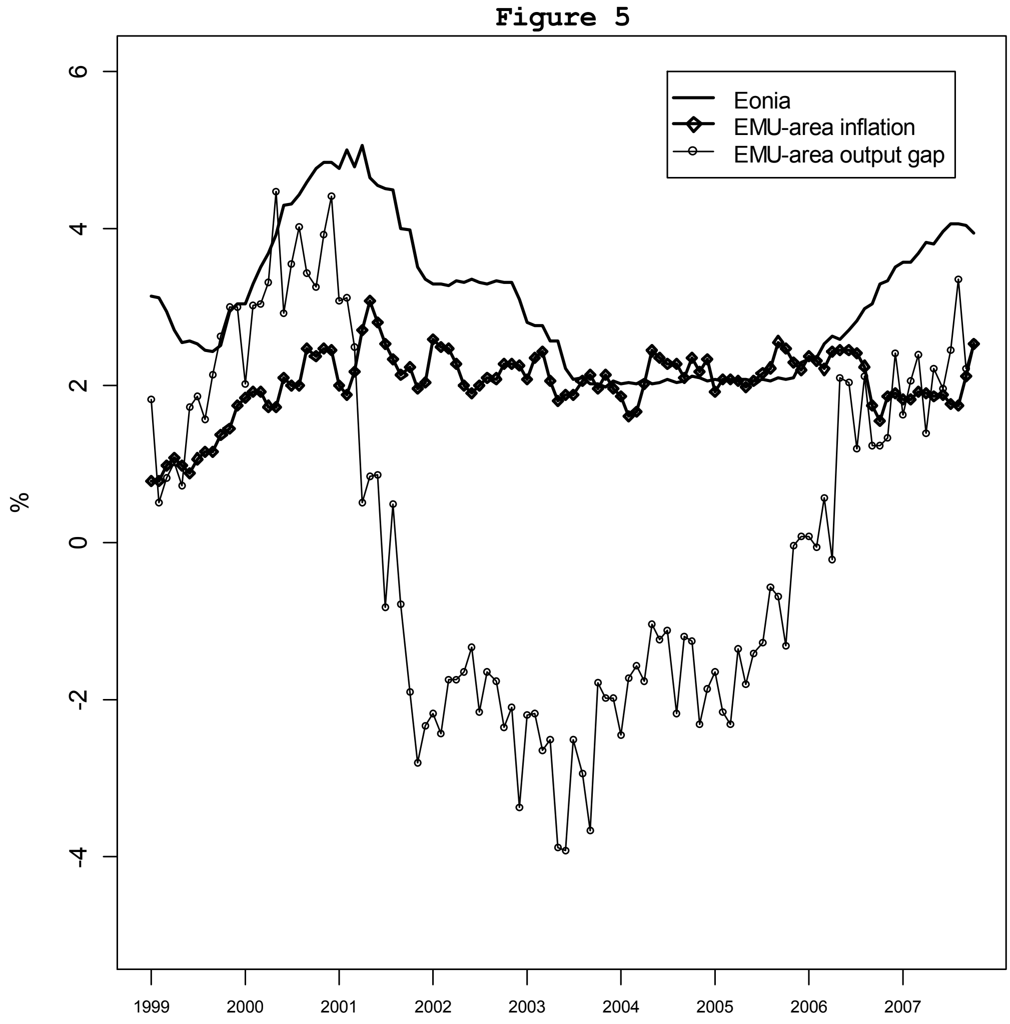
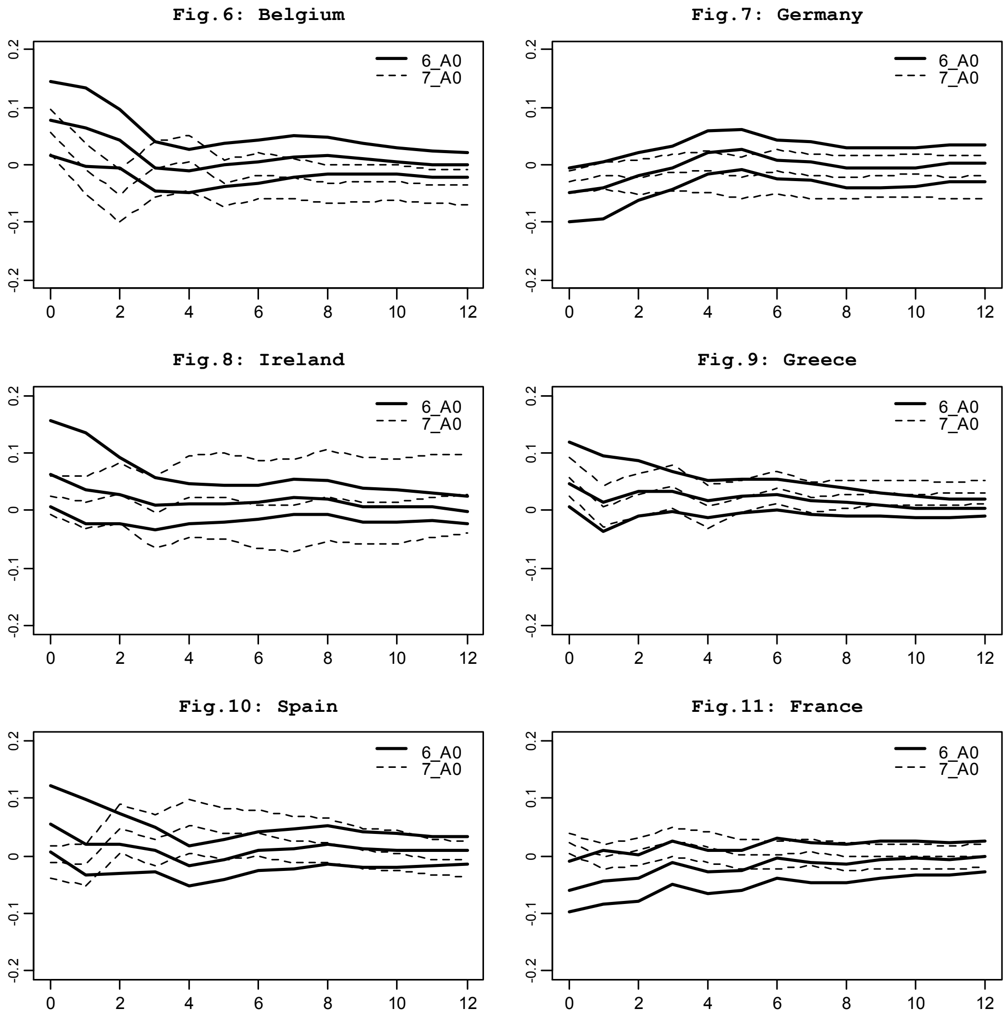


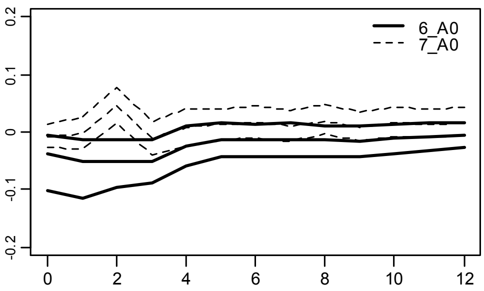
FIGURE 5. Euro area output gap, the euro area year-on-year HICP inflation rate and Eonia interest rate. Sample period for monthly data is Jan 1999 – Oct 2007.

B. Impulse responses for SVAR model with $_6A_0$ and $_7A_0$ restrictions

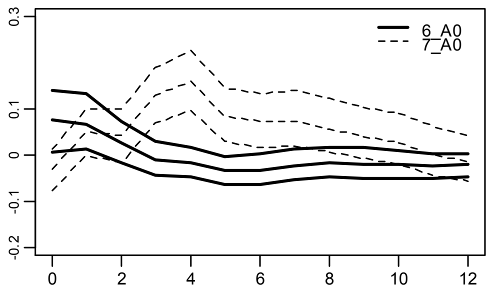


FIGURES 6-11. Impulse responses of the difference in year-on-year HICP inflation between the euro area and various member countries to an expansionary monetary policy shock in $_6A_0$ and $_7A_0$ (Cholesky) restricted SVAR model. The time horizon of the impulse responses is 12 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals.

Fig.12: Italy



Fix.13: Luxembourg



Fix.14: Netherlands

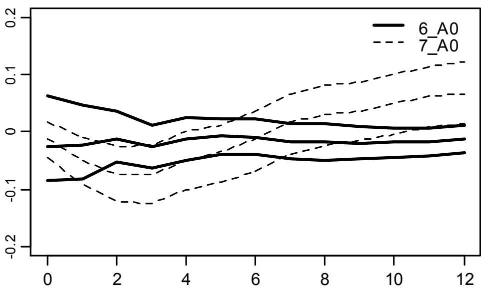


Fig.15: Austria

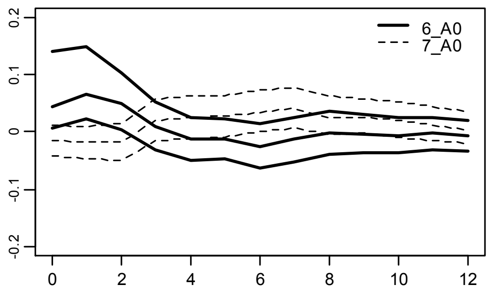


Fig.16: Portugal

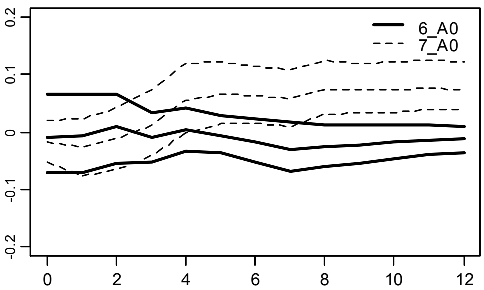
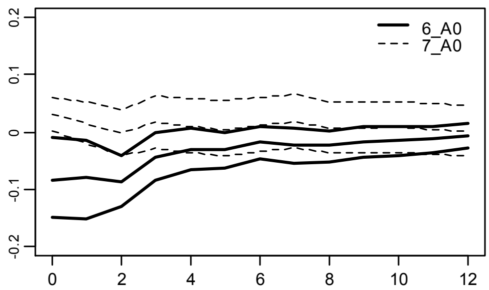


Fig.17: Finland



FIGURES 12-17. Impulse responses of the difference in year-on-year HICP inflation between the euro area and various member countries to an expansionary monetary policy shock in ${}_6A_0$ and ${}_7A_0$ (Cholesky) restricted SVAR model. The time horizon of the impulse responses is 12 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals.

3 Essay 2: Information Sets Used by the ECB in Determining Monetary Policy Operations and Dynamic Monetary Responses of Producer Price Inflation: A Quantitative Study

Jan-Erik Antipin
University of Tampere,
Helsinki School of Economics
and UNU-WIDER

Abstract:

This is a descriptive study of the information sets most likely used by the European Central Bank (ECB) in deciding on monetary policy operations for the euro area. The most likely information set is found by calculating the marginal likelihood value of backward-looking Taylor-rule with interest rate smoothing term. We find that it is possible that the ECB conditions monetary policy on other information than that of the euro area aggregates. Furthermore, similar monetary responses of the year-on-year Producer Price Index (PPI) inflation rates in peripheral EMU member countries (Finland, Ireland and Portugal) can be indicated whether we condition the monetary policy on euro area aggregates or on population and GDP-weighted coalition information on Germany, France and Italy.

JEL Classification: C11, C52, D83, E52, E31.

Keywords: EMU, monetary policy, Taylor rule, Bayesian VAR, marginal likelihood.

3.1 Introduction

This study quantitatively scrutinizes the conditional information sets on which the European Central Bank (ECB) most likely bases its monetary policy decisions in order to meet declared medium-run policy targets, i.e. conditions for sustainable economic growth and price inflation in the whole euro area. The study applies the most likely information set found to calculate values of the impulse response function for the difference in year-on-year producer price inflation to ascertain possible asymmetric monetary responses in peripheral EMU member countries. Our results based on marginal posterior likelihood analysis imply that other information sets than the euro area aggregates cannot be directly laid aside in contemplating what the forces guiding the monetary policy operations in the euro area might be.

It is evident that a considerable amount of economic activity-depicting indices and indicators is constantly being measured, described, monitored and processed by economists and other professional personnel in the departments and affiliates of the ECB. This work is done to deliver updated and refined data for the purposes of the monetary policy decision-makers. Milani (2008) provides, in the spirit of Bernanke and Boivin (2003), quantitative analysis of optimal monetary policy in by deriving more cautious monetary policy rates in data-rich environment where the central bank is allowed to exploit wider information set than in mainstream models. He concludes that introduction of wider information set leads to smoother interest rate path than implied by dynamic optimization under traditional monetary models. However, in this paper we do not expand the ECB’s information set as Milani (2008) does but instead question whether some EMU member countries are given a greater weight while the ECB exercises its monetary policy through Taylor rule. In tentative spirit we thus surmise that the information loaded in the euro area aggregates is the information onto which monetary policy actions and decisions are eventually projected by the ECB. Obviously the information conditional on which monetary policy decisions are made plays a crucial role, since given the information set, the ECB steers overnight interest rates to stabilize price inflation and maintain fertile economic conditions on average in the EMU member countries represented in the information set.

We justify the study by claiming that the information conditional on which the overnight interest rates are eventually steered represents only a subset (or even a typical agent) of euro area countries and we cannot rule out the possibility that the ECB sets its monetary policy in such a way that it favors some individual EMU member country or a member country coalition. Having allowed this, there is a possibility that the effects of unanticipated monetary policy operations, namely unforeseeable adjustments of the overnight interest rates, can be more or less favorable to other EMU member countries not represented in the information set, this is due to the fact that the economic conditions of EMU member countries are assumed to be heterogeneous. The impulse response analysis section of the study is fully motivated, since monetary policy effects on general economic activity and price competitiveness in the short run are of considerable interest, not to mention the possibility of persistent effects. Two crucial questions arise inevitably – can we ex-post say something about the information set on which the ECB might determine the euro area monetary policy, and secondly how does an unanticipated monetary policy shock affect EMU member countries, in the context, for example, production price inflation?

Although this research topic is crucial, little empirical research has been done to shed light on the questions raised. There are a few studies, for example, Hayo and Hofmann (2005), who estimate monetary policy reaction functions and argue that the ECB reacts more aggressively to the output gap than the Bundesbank did, implying that the Bundesbank were more inflation aware in its conduct of monetary policy than the ECB. This result contrasts Buiter's (1999) conclusion that the ECB has adopted many of the procedures and practices of the Bundesbank and thus the ECB will exercise monetary policy that emphasizes inflation stability on the euro area. Hayo (2006) argues that EMU member countries would have set interest rates differently[1] if they had retained their monetary policy independence. Hayo finds that Germany is an exception – Germany has had to adopt much higher interest rates in the EMU era than it had under the Bundesbank. The results of Kool (2005) suggest that the conditions of the German economy are relatively more involved in ECB's monetary policy actions and actual euro area interest rates are in line with German preferences. Further doubts on appropriateness of the ECB's policy in the euro area are casted in Moons and Van Poeck (2008) where they argue that the ECB's policy does not fit individual EMU member countries equally well. We feel that these somewhat polemic findings make it desirable to test quantitatively whether the information and preferences of the German economy alone can present the information the ECB most likely uses in monetary policy.

Obviously, the present purpose is to construct information sets depicting the conditions of EMU member country coalitions and their information

[1] Hayo (2006) concludes that in most cases independently set interest rates would have been set higher.

value in comparison. Regarding the question of monetary policy effects, it would appear to be more complex issue and structural parameter estimates for individual EMU member countries' monetary reaction functions would be needed to understand the dynamic effects of the monetary policy shocks. Despite of this, in this paper we content ourselves to describe the effects of unanticipated monetary policy operations by drawing posterior distributions for the impulse responses of the difference in year-on-year producer price index (PPI) inflation rates between the EMU member country coalition (Germany, France and Italy) and peripheral EMU member countries. For comparison the impulse responses of the year-on-year PPI inflation rate difference between the euro area and peripheral EMU member country are also drawn.

We inspect monetary policy effects in a peripheral EMU member country using a reduced-form model for which monetary policy is conducted conditionally on the information set found to be the most likely. Parallel research on the ECB's monetary policy effects is reported for instance in Antipin and Luoto (2005). They find that monetary responses of the year-on-year HICP inflation rate difference between EMU member countries are asymmetric in the short run in a model where the ECB determines its monetary actions based on euro area aggregates.

To summarize, this study has a twofold purpose – it first calculates marginal likelihood values to obtain the most likely information set which the ECB uses and then specifies a VAR-model to compare the impulse responses of year-on-year producer price inflation rates to expansionary unanticipated monetary policy shock. The analysis is conducted in a reduced-form model framework, since the purpose is to avoid being restricted to a certain specific model formulation but to offer a *descriptive* analysis, as for instance Marschak (1953) finds suitable for policy analysis.

The study is organized as follows: first we present functions that we assume to capture the monetary policy conditions in the euro area. We then show the marginal likelihood calculations and obtain the most probable information set. The empirical section presents the data and statistical methods. Concluding remarks draw the results together. In the appendix section with test statistics, we plot figures for the data, show the posterior density function derivation and draw figures for impulse responses from different identification schemes to validate the impulse responses presented.

3.2 Modeling Monetary Policy Conditions for the Euro Area

We assume that capturing the reduced-form data generating process (DGP) for the variables determined by a simple new Keynesian monetary policy model for a closed economy serves the purposes of a descriptive analysis of the conditions triggering the monetary policy in the euro area[2]. In small-scale closed economy new Keynesian models the expectations augmented forward-looking Phillips curve and demand equation (IS curve) derived based on Euler equation are typically coupled with a variant of the Taylor rule. We find it justified to use a linear reduced-form model in estimation, since the current literature does not present a specific model formulation to describe monetary conditions in the euro area[3]. As a side note, although we are not applying Rational Expectations (RE) theorem, an interested reader should see Kurmann (2006) who provides a reference how to exploit cross-equation restrictions imposed by new Keynesian model in the VAR-model estimation.

We assume in Equation (1)[4] that a monetary policy rule can be written as a function of lagged interest rate (i_{t-1}), future inflation rate ($\pi_{t+1|t}$) and common economic activity (x_t) measured as deviation of output from its flexible-price level (usually called as potential output level). The interest rate rule takes a linear function form as

$$i_t = f\left(i_{t-1}, \pi_{t+1|t}, x_t, \varepsilon_{i,t}\right), \tag{1}$$

where $\varepsilon_{i,t}$ is an i.i.d. zero mean shock to the monetary policy instrument i_t.

We assume that the inflation dynamics is a linear function of future inflation rate ($\pi_{t+1|t}$) and the output gap (x_t) and writes as

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[2] It is debated whether the ECB also takes into account, among other things, the level of large time deposits, institutional money-market funds etc. and the housing price index in tuning its monetary policy. To keep presentation streamlined we will not control for these here.

[3] There is another issue besides the exact specification of the structural form model to be used, namely how expectations are formed. Typically new Keynesian models are forward-looking and the common practice is that in the literature the rational expectations assumption is made assuming that agents know the model and make unbiased forecasts of their control variables. We feel, however, that this may not be a very realistic assumption.

[4] The interest rate rule in Equation (1) covers the Taylor rule often used in the literature. For more on Taylor rules and on new Keynesian macro models see Clarida *et al.* (1999), Clarida *et al.* (2000) and Svensson (2000).

$$\pi_t = g\left(\pi_{t+1|t}, x_t, \varepsilon_{\pi,t}\right), \tag{2}$$

where $\varepsilon_{\pi,t}$ is an i.i.d. zero mean cost-push shock. Equation (2) presents new Keynesian Phillips curve capturing price setting of firms.

The aggregate demand function in Equation (3) depicts common economic activity as a linear function of future inflation rate ($\pi_{t+1|t}$), future economic activity (x_{t+1}) and interest rate (i_t) such as

$$x_t = h\left(x_{t+1|t}, \pi_{t+1|t}, i_t, \varepsilon_{x,t}\right), \tag{3}$$

where $\varepsilon_{x,t}$ as a zero mean i.i.d. demand shock.

We emphasize that we do not impose RE in the above model (1) - (3). Actually we want to allow for deviations from full rationality. Hence, borrowing from the learning literature (Eg. Evans and Honkapohja, 2001) we specify the following forecast functions for π and x. This means that future values of inflation and economic activity are estimated from the data using a linear combination of lagged values of inflation and output gap series, i.e.

$$\pi_{t+1|t} = a_0 + a(L)\pi_t + b(L)x_t. \tag{4}$$

Similarly, the future values of the output gap are predicted using the learning rule

$$x_{t+1|t} = c_0 + c(L)x_t + d(L)\pi_t. \tag{5}$$

Next we proceed to write the model in a VAR form. Forming forecasts as in Equations (4) and (5) allows us to freely find a lag length for the reduced form VAR model to obtain the best model fit. Letting agents form expectations using a univariate time series model is a somewhat restrictive assumption in the sense that correct variables are presumed to be included in the forecast equations and variable value forecasts for time *t* are assumed to be uncorrelated, since they are calculated independently by assumption. We feel comfortable to assume this since Stock and Watson (1999) and Marcellino *et al.* (2003) report that the prediction accuracy of univariate time series models is at least as good as the accuracy of the multivariate models.

3.3 Data

The data for the euro area aggregates, Germany, France, Italy and the peripheral EMU member countries Finland, Ireland and Portugal, are collected from two data sources: seasonally adjusted and construction activities excluded industrial production monthly series (IIP) spanning the period from the beginning of 1980 to the end of the 1980s are from the OECD main economic indicators. EuroStat provides the rest of the IIP series up to April 2006.

The annual series for GDP, population and monthly series for HICP and Eonia interest rates are downloaded from the databanks of EuroStat. Monthly series of the Producer Price Index (PPI) (without construction) over the period 1998 to April 2006 are seasonally non-adjusted (base year 2000) and are likewise provided by EuroStat. The base year of the IIP index series is similarly 2000, GDP is measured in 2005 prices and exchange rates and the base year for the HICP indices is 2005. Annual population is a measure of the total population at the end of the current year. The GDP values are from the years 1991 to 2005 and the population variable covers the period from 1980 to 2005. The monthly series for HICP[5] are from January 1999 to April 2006, likewise the series for the Eonia interest rate depicting the values of the monetary policy instrument.

The output gap (x_t) is measured as a logarithmic difference between the actual and the potential output level. We measure the output gap by constructing the series for the potential IIP output applying a one-sided HP filter in the data from the beginning of 1980 to April 2006 for each of the above-mentioned data sets. In the process we assume that marginal costs are procyclical, i.e. when the observed production level is high relative to potential output level, the competition for available production factors will increase prices and accelerate inflation. The one-sided trend estimate depicts the potential IIP, which is calculated as the Kalman filter estimate Z_t such that

$$\log Y_t = \log \hat{Z}_t + v_t$$
$$(1 - L)^2 \log \hat{Z}_t = \xi_t ,$$

where $\hat{Z}_t$ is an unobserved trend component approximating Z_t and Y_t is the actual IIP output series (Hodrick and Prescott, 1997). Variables v_t and ξ_t are assumed to be mutually uncorrelated white noise sequences with

[5] However, the values for 1998 are used in the calculation of annual changes.

relative variance $\delta = var(\xi_t)/var(v_t)$; see Stock and Watson (1999). We follow Stock and Watson (1999) and set δ = 0.67x10^{-3} which approximately matches the spectral gain for the HP filter. The year-on-year HICP inflation (π_t) series is calculated having a difference of logarithmized values of HICP index as [log($HICP_t$) – log($HICP_{t-12}$)]x100.

In the empirics we will be using in all 6 different datasets to describe the conditions upon which we assume the ECB to determine its monetary policy decisions - these are labeled: euro area, Germany (1L), Germany, France, Italy (3L), Germany and Italy (2La), Germany and France (2Lb) and France and Italy (2Lc). In defining the weight of each country in the information set we give a 50 per cent weight for annual GDP figures and 50 per cent for the population figures. The GDP values for the year 1991 are used in calculating the weights for the 1980s, since we could not acquire these values. Then series are used to define a relative weight for the member country in question in a country coalition, and eventually applied to form an overall index for instance for the consumer prices index.

Figures 1a-d in Section 1 in the Appendix show deviations of the IIP series from potential IIP levels and Figures 2a-d depict year-on-year HICP inflation series for information sets over the period 1999.1 – 2006.4. The Eonia interest rate is also added in figures. We see that the year-on-year HICP inflation series of all information sets have converged to the ECB medium range inflation target of 2 per cent. Overall economic activity in the euro area is close to or converging on its potential levels, as indicated by the thick black line in Figures 1a-d. Convergence to potential is also typical for the country coalitions of 3L, 2La and 2Lb. Output levels for Germany (1L) and country coalition 2Lc tend to diverge from the potential levels. Figures 3a-b plot the year-on-year PPI inflation series for Finland, Ireland, Portugal, euro area and country coalition 3L. After a rather turbulent start in 2000 and 2001 the variance of Irish PPI inflation has converged to other series. The PPI inflation paths for the euro area and 3L are similar.

3.4 Marginal Likelihoods in Model Selection

We take the Bayesian route since in classical inference theory a sufficient number of observations is more important than in Bayesian statistics, and evidently in classical theory the precision of the parameter estimator is low under a small sample size, as is the case with the data used in this study. Furthermore, there is a crucial conceptual difference between the classical school and Bayesians regarding the interpretation of the parameter estimate values – while classical empiricists need to rely on asymptotics, the Bayesians rely totally on observed data and prior distribution[6]. The Bayesians interpret the parameter estimate and its confidence interval on a data basis, meaning they obtain directly possible true values for the unknown parameter and need not calculate confidence intervals which might not even contain the true parameter value inherently present in classical statistics.

To shed light on the question of the information set on which the ECB most likely conditions its monetary policy actions we calculate the values of the marginal likelihood function for different lag lengths for different data sets (information sets), keeping the statistical model the same.

In our view the conditioning information set producing the highest marginal likelihood value for given values of the Eonia interest rate is most likely the set on which the ECB determines its monetary policy actions. The Bayes factors are calculated to quantitatively test the hypothesis regarding which data set should be coupled with the Eonia interest rate to depict the conditions underlying the monetary policy in the euro area. Bayes factors and marginal likelihoods are discussed, for instance, in Robert and Casella (1999), Gelman *et al.* (2004), Geweke (2005) and Zellner (1971).

The Bayes factor in favor of H_i against H_j is given by

$$B_{ij} = \frac{P(H_j)P(H_i \mid X)}{P(H_i)P(H_j \mid X)} = \frac{m(y \mid H_i)}{m(y \mid H_j)}, \tag{6}$$

where $m(y \mid \cdot)$ denotes a marginal likelihood[7] and X contains regressors and y is the regressand.

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[6] However, despite the benefits of Bayesian statistics the Bayesians are criticized for using informative prior distributions probably biasing the estimation results – this could be avoided by using plausible uninformative priors, as in this study.

[7] The notation for B_{ij} can be misleading in the sense that the variables/information set for which the value of the marginal likelihood function is calculated is changed under an alternative hypothesis. A posterior model probability of Model k over m different model specifications can be calculated using $p(Model_k|Y) = \frac{m(Y|Model_k)p(Model_k)}{\sum_{i=1}^{m} m(Y|Model_i)p(Model_i)}$, where p($Model_k$) is the prior probability of *Model k* and m($Y \mid Model_k$) is the marginal likelihood of Model k.

We set hypothesis H_i and H_j as H_1 and H_2. H_1 is fixed to describe the common belief (considered to be the true model) that euro area aggregates are used in the Taylor rule. Rejecting H_1 and accepting the alternative hypothesis H_2 would imply that underlying conditions for H_2 are more likely to be used in the monetary policy tuning of the ECB. The data sets to be used in place of H_2 are those for Germany (1L), Germany, France and Italy (3L), Germany and Italy (2La), Germany and France (2Lb), Germany and Italy (2Lb) and France and Italy (2Lc). With Bayes factors we will be measuring how much our belief in H_1 relative to H_2 changes after we have seen the data.

When testing for the information set which most probably leads ECB monetary policy decisions we follow Canova (2006) and his monetary policy rule specification. He states that a backward-looking Taylor rule with an interest rate smoothing term is consistent with the idea that the central banker only observes lagged values of output gap and inflation in deciding the current level of the interest rate. Backward-looking specification is also eligible because of informational lags and the estimated correlation coefficient between current monthly values and once lagged data is really high (~0.90 or above). Furthermore, specifying the monetary policy rule in this manner avoids causing a bias to parameter estimates due to endogenous regressors.

In line with Canova (2006) the monetary policy rule is a variant of the Taylor rule with interest rate smoothing term

$$i_t = \psi_i i_{t-1} + (1-\psi_i)[\zeta + \psi_\pi \pi_{t-1} + \psi_x x_{t-1}] + \varepsilon_t, \tag{7}$$

where x_t stands for the output gap and π_t for the inflation rate; i_t is for the monetary policy instrument (all the variables measured in percent) and ζ is a constant term. A variable ε_t is a zero-meaned stochastic error and $\mathrm{Var}(\varepsilon_t) = \sigma^2$. Following Geweke (2005) the likelihood function of a linear normal regression model coupled with conjugate prior distributions produces the following marginal likelihood (see Section 2A in the Appendix for details)

$$m(y) = \pi^{-T/2}\{\Gamma[(T+v_0)/2]/\Gamma(v_0/2)\}(|\mathrm{H}_0|/|\overline{H}|)^{1/2}(s_0^2)^{v0/2}$$
$$[s_0^2 + s^2 + (b-\overline{\beta})'\mathrm{X}'\mathrm{X}(b-\overline{\beta}) + (b-\overline{\beta})'H_0(b-\overline{\beta})]^{-(T+v0)/2} \tag{8}$$

In the calculation of Equation (8)[8] we set $\mathrm{E}(\sigma^2) = 1$ in Equation (7) and $v_0 = 10$ such that $s_0^2 = 8 = 10\text{-}2$ due to $\mathrm{E}(\sigma^2) = s_0^2/(v_0\text{-}2)$. Following Taylor

[8] Here the π is pi, not inflation rate.

(1993), the prior means of the parameters of Equation (7) [$(1-\psi_i)\zeta_{,,}$ $(1-\psi_i)$, ψ_π, $(1-\psi_i)\psi_x$, ψ_i] are [(1-0.9)*1, (1-0.9)*1.5, (1-0.9)*0.5, 0.9], since the variables are measured in percent. The prior precision matrix of slope parameters is by assumption a diagonal matrix having 0.1s as diagonal entries. The prior information can be considered uninformative (due to low precision and prior weight v_0 in the posterior distribution).

The marginal likelihood values are reported in Table 1 in Appendix Section 3A. The Bayes factor in Equation (6) receives values letting us propose that the economies of Germany, France and Italy (3L) present the information set which most likely guides the ECB's monetary policy. The Bayes factor of the information contents of euro area aggregates and 3L is 1.38[9], suggesting weak evidence on economic conditions in Germany, France and Italy being emphasized in the monetary policy reaction function in the euro area. For constant prior model probability there is a 20% posterior probability that the Eonia interest rate is conditioned on 3L information, whereas euro area aggregates have 28% posterior probability. The assumption of German economic conditions (1L) being the driving force in euro area monetary policy is not supported by the data, since the marginal function value is lower than the values calculated for other information sets. This finding contradicts Kool (2005), where German economic conditions are found important for the ECB's monetary policy operations. Similarly Buiter's (1999) suggestion that the ECB is an inheritor of the Bundesbank is not verified by the data.

Next we introduce the fractional marginal likelihood method, which we use in inferring the lag length of the VAR model. Thereafter posterior analysis of impulse responses under uninformative prior distributions of VAR model parameters is presented and conducted.

To obtain the suggested lag length for a VAR model we follow Villani (2001), and denote

$$y_t = \sum_{i=1}^{p} y_{t-i}\Pi_i + D_t\Phi + z_t \tag{9}$$

as a form for the reduced VAR model. In Equation (9) the matrix D is for the deterministic variables of the model. The reduced form errors z_t are

[9] Jeffreys (1961) suggests the following threshold values for Bayes factors: B_{ij} < 1/10: Strong evidence for H_j, 1/10 < B_{ij} < 1/3: Moderate evidence for H_j, 1/3 < B_{ij} < 1: Weak evidence for H_j, 1 < B_{ij} < 3: Weak evidence for H_i, 3 < B_{ij} < 10: Moderate evidence for H_i and B_{ij} > 10: Strong evidence for H_i.

assumed to follow a Gaussian distribution with zero mean and Σ covariance matrix i.e. $z_t \sim N(0, \Sigma)$.

The estimation form for the reduced VAR system is $Y = XB + Z$, in which matrix Y is a $(T\times m)$ matrix, X is a $(T\times k)$ matrix (k=1+pm), and Z a $(T\times m)$ matrix, whose tth rows are y'_t,($y'_{t-1},\ldots,y'_{t-p})'$, and z'_t respectively. B is a $(k\times m)$ matrix acquired by stacking Π' and Φ'.

Villani (2001) uses the following uninformative joint prior for Σ and B (the prior for elements in B is constant and Jeffreys prior for Σ)

$$p(\Pi_1, \ldots, \Pi_p, \Phi, \Sigma) = p(B, \Sigma) \propto |\Sigma|^{-\frac{(m+1)}{2}}, \tag{10}$$

and the lags are p = 0, 1, ..., K. An uninformative prior is an objective prior implying that we have little or no pre-knowledge of the parameter values of the model and we let the likelihood function dominate the posterior distribution.

Villani (2001) shows that Gaussian likelihood and the uninformative joint prior in Equation (10) gives the log of the fractional marginal likelihood function as

$$\log\ m_p(y) = -\frac{T-m(K+1)}{2}\log|S_p| + \sum_{j=1}^{m}\log\left(\frac{\Gamma[(T-pm-j+1)/2]}{\Gamma[m(K-p-1)-j+1]/2}\right), \tag{11}$$

where $S_p = (Y - X\hat{B})'(Y - X\hat{B})/T$ and Γ is the gamma function. We will set 8 as a maximum lag length for each data set and hence calculate the values of 8 fractional marginal likelihood functions.

In applying a reduced-form multivariate time series model one should note that we cannot base our inference on causality links between the variables – higher values of the fractional marginal likelihood function compared to the values of the alternative hypothesis mean that we have in general a better model fit for the given lag length. We apply fractional[10] likelihood methods, since we specify posterior distributions of lag parameters with uninformative prior distributions. We calculate the values of fractional marginal likelihood function under each hypothesis, setting the maximum lag length at eight[11] (K = 8) and defining $Y' = [\pi^{HICPj}, \log(IIP^j/potIIP^j), Eonia]$, where j = 1, …, 6 is for

[10] The name fractional marginal likelihood derives from the fact that a fraction of data is used as a training sample.
[11] We see that limiting maximum lag length to 8 suffices to capture the data-generating processes of a 3-variable VAR model.

information describing data sets. Variable *potIIP*^{j} is a potential output for dataset j and is estimated using the HP trend estimate $\hat{Z}_t$. The output gap is hence $x_t = \log(IIP^j/potIIP^j)$. We also calculate average discrepancy statistics due to Gelman *et al.* (2004) in Appendix Section 3C in Table 3. These results back the inference drawn from fractional marginal likelihood values.

Table 2 in Section 3B in the Appendix shows the values of fractional marginal likelihood on a logarithmic scale for lag lengths from 1 to 8 for each information set. Table 2 shows that a candidate for the common lag length capturing the data generating process of the model for the euro area is of the order 3[12]. We decided to use a lag length of order 3, since assigning a lag length of order 8 or even greater would lead to over-parameterization of the VAR model.

3.5 Specifying the Impulse Response Function

We showed that the notion of controlling for the variation of the variables for the country coalition of Germany, France and Italy (3L) instead of the euro area aggregates is not an empty hypothesis. Given the result, we would be interested in seeing how an unanticipated monetary policy shock, while determining the monetary policy on either euro area or 3L aggregates, affects EMU member countries whose information content in conditioning sets can be considered minor. We see that the natural choices of small peripheral EMU member countries would be Finland, Ireland and Portugal[13]. Without going into details we note that Finland represents an economy in which nominal wages are historically centrally agreed and adjustments to common monetary policy shocks can hence be asymmetric. Like Finland, Ireland has gone through a technological change in the past decade and has absorbed massive amounts of foreign capital. Even so, Irish economic conditions cannot be seen to be same as/similar to those of Finland. Portugal on the other hand, as we see it, is a relatively less developed EMU member country and might gain relatively more from the stable conditions EMU membership provides in the long run, as for instance Figures 3a-b for year-on-year producer price inflations in the Appendix (Section 1) show.

[12] Residuals for each estimated 3-variate VAR(3) models are verified to be non-autocorrelated and homoscedastic, and thus they are in line with model assumptions.

[13] Additionally, the relative weight of Finland, Ireland and Portugal in the construction of euro area aggregates is negligible.

To ascertain how an unanticipated monetary policy shock affects above EMU member countries we add a new variable to our system of equations. We propose that adding a variable measuring the difference in year-on-year producer price inflation enables us to investigate the short- and medium-term monetary policy effects of relative traded goods price competitiveness between the euro area (or 3L country coalition) and a peripheral member country[14]. Note that π^{HICP} and deviation from output potential (which proxies output deviations from the flexible price equilibrium) are typically used in defining the loss function of the central bank. We could set as a hypothesis that in par the monetary response of the difference in producer price inflations should be statistically zero and then reason that mutual price competition is not sensitive to random shocks in the monetary policy instrument. The difference in year-on-year producer price inflation between conditioning area /country coalition and member country is chosen to avoid presenting the same variable, for instance series for year-on-year price inflations, twice in the statistical model, thus causing problems in inference. Figures 3a-b show that despite the Portuguese year-on-year producer price inflation spikes in the year 2000 the series for year-on-year producer price inflations have similar values.

To draw an inference on the way a structural shock in a variable *j* affects the dynamics of variable *i* in a VAR model we need first to standardize the reduced-form errors to obtain an interpretation of one standard deviation shock. To start with we write the VAR in structure form

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[14] Adding a new variable to a system of equations may well be criticized on solid theoretical grounds, since the likelihood function of the model does not remain the same. However, we assume that it to be common practice for agents first to observe that a model for three variables capturing the supply, demand and monetary policy rule is a satisfactory model on a statistical basis to describe the monetary conditions for the euro area. Then, adding a new variable to the model for descriptive purposes would seem to be suitable even while conceding that this misspecifies the original three-variable macro model.
We ran a block-exogeneity test (Hamilton (1999), pp. 311-12) to test whether A_2 is a zero matrix in a model

$$y_{1t} = c_1 + A_1^{'}x_{1t} + A_2^{'}x_{2t} + \varepsilon_{1t}$$
$$y_{2t} = c_2 + B_1^{'}x_{1t} + B_2^{'}x_{2t} + \varepsilon_{2t}$$

where y_{1t}= [π^{HICPj}, log($IIPj/potIIP^j$), *Eonia*]$_{1t}$, x_{1t} contains lagged values of y_{1t}. y_{2t} is π^{PPIj}- π^{PPIi} and x_{2t} is constructed similar to x_{1t} but using values of y_{2t}. Term c_1 is a vector of constants and c_2 is a scalar. Error processes are uncorrelated and assumed to follow a zero-mean Gaussian process. Block-exogeneity tests were ran using lag lengths 3-8 in models for Finland, Ireland and Portugal on the assumption that the monetary policy is determined using euro area and 3L aggregates. We found that in all lag lengths and in all models the variable π^{PPIj}- π^{PPIi} provides precision in forecasting variables in the original, three-variable model. Hence producer price inflation should be introduced into the model as well. We admit that this raises a problem and we suggest that a theoretically more plausible way of solving it would be to use a different macro model also providing structural equations for producer price inflation series. In that case we would no longer restrict ourselves to a closed-economy macro model. However, in view of the descriptive purposes of the study we point to this also as a possible direction for future research.

$$\Gamma(L)y_t = c + \varepsilon_t, \tag{12}$$

where $\Gamma(L) = \Gamma_0 - \Gamma_1 L - \ldots - \Gamma_p L^p$ and $\varepsilon_t \sim N(0, \Lambda)$. We assume that the structural shocks are not simultaneously correlated, i.e. for instance the cost shock ε_π does not simultaneously affect the monetary policy shock ε_i. Therefore the covariance (mxm) matrix Λ of structural shocks is diagonal. The diagonal elements of simultaneous effects in matrix Γ_0 are normalized to 1. Term c is a vector of constants.

Standardization is done by premultiplying Equation (12) by $\Lambda^{-1/2}$ to obtain $A(L)y_t = a + v_t$, where $A(L) = \Lambda^{-1/2}\Gamma_0 - \Lambda^{-1/2}\Gamma_1 L - \ldots - \Lambda^{-1/2}\Gamma_p L^p$ and $\mathrm{Cov}(v_t) = \mathrm{I}$. The reduced-form model is $A_0^{-1} A(L)y_t = b + A_0^{-1} v_t$. This is $(\mathrm{I} - A_0^{-1} A_1 L - \ldots - A_0^{-1} A_p L^p)y_t = z_t$ and the $\mathrm{Cov}(z_t) = \left(A_0 A_0^{'}\right)^{-1} = \Sigma$. Arranging the terms gives us $y_t = b + (A_0^{-1} a + A_0^{-1} A_1 L + \ldots + A_0^{-1} A_p L^p)y_t + z_t = b + \sum_{i=1}^{p} B_i y_{t-i} + z_t$ which can be written in the matrix form $Y = XB + Z$, where Y is a $(T\times m)$ matrix, X is a $(T\times k)$ matrix $(k=1+pm)$, and Z is a $(T\times m)$ matrix whose tth rows are $y'_t, (y'_{t-1},\ldots,y'_{t-p})'$, and z'_t respectively. Further, B is a $(k\times m)$ matrix achieved by stacking b' and B_i'. The responses of model variables to one standard deviation shock in the jth variable are derived using a common route first transforming the VAR into moving average presentation and then differentiating w.r.t standardized shock of a variable j (see further discussion of this for instance in Hamilton, 1994).

3.5.1 Posterior Distributions

The likelihood function is assumed to be Gaussian, meaning that we assume symmetric shocks to linear Equations (1)–(3) and have a common form of

$$\mathrm{p}(Y \mid X, B, \Sigma) \propto |\Sigma|^{-\frac{T}{2}} \exp\left\{-\frac{1}{2} tr\Sigma^{-1} S - \frac{1}{2} tr\Sigma^{-1}\left(B - \hat{B}\right)^{'}\left(X^{'}X\right)\left(B - \hat{B}\right)\right\}, \tag{13}$$

where $S = (Y - X\hat{B})'(Y - X\hat{B})$ and $\hat{B} = (X'X)^{-1}X'Y$.

To be in line with the marginal likelihood analysis we will use the same joint prior distribution for reduced-form parameters and the model error covariance matrix. In general, an uninformative prior distribution serves our purposes of descriptive data analysis well – we let the data speak by assigning uninformative prior knowledge to the model parameters.

In Section 2B in the Appendix it is shown how to derive the marginal posterior of Σ in Equation (14) and the full conditional posterior of β = vec(B) in Equation (15). We will generate values from the following density functions

$$\mathrm{p}(\Sigma \mid X, Y) \propto |\Sigma|^{-\frac{(T-(pm+1)+m+1)}{2}} \exp\left\{-\frac{1}{2} tr\Sigma^{-1} S\right\} \tag{14}$$

and

$$\mathrm{p}(\beta \mid X, Y, \Sigma) \propto \exp\left\{-\frac{1}{2}\left(\beta-\hat{\beta}\right)^{'}\left[\Sigma^{-1} \otimes \left(X^{'}X\right)\right]\left(\beta-\hat{\beta}\right)\right\}. \tag{15}$$

We introduce a new variable into the model to measure the monetary responses of the difference in annual producer price inflation between coalition/country j and a peripheral EMU member country i. By adding this new variable to the system we can, without assuming any explicit functional form for it but a reduced VAR form, inspect how a monetary policy shock affects the relative production price competition of EMU member countries. In estimation we change the sign of the monetary policy instrument to enable us to make an inference as to how an expansionary monetary policy shock affects the model variables. The VAR is identified using Cholesky decomposition[15], which obviously rests on the assumption that an unanticipated monetary policy shock is allowed simultaneously to have an effect on the difference in producer price inflation series together with HICP and IIP series. We define j = euro area and 3L and i = Finland, Ireland and Portugal. The variables used in VAR estimation are now Y^* = [π^{HICPj}, $log(IIP^j/potIIP^j)$, *-Eonia*, (π^{PPIj}- π^{PPIi})]. The identification of our 4-variable reduced-form VAR is obtained assuming simultaneous effects to possess a lower-triangular matrix in the form of

$$A_0 = \begin{pmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix}, \tag{16}$$

where a parameter a_{ij} is the simultaneous effect of a variable j on a variable i. To fix the simultaneous effects of the VAR in the form of Equation (16) we need to cope with the assumption that the

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[15] Both the order and rank conditions for identification are fulfilled. Furthermore, using Cholesky decomposition and presenting the difference of year-on-year producer price inflation as the last variable in matrix Y^* we in fact assume that the producer price inflation difference cannot have a simultaneous effect on other model variables.

simultaneous effect of both output gap and interest rate on HICP inflation is zero. We control the results for impulse responses using different identification schemes in the Appendix. Note that MCMC methods would be required if we were driving exact simultaneous restrictions implied by Equations (1) – (5) and allowed the monetary policy instrument to affect only the difference in producer price inflation[16].

3.6 Results for Monetary Policy Shock

The lag length of all reduced-form VARs is estimated to be three (i.e. VAR(3)), as suggested in Table 2 in Appendix Section 3B. The assumed independence of the reduced-form residuals is verified by calculating autocorrelations crosswise – all the correlograms drawn indicate that the residuals are all well-behaving, i.e. autocorrelations between residuals are not significant at the 95 per cent level and we can rest on the assumption of white noise residuals and on a homoscedastic covariance structure of reduced-form residuals.

Conditioning monetary policy on two different information sets (the euro area and 3L aggregates) and driving an unanticipated expansionary shock of the order of one standard deviation in the monetary policy instrument causes somewhat similar reactions in the difference in producer price inflations between the euro area/3L and Finland and Ireland. Portugal constitutes an exception – the 68 per cent posterior errors bands for responses are tighter if 3L information is used in monetary policy. The robustness of impulse responses in Figures 4 - 6 presented in Appendix Section 4 is validated using the different variable ordering schemes for the Cholesky identification[17]. Variable ordering schemes and impulse responses are depicted and drawn in Section 5 in the Appendix. According to these validating results we can consider the impulse response drawn by Figures 4 – 6 as robust[18].

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[16] To allow for over-restricted simultaneous effects we would need to assume, for instance, a constant joint prior instead of an uninformative prior. This would entail using the Metropolis-Hastings step in fractional marginal likelihood calculation and posterior p.d.f. for reduced-form parameters. Even in this case we would not be able to run the VAR calibrated for simultaneous effects given by the model; it would be necessary to make further assumptions of zero-simultaneous effects for variables in the VAR model to keep identification conditions (namely the rank condition) fulfilled.

[17] In Section 5 in the Appendix we show for 6 different variable ordering schemes that the monetary responses of annual producer price inflations have similar distributions and that the results are not sensitive to the ordering of model variables.

[18] To be more specific, this is the case when the instrument for monetary policy, the Eonia interest rate, is allowed to have a simultaneous effect on the PPI inflation differential π^{PPIj}- π^{PPIi}.

In Figures 4 – 6 we have plotted the 68 per cent posterior probability interval for the impulse response function for the difference in annual producer price inflations, i.e. dPPI(*information set*)–dPPI(*member country j*) to an unanticipated expansionary monetary policy shock. The middle line is the median response value. The lines in bold face are for the H_1 hypothesis that the ECB conditions monetary policy on euro area aggregates, meaning that these constitute the information set. Additionally, the thinner lines are for the H_2 hypothesis, i.e. the assumption that the information content of the country coalition of Germany, France and Italy (3L) does have more weight than officially announced in the conduct of monetary policy. Note that the immediate response of the producer price inflation difference to a positive one standard deviation in monetary policy shock is labeled as the first value on the x-axis.

Figure 4 shows that the Finnish year-on-year producer price inflation responds initially more aggressively to an expansionary monetary policy shock than on average in the euro area or in 3L. Thereafter the adjustment processes are statistically the same. The width of the 68 per cent posterior confidence interval is nearly the same for these two reduced form VAR models with different information content. The burden of Figure 5 is that in the short run the producer price inflation difference between the euro area/3L and Ireland behaves statistically similarly. However, there would seem to appear persistent asymmetric responses if we condition the monetary policy on the euro area aggregates – in this case the impulse responses drawn indicate that the euro area year-on-year producer price inflation is persistently higher than in Ireland. The width and the level of the confidence intervals is practically the same for the first 3 months after the shock and thereafter the location of the density function for impulse response values for a model conditioned on 3L aggregates shifts towards a statistically zero inflation difference.

If we condition monetary policy with 3L coalition variables, we find for Portugal that the short-run impulse responses would show response patterns similar to those in Figure 5 – in the Portuguese case the inflation difference diminishes statistically to zero in 4 periods, while for Ireland it takes 5 periods to die out. A crucial finding in Figure 6 is that the immediate response of the year-on-year producer price inflation difference is statistically zero under both information contents. The Portuguese posterior density functions for producer price annual inflation do not generate similar patterns for euro area and 3L information content. Perhaps the results for Portugal could be influenced by implicitly different producer price inflation dynamics. In Figures 3a-b in the Appendix we see that the Portuguese year-on-year producer price inflation remained over 10 per cent, peaking at nearly 20 per cent in the middle of the year 2000, while producer price inflation in the euro area, 3L coalition, Finland and Ireland was more moderate.

3.7 Concluding Remarks

We described the monetary policy conditions in the euro area with variables specified in a closed economy new Keynesian macro model and assumed that central bank operations follow a Taylor rule -type instrument rule. We showed that the weight of the EMU member country coalition of Germany, France and Italy (3L) cannot be ignored as the information set possibly driving monetary policy operations conducted by the ECB. Our findings are not in line with the results of Kool (2005) and Buiter (1999). We found that the ECB does not weight relatively more German (1L) conditions while exercising monetary policy in the euro area.

Monetary responses of the difference in year-on-year producer price inflation between the euro area (or the 3L country coalition) and three peripheral EMU member countries were found to be statistically asymmetric. Monetary policy determined on both (euro area and 3L aggregates) information sets produces immediate and for the first month positively asymmetric year-on-year producer price inflation responses for Finland. The Irish producer price inflation tends to adjust to an expansionary monetary policy shock more steadily than the euro area or in the 3L country coalition for 5 successive months after the shock. From the impulse responses for Ireland we deduce that persistent asymmetric monetary inflation responses prevail when the monetary policy is tuned conditional on euro area aggregates.

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Appendix

1. Figures

Figure 1a: Germany (1L), EMU-area and Eonia

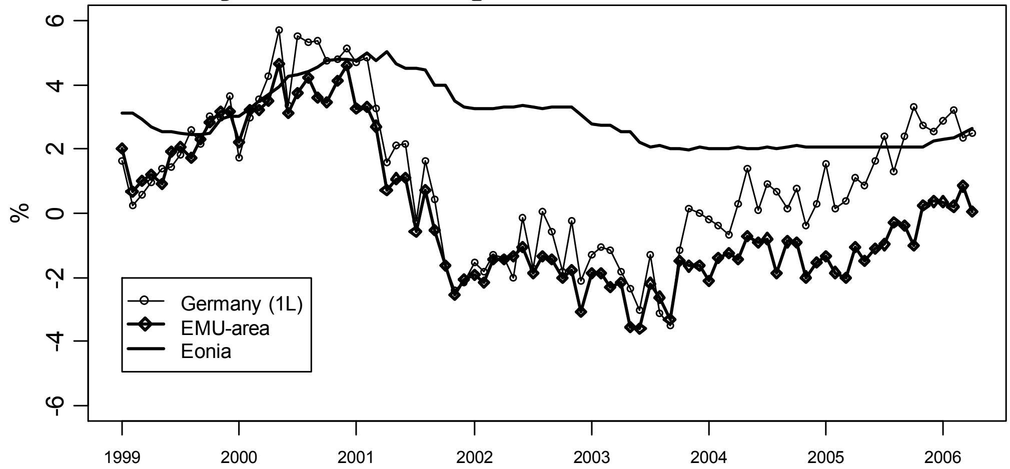
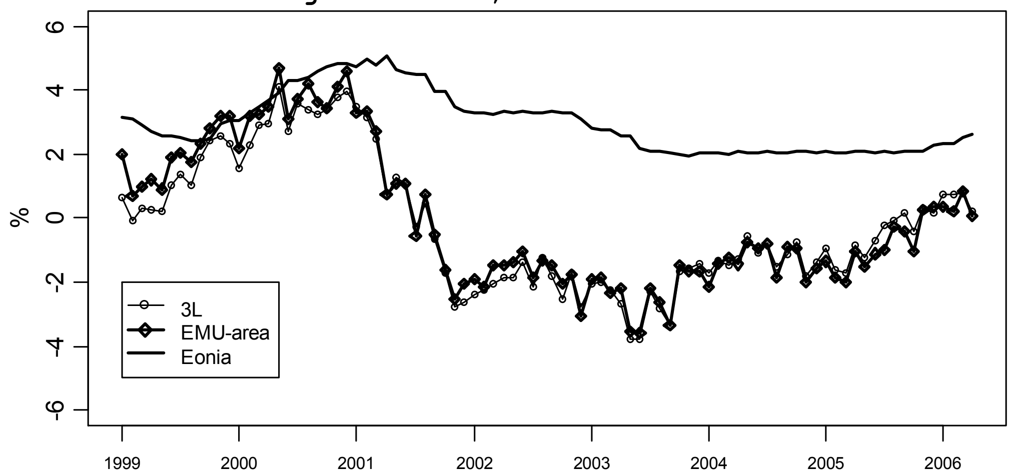
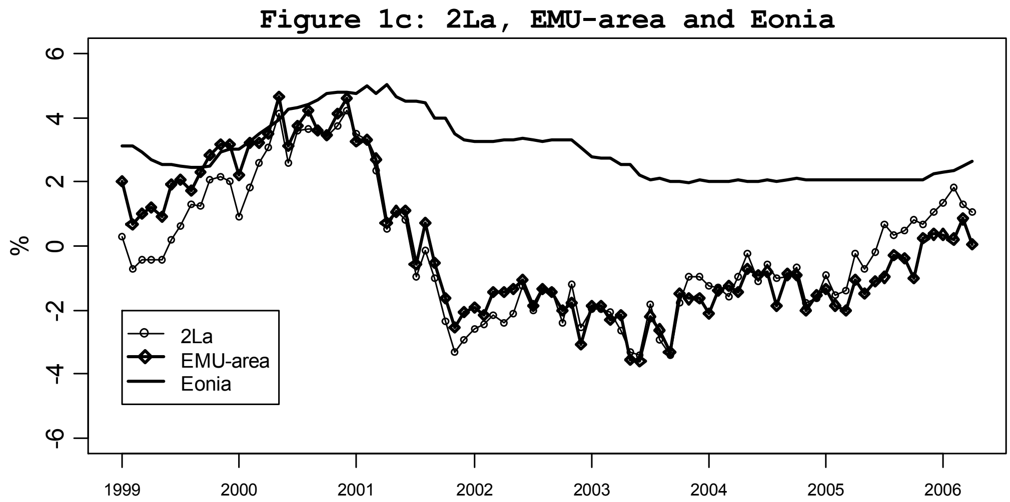
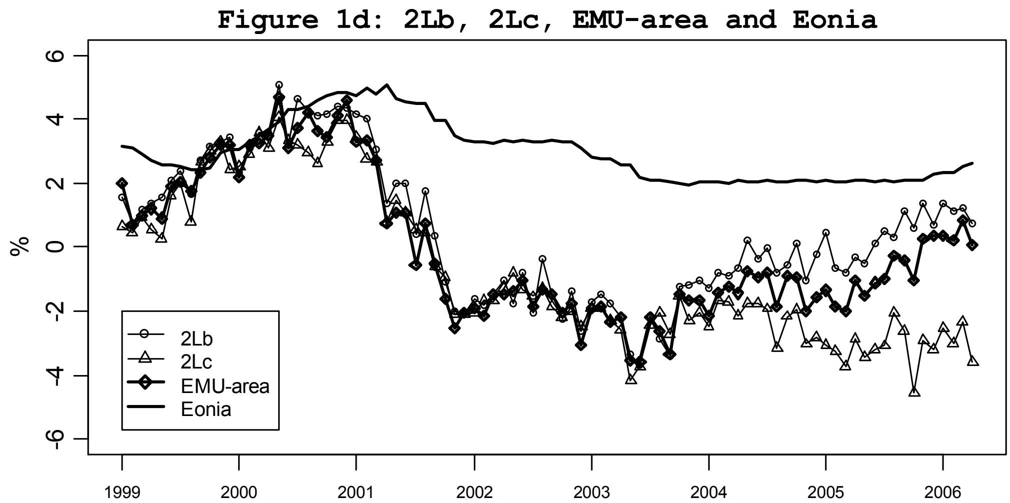


Figure 1b: 3L, EMU-area and Eonia



FIGURES 1A-B. Percentage deviations of IIP from potential level and Eonia interest rate, sample period Jan 1999 – April 2006.





FIGURES 1C-D. Percentage deviations of IIP from potential level and Eonia interest rate, sample period Jan 1999 – April 2006.

Figure 2a: Germany (1L), EMU-area and Eonia

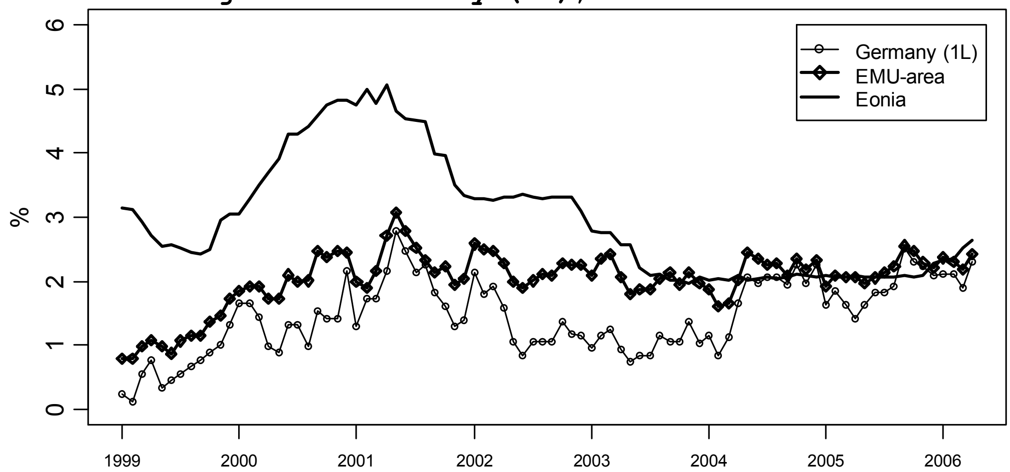
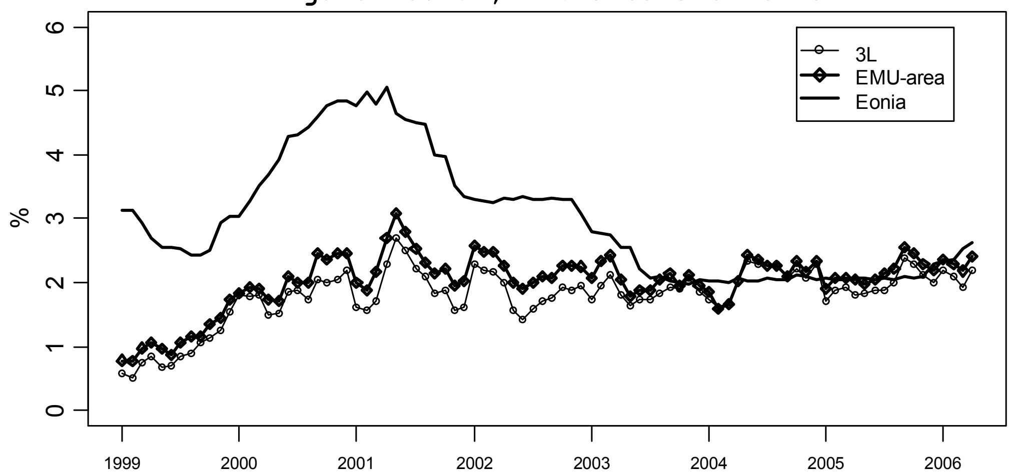


Figure 2b: 3L, EMU-area and Eonia



FIGURES 2A-B. Year-on-year HICP inflation rates and Eonia interest rate, sample period Jan 1999 – April 2006.

Figure 2c: 2La, EMU-area and Eonia

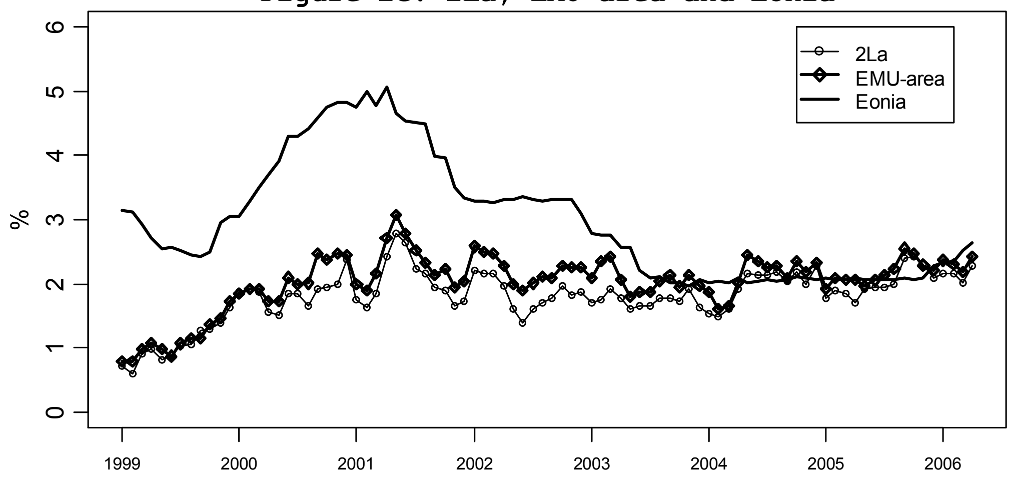
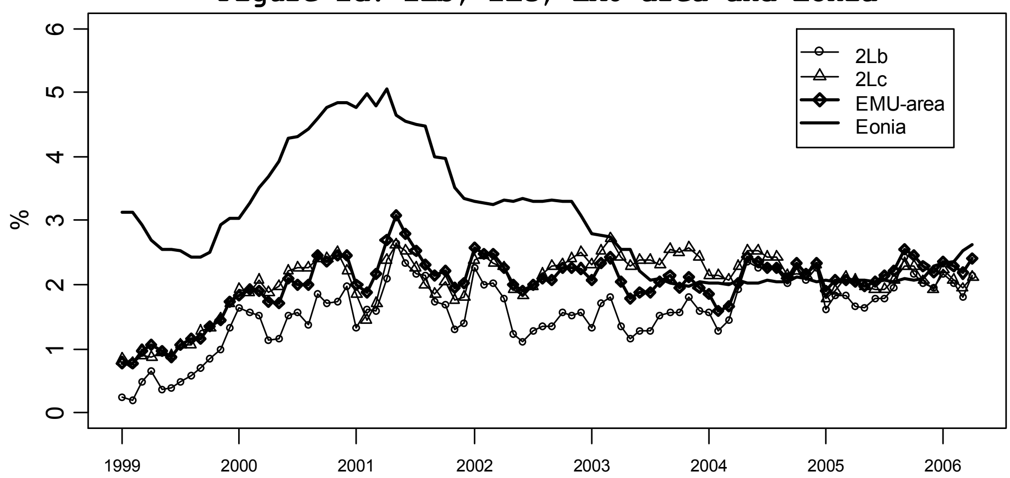
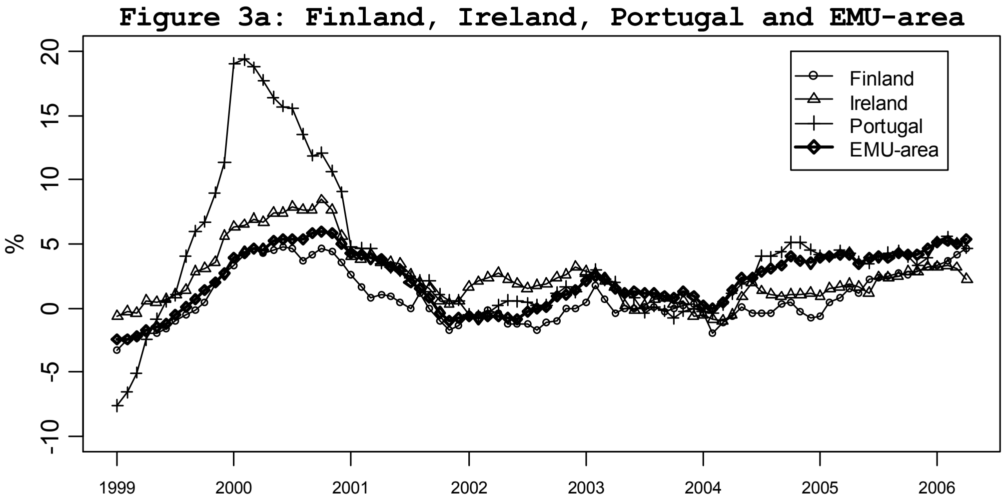
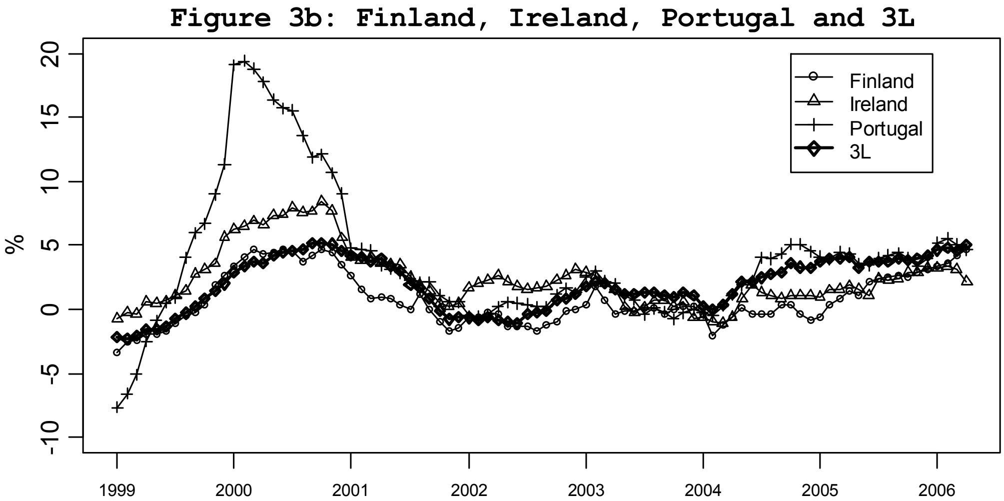


Figure 2d: 2Lb, 2Lc, EMU-area and Eonia



FIGURES 2C-D. Year-on-year HICP inflation rates and Eonia interest rate, sample period Jan 1999 – April 2006.





FIGURES 3A-B. Year-on-year PPI inflation rates, sample period Jan 1999 – April 2006.

2. Marginal likelihood and posterior distributions

A) Marginal likelihood of a normal linear regression with conjugate prior distributions

The following derives from Geweke (2005).

A normal linear regression model writes as

$$y = X\beta + \varepsilon$$

such that $y|(\beta, h, X) \sim N(X\beta, h^{-1}I)$. In the model y is a (Tx1) vector of observed outcomes and a (Txk) matrix X of covariates is a full rank matrix. Parameter h is the precision of each of the i.i.d. disturbances ε, $h = 1/\sigma^2$ is precision and Var(ε_t) = σ^2 and β is a (kx1) vector of coefficients.

The likelihood function for the above model under Gaussian errors is

$$p(y \mid \beta, h, X) = (2\pi)^{-T/2}h^{T/2}\exp(-h(y - X\beta)'(y - X\beta)/2).$$

The conjugate prior distributions of β and h are

$$s_0^2 h \sim \chi^2(v_0)$$

and

$$\beta \mid h \sim N\left(\beta_0, h^{-1}H_0^{-1}\right),$$

where β_0, H_0 and H_0^{-1} are the prior mean, prior precision and prior variance of β, respectively. Matrix H_0 is a (kxk) positive definite matrix of constants. E(h) = v_0/s_0^2 and Var(h) = $2v_0/s_0^4$ due to properties of the Chi-squared distribution. A change of variable yields the expected value of σ^2, E(σ^2) = $s_0^2/(v_0-2)$.

The marginal likelihood of y is

$$m(y) = \pi^{-T/2}\{\Gamma[(T+v_0)/2]/\Gamma(v_0/2)\}(|H_0|/|\overline{H}|)^{1/2}(s_0^2)^{v0/2}$$
$$[s_0^2 + s^2 + (b-\overline{\beta})'X'X(b-\overline{\beta}) + (b-\overline{\beta})'H_0(b-\overline{\beta})]^{-(T+v0)/2},$$

where $s^2 = (y - Xb)'(y - Xb)$, $b = (X'X)^{-1}X'y$, $\overline{H} = H_0 + X'X$,
$\overline{\beta} = \overline{H}^{-1}(H_0\beta_0 + X'Xb)$ and Γ denotes the gamma function.

B) Derivation of posterior distributions

The product of likelihood Equation (11) and the joint prior produces the joint posterior distribution of B and Σ, and has the form

$$p(B, \Sigma \mid X, Y) \propto |\Sigma|^{-\frac{(T+m+1)}{2}} \exp\left\{-\frac{1}{2} tr\Sigma^{-1}S - \frac{1}{2} tr\Sigma^{-1}\left(B-\hat{B}\right)'\left(X'X\right)\left(B-\hat{B}\right)\right\}.$$

The marginal posterior of Σ is obtained by integrating over the range of possible values of reduced-form coefficients in matrix B. Matrices B and $\hat{B}$ are vectorized, i.e. vec(B) = β and vec($\hat{B}$) = $\hat{\beta}$, then

$$p(\Sigma \mid X, Y) \propto |\Sigma|^{-\frac{(T+m+1)}{2}} \exp\left\{-\frac{1}{2} tr\Sigma^{-1}S\right\} \left|\Sigma \otimes \left(X'X\right)^{-1}\right|^{\frac{1}{2}}$$

$$\int_{\beta \in \Re^{pm^2+m}} \frac{1}{\left|\Sigma \otimes \left(X'X\right)^{-1}\right|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}\left(\beta-\hat{\beta}\right)'\left[\Sigma \otimes \left(X'X\right)^{-1}\right]^{-1}\left(\beta-\hat{\beta}\right)\right\} d\beta .$$

The integral term is 1. Then

$$p(\Sigma \mid X, Y) \propto |\Sigma|^{-\frac{(T+m+1)}{2}} |\Sigma|^{\frac{(pm+1)}{2}} \exp\left\{-\frac{1}{2} tr\Sigma^{-1}S\right\}$$

since $\left|\left(X'X\right)^{-1}\right|^{\frac{1}{2}m}$ is a matrix of constants. The marginal posterior of Σ is

$$p(\Sigma \mid X, Y) \propto |\Sigma|^{-\frac{(T-(pm+1)+m+1)}{2}} \exp\left\{-\frac{1}{2} tr\Sigma^{-1}S\right\},$$

and above is the kernel for the inverted Wishart distribution –
$\Sigma \sim IW(T\text{-}(pm+1), S)$, S is a ($m \, x \, m$) scale matrix.

Applying the rule p(B | X, Y, Σ) = p(B, Σ | X, Y) / p(Σ | X, Y) gives the conditional posterior of β as

$$p(\beta \mid X, Y, \Sigma) \propto \exp\left\{-\frac{1}{2}\left(\beta-\hat{\beta}\right)'\left[\Sigma^{-1} \otimes \left(X'X\right)\right]\left(\beta-\hat{\beta}\right)\right\}.$$

3. Marginal likelihoods and estimated average discrepancy

A) Marginal likelihood values of backward-looking Taylor rule

TABLE 1. Logarithmic values of marginal likelihood and posterior model probabilities (constant prior model probability) for backward-looking Taylor rule.

Marginal likelihood values						
	Euro area	Germany (1L)	3L	2La	2Lb	2Lc
log(m(*y*|*Model*))	-33.2864	-34.5784	-33.6059	-33.6598	-34.3118	-33.8590
p(*Model* |*y*)	0.277	0.076	0.201	0.191	0.099	0.156

B) Fractional marginal likelihood

TABLE 2. Logarithmic values of fractional marginal likelihood for a given lag length of the VAR model.

Fractional marginal likelihood values						
Lag length	Euro area	Germany (1L)	3L	2La	2Lb	2Lc
1	328.7073	308.7546	330.3278	327.5213	319.1078	330.4018
2	330.4527	310.3252	331.8220	328.2585	320.6692	331.6629
3	335.1425	314.5401	334.7345	331.9970	324.2190	331.0868
4	334.5760	315.1097	334.1908	331.9968	323.8044	331.7844
5	333.4834	314.8438	333.4710	331.1316	323.0003	332.0654
6	332.0600	313.7257	332.8194	329.9786	322.4973	331.0811
7	332.6861	313.3556	333.5474	330.4848	322.3325	332.2314
8	334.0818	313.3434	333.6386	331.2437	322.4421	330.5382

C) Estimated average discrepancy

The discrepancy between data and model depends on the parameters in θ as well as y. Bayesians are eventually interested in averaging the discrepancy itself over the posterior distribution

$$D_{AVG}(y) = E[D(y,\theta)|y],$$

whose value is estimated by calculating the estimated average discrepancy using posterior simulations θ_l in the formula

$$\hat{D}_{AVG}(y) = \frac{1}{L}\sum_{i=1}^{L} D(y, \theta_l),$$

where the deviance is $D(y,\theta)$ = -2logp($y \mid \theta$) and L is the total number of draws. p($y \mid \theta$) denotes the Gaussian likelihood function. θ_l is the lth draw from the posterior density of β and Σ given in Equations (14) and (15). The small values of $\hat{D}_{AVG}(y)$ indicate a better model fit.

TABLE 3. Estimated average discrepancy for a given lag length of the VAR model.

Estimated average discrepancies for different information sets for lag lengths spanning from 1 to 8

Lag length	Euro area	Germany (1L)	3L	2La	2Lb	2Lc
1	-634.3551	-512.8945	-644.1243	-626.9115	-576.0931	-644.4998
2	-646.5801	-524.1016	-654.8497	-633.6168	-587.5718	-653.7335
3	-676.7119	-552.0876	-674.3843	-658.4536	-611.1793	-653.4035
4	-676.3681	-558.3638	-674.2018	-661.1106	-611.6683	-659.6845
5	-673.3077	-559.1672	-672.7438	-658.1860	-608.7717	-664.3293
6	-667.2893	-556.5937	-672.4192	-655.1114	-608.6847	-661.3049
7	-675.5522	-557.5919	-680.5318	-662.0906	-612.8297	-671.4635
8	-688.7311	-561.3821	-685.5297	-672.3674	-616.9058	-666.2163

4. Impulse responses

Figure 4: EMU/3L vs. Finland

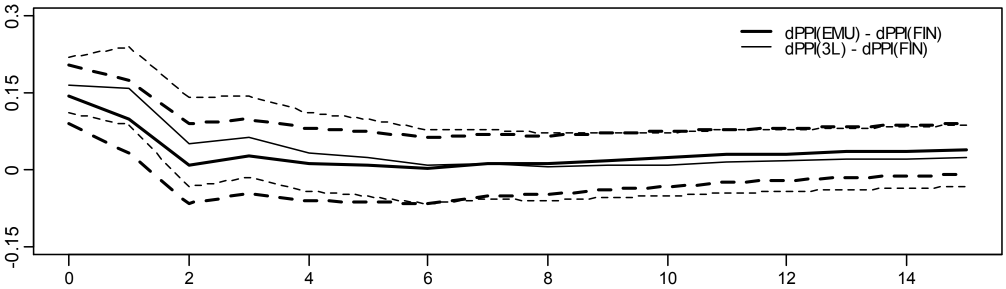


Figure 5: EMU/3L vs. Ireland

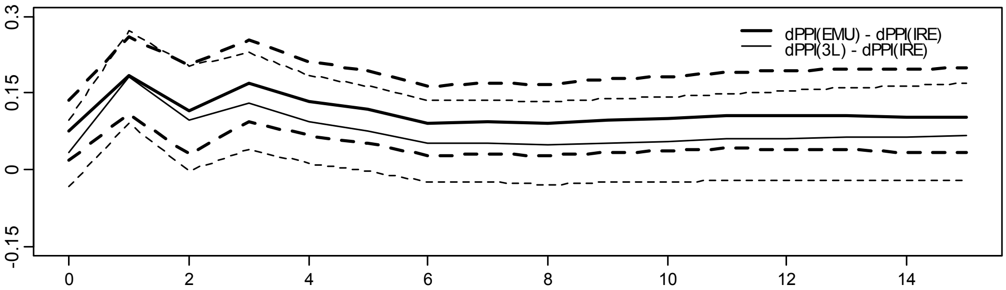
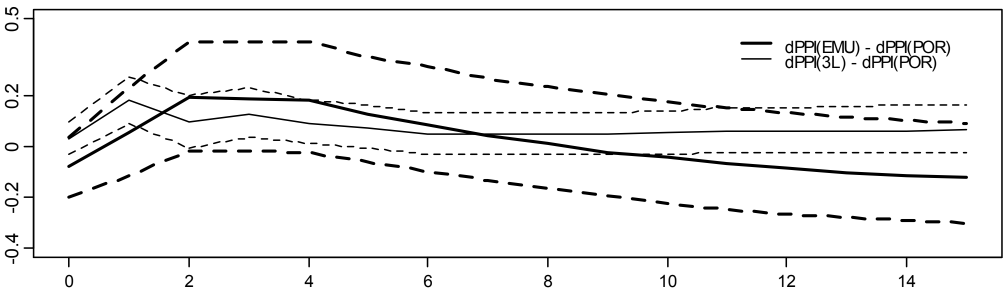


Figure 6: EMU/3L vs. Portugal



FIGURES 4-6. Impulse responses of the difference in year-on-year producer price (PPI) inflation rates between euro area/3L and Finland, Ireland and Portugal to an expansionary monetary policy shock. The time horizon of the impulse responses is 15 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals.

5. Variable orderings

Variable ordering *

$Y^{*\prime} = [\pi^{HICPj}, \log(IIP^j/potIIP^j), -Eonia, (\pi^{PPIj} - \pi^{PPIi})]$.

The superscript j (euro area, 3L) is for the information content and i is for a peripheral EMU member country (Finland, Portugal, Ireland).

Variable ordering #1

$Y_1' = [(\pi^{PPIj} - \pi^{PPIi}), \pi^{HICPj}, \log(IIP^j/potIIP^j), -Eonia]$

A monetary policy shock is not allowed to have a simultaneous effect on the year-on-year producer price inflation rate difference. Contemporaneous values of output gap and year-on-year HICP inflation rate affect the monetary policy instrument.

Variable ordering #2

$Y_2' = [(\pi^{PPIj} - \pi^{PPIi}), \log(IIP^j/potIIP^j), \pi^{HICPj}, -Eonia]$

A monetary policy shock is not allowed to have a simultaneous effect on year-on-year producer price inflation rate difference. Contemporaneous values of output gap and year-on-year HICP inflation rate affect the monetary policy instrument, but HICP inflation rate has no simultaneous effect on the output gap.

Variable ordering #3

$Y_3' = [\log(IIP^j/potIIP^j), \pi^{HICPj}, -Eonia, (\pi^{PPIj} - \pi^{PPIi})]$

The same as ordering * but ordering #3 has a changed order for the year-on-year HICP inflation rate and the output gap.

Variable ordering #4

$Y_4' = [-Eonia, \pi^{HICPj}, \log(IIP^j/potIIP^j), (\pi^{PPIj} - \pi^{PPIi})]$

Model variables are not allowed to have simultaneous effect on the monetary policy instrument. The year-on-year producer price inflation rate difference is affected simultaneously by all model variables.

Variable ordering #5

$Y_5' = [-Eonia, \log(IIP^j/potIIP^j), \pi^{HICPj}, (\pi^{PPIj} - \pi^{PPIi})]$

The same as ordering #4 but the output gap and year-on-year HICP inflation rate have changed places.

Variable ordering #6

$Y_6' = [-Eonia, (\pi^{PPIj} - \pi^{PPIi}), \pi^{HICPj}, \log(IIP^j/potIIP^j)]$

Model variables are not allowed to have simultaneous effect on the monetary policy instrument and only the monetary policy instrument has a simultaneous effect on year-on-year producer price inflation rate difference.

In the first column of Figures 7-9 we allow euro area aggregates to depict monetary policy conditions. In the second column 3L aggregates form the conditional information set. The thick lines are for impulse response function values for variable ordering $Y^{*\prime} = [\pi^{HICPj}, \log(IIP^j/potIIP^j), -Eonia, (\pi^{PPIj} - \pi^{PPIi})]$. The outer lines are the lower and upper bound limits for 68 posterior probability interval and the midmost is the median value. The thin lines and response patterns depicted with triangles are for impulse function values for variable ordering mentioned first and last in the title, respectively. Within each subfigure in Figures 7-9 impulse response functions from *three* different models are drawn and in some cases the values of impulse response functions are visually the same.

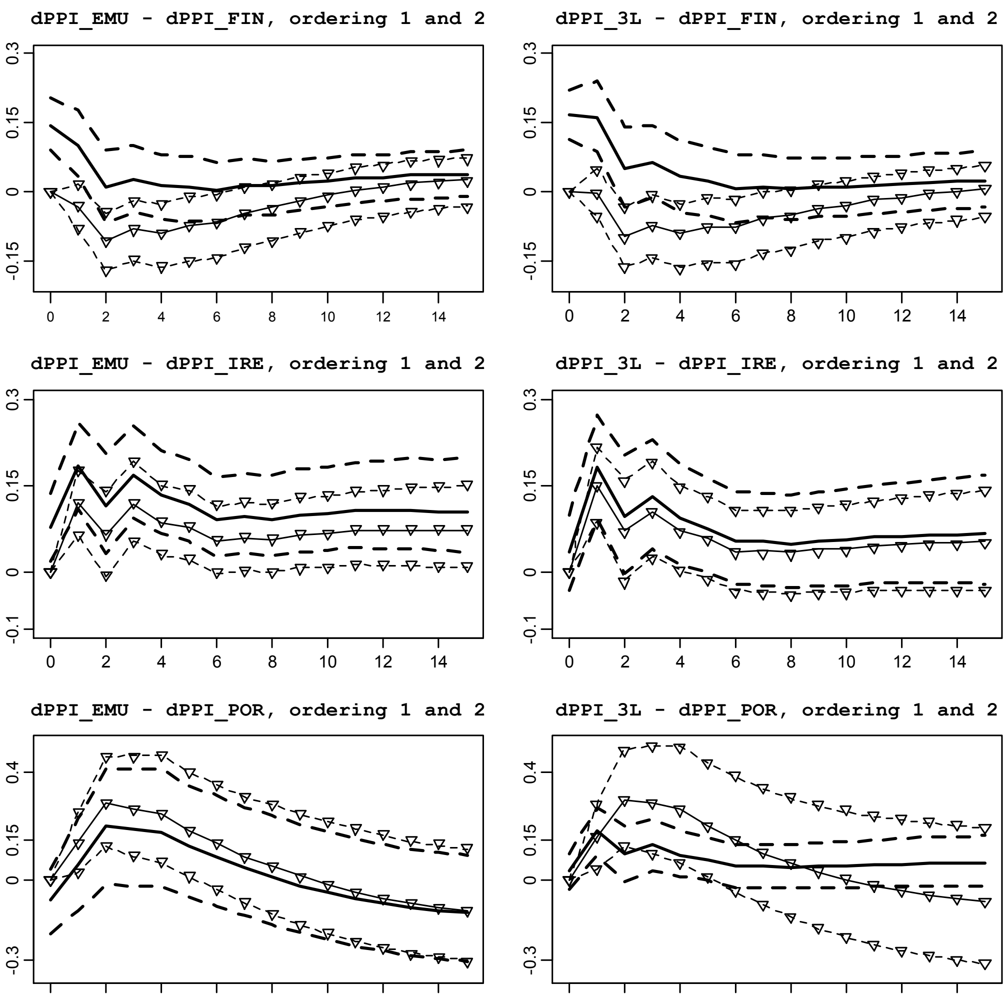


FIGURE 7. Impulse responses of the difference in year-on-year producer price (PPI) inflation rate between euro area/3L and Finland, Ireland and Portugal to an expansionary monetary policy shock with variable orderings 1, 2 and *. The time horizon of the impulse responses is 15 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals.

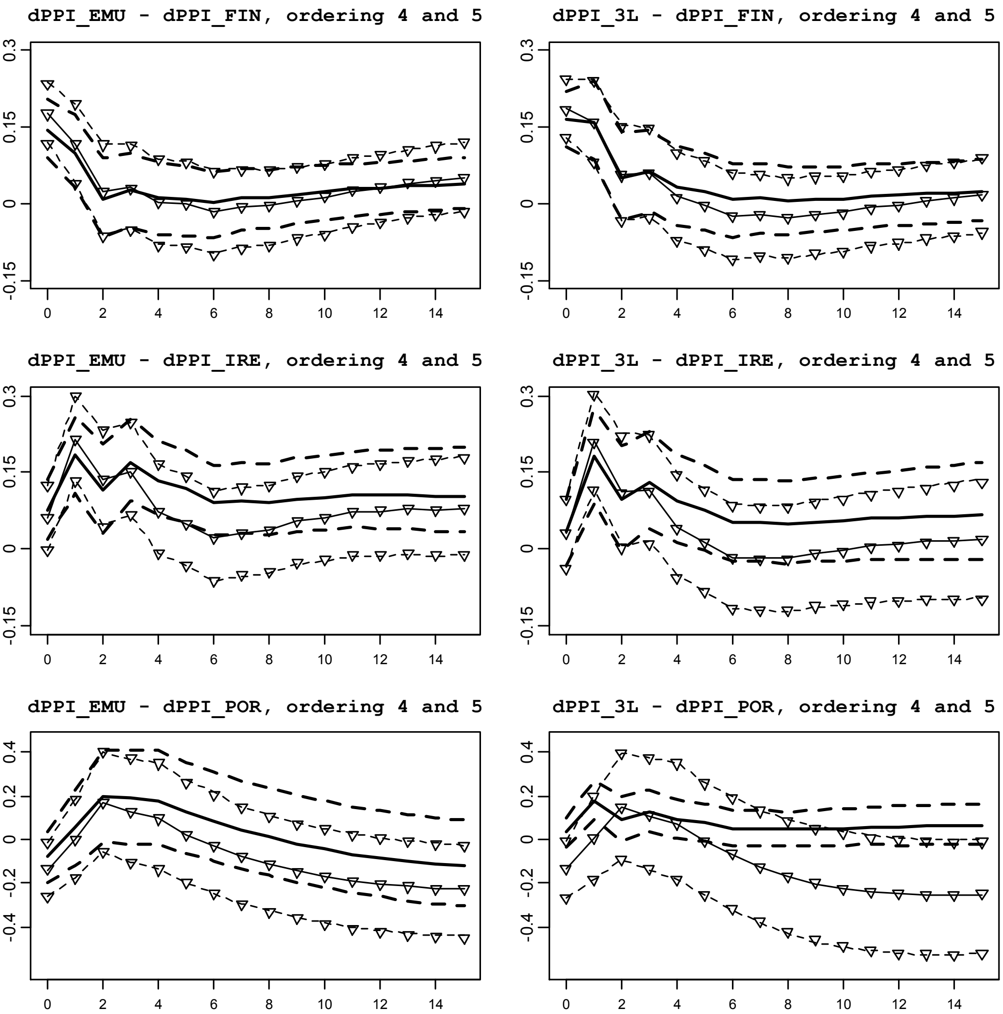


FIGURE 8. Impulse responses of the difference in year-on-year producer price (PPI) inflation rate between euro area/3L and Finland, Ireland and Portugal to an expansionary monetary policy shock with variable orderings 4, 5 and *. The time horizon of the impulse responses is 15 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals.

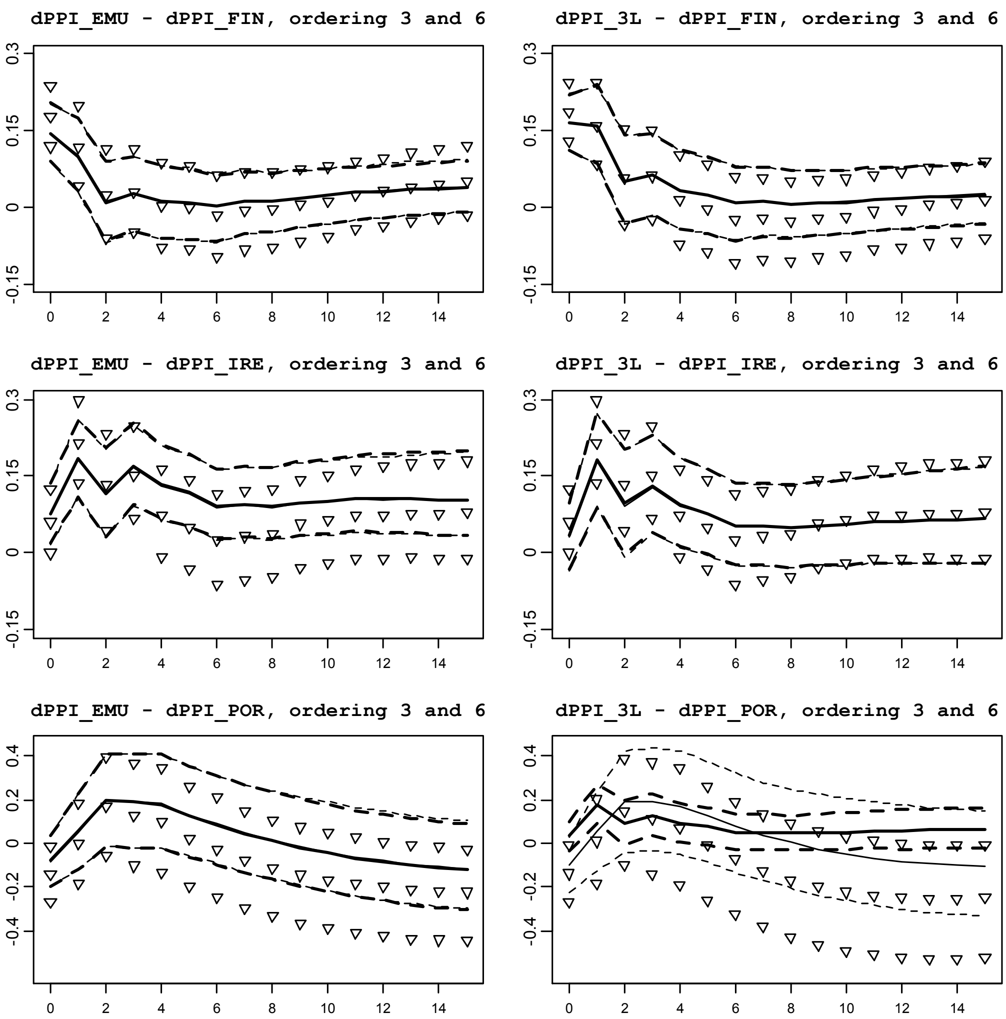


FIGURE 9. Impulse responses of the difference in year-on-year producer price (PPI) inflation rate between euro area/3L and Finland, Ireland and Portugal to an expansionary monetary policy shock with variable orderings 3, 6 and *. The time horizon of the impulse responses is 15 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals.

4 Essay 3: Are There Asymmetric Inflation Responses in the EMU?

Jan-Erik Antipin
University of Tampere,
Helsinki School of Economics
and UNU-WIDER

Abstract:

This paper employs an open economy new Keynesian macro model in deciding upon the variables and identification scheme to be used in the Bayesian structural vector autoregressive model. Empirical results suggest that the simultaneous effect parameter restrictions implied by the macro model are supported in the monthly euro area data, and that the European Central Bank's monetary policy has, surprisingly, a similar impact on price inflation in individual EMU member countries.

JEL Classification: C11, E52, E31.

Keywords: The ECB's monetary policy, asymmetry, Bayesian structural vector autoregressive model, hierarchical prior design.

4.1 Introduction

The word inflation appears to be one of the most commonly used economic terms among the general public. People are interested in inflation because most think that inflation hurts their standard of living, as Shiller (1997) puts it. Consequently, the complicated challenge of modern central banks is to practise low inflation policy to keep the consumption path of the general public stable. This challenge may be even more complicated for the European Central Bank (ECB), because the diversity in the economic and institutional structures across the member countries constitutes a rationale for the expectation that a common monetary policy will have impacts of different magnitudes in the member countries in the European Monetary Union (EMU) area. Thus, due to nominal rigidities in the euro area (see for instance Burda (2001) and López-Salido *et al.* (2005)), possible asymmetric inflation responses may indeed lead to undesired real effects in EMU member countries and monetary policy loses its stabilising role in the short or medium term.

Not surprisingly, there is a body of vector autoregressive (VAR) studies[1] in which the monetary policy shock in each of the individual countries of the euro area is investigated and cross-country comparisons are made. The differences in the results presented in this literature are striking, since a host of theoretical, statistical and data issues are involved in empirical analyses. We pinpoint the following major problems in this literature, also highlighted by Peersman (2004):

i) Typically, the same model is estimated for each individual country. This tends to be misleading, since each country has a different economic structure and has its own monetary policy reaction function.

ii) The size of the estimated monetary policy shock differs across countries. This tends to complicate the comparability of the

[1] For more detailed surveys, see for example Mojon and Peersman (2001) and Peersman (2004). See also Angeloni and Ehrmann (2004), who use quarterly EMU panel data over the period 01/1998-02/2003 to track down the sources of the inflation differences among the EMU member countries. They employ a similar but open-economy version of the model to that we use by, letting the real exchange rate variable exist in both the Phillips and IS equations. They estimate a structural 12-country model consisting of all (original) EMU member countries with instrumental variable techniques and then simulate the model. They also perform a sensitivity analysis, changing the values of interesting parameters inside their confidence intervals. They find that the magnitude of inflation persistence is the driving force generating inflation divergence, not the monetary policy transmission mechanism, as has been suggested in the literature. One could also read Sala (2001) and Clements *et al.* (2001) on transmission of monetary policy in the euro area.

effect of shocks.

iii) It is not clear whether differences in monetary policy responses between countries are statistically significant, given the relatively wide confidence bands around the responses.

Peersman (2004) takes into account the aforementioned and finds support for statistically significant asymmetric price level responses in the euro area. His empirics are based on synthetic euro area data for seven EMU member countries and a large-scale near-VAR model. We find it problematic in Peersman's analysis that, while the autoregressive coefficients are estimated consistently, the standard bootstrapped error bands for impulse responses may well be biased as a consequence of small sample size; this is especially the case in the presence of non-stationary data; see arguments for this view for instance in Kilian (1998).

This paper adds to the literature in the following respects: empirical results are based on actual European Central Bank's monetary policy conduct, guaranteeing that the size of the monetary policy shock is the same across the EMU member countries. Secondly, in model estimation we follow an approach which adopts the structural VAR (SVAR) model using parameter restrictions derived from the macro model to achieve the identification of structural in VAR model. This means that we can deduce identifying parameter restrictions from a 5-equation open-economy dynamic stochastic general equilibrium (DSGE) model that captures economic conditions of the euro area.

The parameter restrictions implied by the underlying model are taken as *a priori* knowledge in estimating the posterior distribution of the SVAR model. The approach parallels Sims' (1980) suggestion that one should restrict the VAR model parameters consulting economic theory. A fruitful general discussion of new Keynesian DSGE models can be found e.g. in, Clarida *et al.* (1999, 2000), Hetzel (2000), Roffia and Gerdesmeier (2003) and Walsh (2003). The survey of Sungbae and Shorfheide (2007) summarizes advances made in Bayesian estimation of DSGE models.

Thirdly, in this study we employ a posterior distribution of structural VAR parameters to calculate empirical impulse responses of inflation in the euro area aggregate and the individual EMU member country to an unanticipated shock to a common monetary policy instrument. We emphasize that using posterior-based error bands rather than classical confidence bands allows us to report bands which characterize the true shape of the likelihood. This provides unbiased statistical analysis, especially in the case of finite samples or nearly unit root series; see e.g. Sims and Zha (1999).

The empirical results of the paper are in contrast to those of Peersman (2004), Antipin and Luoto (2005) and Antipin (2008). This paper finds that data very weakly supports asymmetric price inflation responses to a common monetary policy shock in the euro area. Only for Belgium, Germany, Spain, Netherlands and Portugal one sees slight asymmetric price inflation response behaviour. However, these inflation responses vanish one month after the shock.

The paper is organized as follows: Section 2 presents the statistical framework, Section 3 illustrates the estimating data and comments on the drawn impulse response functions and Section 4 comprises concluding remarks.

4.2 Estimating Model

In the model presented below we assume that the euro area's *j*th member country represents the domestic small open economy. Secondly, we let the rest of the member countries in the euro area together represent the rest of the world. Thus, in what follows, a foreign country is a small EMU member country, and variables with * superscripted correspond to the rest of the euro area.

Model equations[2] write as

$$\begin{aligned} \pi_t &= \alpha_1 E_t\{\pi_{t+1}\} - \alpha_2 E_t\{\Delta\hat{s}_{t+1}\} + \alpha_3 \Delta\hat{s}_t + \\ &\quad \alpha_4 \hat{s}_t + \alpha_5 \hat{y}_t^* - \alpha_6 z_t, && (1) \\ \pi_t^* &= \beta_1 E_t\{\pi_{t+1}^*\} + \beta_2 \hat{y}_t^* - \beta_3 z_t^*, && (2) \\ \hat{y}_t &= \hat{y}_t^* + \kappa_1 \hat{s}_t, && (3) \\ \hat{y}_t^* &= E_t\{\hat{y}_{t+1}^*\} - \psi_1\left(r_t^* - E_t\{\pi_{t+1}^*\}\right) \quad \text{and} && (4) \\ \hat{s}_t &= \gamma_1 E_t\{\hat{s}_{t+1}\} + \gamma_2 \hat{s}_{t-1} + \gamma_3\left(z_t - z_t^*\right), && (5) \end{aligned}$$

where consumer price inflation is defined as $\pi_t = \log(P_t / P_{t-1})$ and z_t and z_t^* are total factor productivity (TFP) following both independent AR(1) processes with i.i.d. technology shocks, u_t and u_t^*, respectively.

2 The model is based on Galí and Monacelli (1999) and Galí and Monacelli (2005). The detailed derivations of the model equations are available upon a request.

Equations (1) and (2) are derived from optimal price-setting conditions of firms located in the individual EMU member country and in the euro area. These equations govern the inflation dynamics (supply side) of the respective economies. Equation (3) determines the demand in EMU member country as a function of the euro area demand. Equation (4) is the output gap measuring demand in the euro area. Equation (5) is the stochastic difference equation for the terms of trade (TOT) and it has been derived assuming that the weight of the imports in the euro area's consumer price index can be considered negligible, and that at time *t*, euro area (π_t^*) and individual EMU member country (π_t) inflation series are mutually uncorrelated. r_t^* is the euro area's nominal interest rate and will eventually be modelled using a variant of the Taylor rule.

The model[3] described in Equations (1) – (5) contains forward looking variables. One can write these as function of past values of model variables and exogenous TFP processes such as

$$E_t\{\pi_{t+1}\} = \frac{1}{\alpha_1}\left[\pi_t + \left(\frac{\alpha_2}{\gamma_1} - \alpha_2 - \alpha_3 - \alpha_4\right)\hat{s}_t + \left(\alpha_3 - \frac{\alpha_3\gamma_2}{\gamma_1}\right)\hat{s}_{t-1} - \alpha_5\hat{y}_t^* + (\alpha_6 - \alpha_2\gamma_3)z_t + \alpha_2\gamma_3 z_t^*\right], \quad (1^*)$$

$$E_t\{\pi_{t+1}^*\} = \frac{1}{\beta_1}\left[\pi_t^* - \beta_2\hat{y}_t^* + \beta_3 z_t^*\right], \quad (2^*)$$

$$E_t\{\hat{y}_{t+1}^*\} = \left(1 + \frac{\psi_1\beta_2}{\beta_1}\right)\hat{y}_t^* + \psi_1\left(r_r^* - \frac{1}{\beta_1}\left(\pi_t^* + \beta_3 z_t^*\right)\right), \quad (4^*)$$

and

$$E_t\{\hat{s}_{t+1}\} = \frac{1}{\gamma_1}\left[\hat{s}_t - \gamma_2\hat{s}_{t-1} - \gamma_3\left(z_t - z_t^*\right)\right]. \quad (5^*)$$

We presume that the form of the theoretical model might be unknown for households and firms, but we assume that they know that endogenous variables depend on autocorrelated exogenous processes (TFP)[4]. Endogenous variables are autocorrelated also since the TPF processes are autocorrelated by assumption. Households and firms use available information to form expectations of relevant variables i.e. these forecasts are consistent with the model framework outlined above. Hence, we borrow from the learning literature (Eg. Evans and Honkapohja, 2001) and specify forecasting functions for π, π^*, $\hat{y}^*$ and

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[3] We drop Equation (3) from the system, since by assumption domestic (individual EMU member country) output term has no influence on the rest of the system.

[4] The model in Equations (1) – (5) (excluding Eq. (3)) is of form $x_t = BE_t(x_{t+1}) + Gz_t$ where $z_t = \rho z_{t-1} + u_t$ with diagonal covariance matrix for u_t. The minimum state variable (MSV) solution for a model is $x_t = Qz_t$ (it is assumed that households know this). Hence $E_t(x_{t+1}) = \rho Qz_t$ which leads to $x_t = [B\rho Q + G]z_t = [B\rho Q + G]\rho Q^{-1}x_{t-1} + [B\rho Q + G]u_t$.

$\hat{s}$. Since the prediction accuracy of univariate time series models is reported to be at least as good as the accuracy of the multivariate models, we thereby assume that households and firms apply univariate autoregressive models in forming their inflation, output gap, and/or terms of trade expectations; see Stock and Watson (1999) and Marcellino *et al.* (2003). Specifically, forecast functions for the model variables are

$$E_t\{\pi_{t+1}\} = b_1(L)\pi_t + b_2(L)\hat{y}_t^* + b_3(L)\hat{s}_t, \quad (6)$$
$$E_t\{\pi_{t+1}^*\} = b_4(L)\pi_t^* + b_5(L)\hat{y}_t^*, \quad (7)$$
$$E_t\{\hat{y}_{t+1}^*\} = b_6(L)\hat{y}_t^* + b_7(L)r_t^* + b_8(L)\pi_t^* \quad (8)$$

and

$$E_t\{\hat{s}_{t+1}\} = b_9(L)\hat{s}_t, \quad (9)$$

where $b_i(L)$ is the polynomial of lag operator L with lag length p. Equations (6) and (7) are backward-looking Phillips curves. Equations (8) and (9) are attained in the spirit of equations of the log-linearized model above. One should note that we have assumed that the processes have converged, providing that decisions made by agents are optimal.

When it comes to choosing the statistical model, we could use e.g. a simple, empirical-based interest rate rule and approach the problem as do by e.g. Christiano *et al.* (2005) and generate values for the impulse response function from the structural model. However, we find that there is a possibility that a simple structural model cannot approximate the true data generating process sufficiently satisfactorily and we therefore suggest the following strategy to generate impulse responses from a SVAR model using the information of the model presented above; see for a discussion of the identification of SVAR models, e.g. Sims (1986), Gordon and Leeper (1994), and Cushman and Zha (1996). We assume that the ECB uses an empirical-based Taylor rule with a smoothing term in its conduct of monetary policy. Now, having defined the necessary variables we combine Equations (1)-(9) and write the estimating model in a form

$$r_t^* = \beta_0 + (1-\rho)\left[\beta_1\pi_t^* + \beta_2 y_t^*\right] + \sum_{i=1}^{p}\rho_i r_{t-i}^* + \varepsilon_{r_t^*,t}, \quad (10)$$

$$(1-c_{0,1})\pi_t = c_1 + c_{0,2}\hat{y}_t^* + c_{0,3}\hat{s}_t + \sum_{i=1}^{p}c_{i,1}\pi_{t-i} + \sum_{i=1}^{p}c_{i,2}\hat{y}_{t-i}^* + \sum_{i=1}^{p}c_{i,3}\hat{s}_{t-i} - \sum_{i=0}^{p}c_{i,4}z_{t-i}, \quad (11)$$

$$(1-c_{0,5})\pi_t^* = c_{0,6}\hat{y}_t^* + \sum_{i=1}^{p}c_{i,5}\pi_{t-i}^* + \sum_{i=1}^{p}c_{i,6}\hat{y}_{t-i}^* - \sum_{i=0}^{p}c_{i,7}z_{t-i}^*, \quad (12)$$

$$\left(1-c_{0,8}\right)\hat{y}_t^* = c_{0,9}r_t^* + c_{0,10}\pi_t^* + \sum_{i=1}^{p} c_{i,8}\hat{y}_{t-i}^* + \sum_{i=1}^{p} c_{i,9}r_{t-i}^* + \sum_{i=1}^{p} c_{i,10}\pi_{t-i}^* + \sum_{i=0}^{p} c_{i,11}z_{t-i}^* \qquad (13)$$

and

$$\left(1-c_{0,12}\right)\hat{s}_t = c_2 + \sum_{i=1}^{p} c_{i,12}\hat{s}_{t-i} + c_{13}\left(z_t - z_t^*\right). \qquad (14)$$

The empirical analysis is based on the Equations (10)–(14). In particular, as Sims and Zha (1998, 1999) we specify and estimate SVAR model of the following form

$$A(L)y(t) + D = \eta(t), \qquad (15)$$

where $y(t)$ is an (mx1) vector of observations, $A(L)$ is an (mxm) matrix polynomial of lag operator L with lag length p and non-negative powers, D is a constant vector, $A = \Lambda^{-0.5}\Gamma$, and $\eta(t) = \Lambda^{-0.5}\varepsilon(t)$ so that

$$\eta(t)\big|\, y(s), s < t \sim N\Big(0, \underset{m\times m}{I}\Big).$$

For Equation (15) we let

$$y(t) = \begin{pmatrix} \pi_t^* \\ \hat{y}_t^* \\ r_t^* \\ \pi_t \\ \hat{s}_t \end{pmatrix} \quad \text{and} \quad A(0) = \begin{pmatrix} a_{0,11} & a_{0,12} & 0 & 0 & 0 \\ a_{0,21} & a_{0,22} & a_{0,23} & 0 & 0 \\ a_{0,31} & a_{0,32} & a_{0,33} & 0 & 0 \\ 0 & a_{0,42} & 0 & a_{0,44} & a_{0,45} \\ 0 & 0 & 0 & 0 & a_{0,55} \end{pmatrix},$$

suggesting that $A(0)$, where the zero restrictions are set using the system of Equations (10)-(14), is a non-singular matrix, so that the model provides a complete description of the p.d.f. for the data conditional on the initial observations.

Equation (15) is of the same form as the system of Equations (10)-(14), except that the unobservable error vector $\varepsilon(t)$ approximates the moving average of the productivity shocks u_t and u_t^* (except the third row of the vector, that is $\varepsilon_{r_t^*,t}$), and there are zero restrictions only on the $A(0)$ matrix. We write the model in Equation (15) in matrix form

$$YA_0 - XA_+ = E, \qquad (16)$$

where the tth rows of the Y (Txm) matrix, the X (Txk) matrix, and the E (Txm) matrix are given by $y(t)$, $(1\ y'(t\text{-}1)\ \ldots\ y'(t\text{-}p))'$, and $\eta(t)$ respectively. Thus, $k = mp+1$ is the number of coefficients corresponding to X, T is the number of observations, $A(0)' = A_0$ (mxm) matrix and A_+ is the (kxm) matrix of parameters of lagged model variables.

Since the model errors in Equation (15) are assumed to be normally distributed, we specify the likelihood function of the model accordingly. The likelihood function takes the following Gaussian form

$$L(Y|A) \propto |A_0|^T \exp\{-0.5tr(YA_0 - XA_+)'(YA_0 - XA_+)\}. \tag{17}$$

We denote $vec(A_0) = a_0$ and $vec(A_+) = a_+$. By defining $a = (a'_0\ a'_+)'$, we are now able to write the joint prior p.d.f. of a as

$$p(a) = p_0(a_0)N(\tilde{a}_+, H), \tag{18}$$

where $p_0(a_0)$ is the marginal distribution of a_0 and $N(\tilde{a}_+, H)$ is the standard multivariate normal p.d.f. with $\tilde{a}_+$ as mean and H as covariance matrix. Thus, the posterior density of the parameters in vector a writes

$$\begin{aligned} q(a) \propto |A(0)|^T \exp\{-0.5[a_0'(I \otimes Y'Y)a_0 - 2a_+'(I \otimes X'Y)a_0 + a_+'(I \otimes X'X)a_+]\} \\ \times p_0(a_0)|H|^{-0.5} \exp\{-0.5(a_+ - \tilde{a}_+)' H^{-1}(a_+ - \tilde{a}_+)\}. \end{aligned} \tag{19}$$

Although the posterior density in Equation (19) is non-standard in general, the exponent in Equation (19) is quadratic in a_+ for given a_0. This suggests that the conditional distribution of a_+ for a_0 is Gaussian, allowing Monte Carlo sampling and analytic integration along the a_+ dimension; see Sims and Zha (1998).

We assume that the elements in vector a_+ are zero a priori. To specify our prior variance for parameters (a_+) of lagged variables (we call the model of this prior specification *Model 1*), we let a_{+i} represent the regression parameters of lagged variables of the ith equation in linear multivariate model in Equation (15). Then

$$Var(a_{+i}) = \begin{cases} \lambda_1 p^{-1}, & \text{for non-zero parameters in the system of equations (10) - (14)} \\ \lambda_2 p^{-1}, & \text{for zero 'parameters' in the system of equations (10) - (14)} \\ \lambda_3\ , & \text{for a constant parameter} \end{cases}$$

As usual, p denotes the lag length, and the hyper parameters λ_i (i = 1, 2, 3) control the tightness of prior beliefs. We set the hyper parameters $\lambda_1 = \lambda_3 = 10{,}000$ and evaluate the posterior density of hyper parameter λ_2. In setting the prior variance, we do not use typical scale factors, as e.g. Kadiyala and Karlsson (1997) and Sims and Zha (1998), since we have no prior knowledge of these. One could follow Litterman (1986) and choose prior variances as the sample standard deviations of residuals from univariate autoregressive models. However, we feel uncomfortable doing this since, at least in principle, these should be chosen on the basis of a priori reasoning or knowledge.

The idea behind the prior variance structure of *Model 1* is that with a smaller value of λ_2, the linear multivariate model in Equation (15) is closer to the form of the system of Equations (10)-(14), while high values of λ_1 and λ_3 indicate the importance of lagged variables which the system of Equations (10)-(14) predicts to have influence on left-hand side variables. However, it is reasonable to assume that the importance of the lagged variables decreases with lag length; see e.g. Kadiyala and Karlsson (1997).

One can show that, for the posterior in Equation (19), with an exponential prior for hyper parameter λ_2, the conditional distribution of a_+ and the joint marginal distribution of λ_2 and a_0 can be derived as

$$q(a_+|a_0,\lambda_2) = N\left(\bar{a}_0; \left(I \otimes X'X + H(\lambda_2)^{-1}\right)^{-1}\right), \tag{20}$$

$$q(a_0,\lambda_2) \propto p_0(a_0)|A(0)|^T \left|\left(I \otimes X'X\right)H(\lambda_2) + I\right|^{-0.5} \exp\left(-\frac{\lambda_2}{\tau}\right)$$
$$\times \exp\left\{-0.5\left[a_0'\left(I \otimes Y'Y\right)a_0 + \tilde{a}_+' H(\lambda_2)^{-1}\tilde{a}_+ - \bar{a}_0'(\lambda_2)\left(I \otimes X'X + H(\lambda_2)^{-1}\right)\bar{a}_0(\lambda_2)\right]\right\}, \tag{21}$$

where H is chosen to match the prior variance defined above. Parameter τ is the prior mean of hyper parameter λ_2 and

$$\bar{a}_0(\lambda_2) = \left(I \otimes X'X + H(\lambda_2)^{-1}\right)^{-1}\left(\left(I \otimes X'Y\right)a_0 + H(\lambda_2)^{-1}\tilde{a}_+\right).$$

In the estimation, we set $\tau = 100$ so that the prior variance of hyper parameter λ_2 is 10,000. We use a *flat* prior on $A(0)$; see Sims and Zha (1998) for a discussion of flat priors.

In order to satisfy the rank condition for identification, we fix the Taylor rule parameters such that $\beta_1 = 1.5$, $\beta_2 = 0.5$, and $\rho = 0.9$; see on motivation for use of these parameter values of β_1, β_2, and ρ as in Roffia and

Gerdesmeier (2003). Specifically, we acquire posterior modes of parameter matrices $\Gamma(0)$ and Λ in linear multivariate model in Equation (15), where diagonal elements of $\Gamma(0)$ are normalized to one and β_1, β_2 and ρ remain fixed[5]. We transform the estimated modes of $\Gamma(0)$ and Λ back to the $A(0)$ parameter space using the following relation $A(0) = \Gamma(0)\Lambda^{-0.5}$. We apply transformed values to set the non-zero restrictions on the elements $a_{0,31}$ and $a_{0,32}$ in matrix $A(0)$.

Since the sign of a row of $A(0)$ can be reversed without changing the likelihood function, we follow Waggoner and Zha (1997) and Sims and Zha (1999) in choosing a normalization for each draw that minimises the distance of $A(0)$ from the posterior mode estimate of $A(0)$. As Sims and Zha comment, this method will tend to hold down spurious sign-switching of impulse responses and thereby deliver sharper results than e.g. normalization, where diagonal elements of $\Gamma(0)$ are normalized to one.

We also modify the specification of *Model 1* such that we assume large-country variables to be block-exogenous with respect to small-country variables (let us call this *Model 2*). For *Model 2*, we use a posterior density of Equation (19) with zero prior mean for a_+ and prior variance specified as

$$Var(a_{+i}) = \begin{cases} \lambda_1 p^{-1}, & \text{for parameter on endogenous variables} \\ \lambda_2 p^{-1}, & \text{for parameter on exogenous variables} \\ \lambda_3 \ , & \text{for constant parameter} \end{cases},$$

where $\lambda_1 = \lambda_3 = 10{,}000$ and $\lambda_2 = 0.005$. Our exogenous prior restrictions for lagged variables are determined using the assumption that the terms of trade and the small open economy's inflation has zero effects on the euro area inflation, output and interest rates series (see Cushman and Zha, 1996). The prior for $A(0)$ is equal to that above and the conditional and marginal posterior densities are

$$q(a_+|a_0) = N\left(\overline{a}_0; \left(I \otimes X^{'}X + H^{-1}\right)^{-1}\right), \tag{22}$$

$$q(a_0) \propto |A(0)|^T \left|\left(I \otimes X^{'}X\right)H + I\right|^{-0.5}$$
$$\times \exp\left\{-0.5\left[a_0^{'}\left(I \otimes Y^{'}Y\right)a_0 + \widetilde{a}_+^{'}H^{-1}\widetilde{a}_+ - \overline{a}_0^{'}\left(I \otimes X^{'}X + H^{-1}\right)\overline{a}_0\right]\right\}, \tag{23}$$

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[5] We use a flat prior on $A(0)$, which is transformed to the $(\Gamma(0), \Lambda)$ parameter space, including the appropriate Jacobian term $|\Lambda|^{-(m+1)/2}$; see Sims and Zha (1999) and Waggoner and Zha (1997).

in which H is chosen to match the (exogenous) prior variances defined above, and

$$\bar{a}_0 = \left(I \otimes X^{'}X + H^{-1}\right)^{-1}\left(\left(I \otimes X^{'}Y\right)a_0 + H^{-1}\tilde{a}_{+}\right).$$

The joint marginal p.d.f. of a_0 and λ_2 for *Model 1* in Equation (21) and marginal p.d.f. of a_0 for *Model 2* in Equation (23) are not in the form of a standard p.d.f. We have therefore used a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MCMC) sampling to generate a Monte Carlo samples from them.

4.3 Data

The euro area data and the series for each EMU member country[6] are downloaded from two data sources. Seasonally adjusted and construction activities excluded, monthly industrial production indices (IIP; in empirics $\hat{y}_t^*$ is calculated using euro area's IIP and its potential level) from the beginning of 1980 to the end of the 80s are from the OECD main economic indicators. The EuroStat provides the IIP series up to April 2006. The annual series for gross domestic product (GDP), population, and monthly series for the harmonized index of consumer price (HICP; $HICP_t^*$ and $HICP_t$) and Euro overnight index average (Eonia, r_t^*) interest rates are also downloaded from EuroStat. The monthly series of the producer price index (PPI) (without construction) over the period 1998 to April 2006 is seasonally unadjusted with base year 2000, and is also provided by EuroStat. The base year for the IIP index is 2000, the GDP is measured in 2005 prices and the base year for the HICP indices is 2005. Annual population is a measure of the total population at the end of the current year. GDP values are from 1991[7] to 2005 and the population variable covers the period from 1980 to 2005. The monthly series for HICP[8] are from January 1999 to April 2006, as are series for the Eonia interest rate depicting the values of the monetary policy instrument.

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[6] EMU member countries are Belgium, Germany, Spain, Austria, France, Italy, Ireland, Luxembourg, Netherlands, Portugal and Finland. No dataset for Greece is constructed, since Greece has been an EMU member country only from the beginning of 2001, and hence we would not have an equal body of observations.

[7] GDP values for 1991 are used to replace the unavailable GDP values for the years 1980 to 1990.

[8] However, values for 1998 are used in the calculation of monthly and year-on-year differences of HICP series required in *Model 1* and *Model 2* and robustness VAR model specifications.

Leaving the empirics in line with the model we assign each EMU member country in turn to be the small country and let the rest of the member countries represent the large country whose variables are denoted with the *-superscript as indicated above. We will construct in total 11 different datasets such that the observations for the given EMU member country (small country) are neglected while calculating the variable values for the euro area (large country). In so doing, we assume that the annual GDP and the annual population both have 50% weight in constructing the weight of the given country. In empirics, the original monthly series for the HICP and PPI series are used for the member country *j* and the values of the relevant variables for the euro area (large country) are constructed such that we first multiply the variable values of the remaining member countries with the annual weight share and sum these to obtain the GDP and population-weighted averaged variables. Proceeding thus ensures that the information content of the member country variables is not included in the euro area variables.

In the estimation of *Model 1* and *Model 2* we let $y'(t)=\left(\pi_t^* \ \hat{y}_t^* \ r_t^* \ \pi_t \ \hat{s}_t\right)$, where

π_t^* is the annualized price inflation rate for the euro area i.e. $12\log(HICP_t^* / HICP_{t-1}^*)$,

π_t is the annualized price inflation rate for member country i.e. $12\log(HICP_t / HICP_{t-1})$,

$\hat{y}_t^*$ is the euro area output gap,

r_t^* is the eonia interest rate and

$\hat{s}_t$ is the terms of trade between the euro area and the member country; $\log(PPI_t^* / PPI_t)$.

Additionally in chapter 4.5 while validating the robustness of *Model 1* and *Model 2* results we use year-on-year inflation rates (denoted as $a\pi_t^*$ and $a\pi_t$) together with monthly and annual IIP growth rates (denoted as $\Delta \log Y_t^*$ and $\Delta_{12} \log Y_t^*$).

Figure A (in Appendix 1) plots the euro area IIP aggregate and Eonia interest rate series, and Table 1 below Figure A contains the simple correlation coefficients between the log-differenced values for the actual euro area IIP aggregate and log-differenced[9] values for the above described IIP series. One notes that the correlation coefficients are high.

[9] To avoid the possibility of spurious regression (correlation), we use first a differenced series of variables in calculating the correlation coefficients.

Figures B-E draw the euro area annualized HICP inflation series together with the annual HICP inflation series for each EMU member country together with the Eonia interest rate. In Figure B, we see that in general, the HICP inflation series for the euro area and Germany, France, and Italy indeed show convergent behavior, while this is not the case for the rest of the EMU member countries. Table 2 collects the correlation coefficients between the log-differenced values of the constructed euro area HICP and the actual euro area HICP series. From the table we observe that these coefficients are really high. The estimated sample correlation coefficients indicate nearly perfect correlation (excluding Germany).

Figure F shows how the producer price inflation in the euro area and the Eonia interest rate both have evolved during the common monetary policy era. Interestingly, while the euro area producer prices have had an upward trend and the values of the monetary policy instrument have practically remained constant. As shown in Table 3, the correlation coefficient between the log-differenced values of the constructed euro area PPI and the actual euro area PPI series are high, but not as high as the correlation coefficients for the log-differenced HICP series.

We use a one-sided version of the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) to produce a trend estimate for the euro area's IIP[10] series when we measure the output gap for the euro area ($\hat{y}_t^*$). The one-sided trend estimate approximating the potential output is constructed as the Kalman filter estimate in the model

$$\log Y_t^* = \log \hat{Z}_t^* + v_t \tag{24}$$

$$(1-L)^2 \log \hat{Z}_t^* = \xi_t, \tag{25}$$

where $\hat{Z}_t^*$ is the unobserved trend component, and v_t and ξ_t are mutually uncorrelated white noise sequences with relative variance δ = var(ξ_t)/var(v_t). We follow Stock and Watson (1999) and set $\delta = 0.67 \text{x} 10^{-3}$, which approximately matches the spectral gain for the HP filter.

In the literature, for example in Galí and Gertler (1999), the labor's share in output is also used as a proxy for marginal costs in spite of the output gap variable. Neiss and Nelson (2005), in contrast, report using data for the United States, the United Kingdom, and Australia, where labor costs do not suffice to explain inflation dynamics as well as the output gap.

[10] Most of the methods which detrend output variables use both future and past values of the series. This makes these methods unsuitable for forecasting purposes because households and firms cannot observe future observations when they form their expectations.

4.4 Results

We begin the analysis by first estimating the lag length for *Models 1* and *2* (we estimate in total 22 SVAR models). VAR model lag length estimates are based on the fractional marginal likelihoods (FML) of the models; see Villani (2001). The lag lengths of the estimated SVAR models are reported in Table 5 in Section B in Appendix 2.

To generate a Monte Carlo sample from the joint posterior of the elements of a_0 and λ_2 in Equation (21) and the posterior of the elements of a_0 in Equation (23), we use a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MMCMC). The algorithm uses a multivariate normal distribution for the jump distribution on changes in the elements of a_0. In the case of *Model 1*, our simulation procedure is as follows (others are close variants of this). We first simulate 20,000 draws using a diagonal covariance matrix with diagonal entries 0.00001 in the jump distribution. Then we use the last 10,000 draws to estimate the posterior covariance matrix of λ_2 and the elements of a_0 and scale it by the factor $(2.4)^2/11$ (since there are 11 unknown parameters) to obtain an optimal covariance matrix for the jump distribution; see e.g. Gelman *et al.* (2004). If necessary, we continue the simulation and use these new draws to calculate a more accurate covariance matrix for λ_2 and the elements of a_0. Finally, we run 50,000 draws, and after eliminating the burn-in period, we pick up every 100th draw. In the other cases, the Markov Chains converge to stationary distributions after 50,000 draws. The convergence diagnostics, numbers of draws, the burn-in period and the acceptance ratios are listed in Table 4 in Appendix 2, Section B. The acceptance ratios indicate that chains were moving in the sampling process and Geweke z-statistics display that chains have converged to stationary distributions (see Eg. Roberts *et al.*, 1997).

Figures 1a and 1b in Section 2 in Appendix 1 show the difference in the response of inflation in the area-wide inflation (excluding domestic values) with the individual country inflation response. The impulse responses shown are based on *Model 1* and *Model 2*. The figures display a point estimate (median) of the impulse response and 68 per cent posterior intervals. The monetary policy shock has the size of one standard deviation.

The impulse responses show that the reactions of inflation to a shock to a common monetary policy are similar across the EMU countries. That is, our data lend rather strong support for the impulse responses being zero. This result contradicts the results of Peersman (2004). The major reason for the difference between his and our results could be due to our standard treatment of unit root price series; we use the log-differenced series while Peersman estimates his model with variables in levels. We also note that standard bootstrapped confidence intervals may give too optimistic a view of precision due to the assumption of stationary data-generating processes, which does not typically hold when the variables are modelled in levels (Kilian, 1998).

Taking a closer look at the impulse responses drawn, we see that immediate asymmetric inflation responses can be found for Spain. However, since responses die out during the first period, we should be very careful in asserting that the ECB's monetary policy causes asymmetric price responses in the euro area. A finding that inflation responses are similar across EMU member countries is due to that the error bands of the impulse responses contain zero. Worthwhile to note is that in most cases also the median response is fairly close to zero.

Finally, Table 4 in Appendix 2 (Section B) shows central tendency estimates (median and mean) of hyper-parameter λ_2. The hyper-parameters are estimated to be relatively small, suggesting that parameter zero restrictions derived from the underlying macro model should be acknowledged in the estimation.

4.5 Robustness of Results

To control for the robustness of the results we derive impulse responses from the reduced-form VAR models. We identify the VAR models using a recursive approach (Cholesky identification) with different orderings of variables.

The estimation form of a reduced VAR is given by

$$B(L)y(t) + D = v(t), \tag{26}$$

where $y(t)$ is a (mx1) vector of observations, $B(L)$ is a (mxm) matrix polynomial of lag operator L with lag length p and non-negative powers, D is a vector of constants, $B(0) = I$ and vector of error terms $v(t)$ is assumed to be normally distributed with zero mean and Ω covariance matrix. In the linear multivariate model above, we use normal likelihood coupled with traditional uninformative Jeffreys' priors for the model parameters, and lower triangular identification restrictions to generate identified impulse responses. For further discussion of Jeffreys priors in multivariate regressions see Zellner (1971).

Section A in Appendix 2 gives alternative orderings of variables in the estimated reduced-form VAR models. The lag lengths used in the reduced-form VAR models for different variable orderings are listed in Table 5 in the Appendix 2 (Section B). The lag lengths were attained in the way as they were for *Model 1* and *Model 2*.

Figures 2a-c in Appendix 1 (Section 3) draw the impulse responses of the Cholesky identified VAR models with different ordering of variables. In general, we find moderate support in the data for symmetry of inflation responses. Specifically, the differences of the response of inflation in the euro area from the individual EMU member country inflation response are flat except in the cases of Belgium, Germany, Spain, Netherlands and Portugal, for which the Cholesky identification yields asymmetric behavior in inflation responses. A closer inspection shows that these results are in line with the impulse responses drawn in the first essay where Cholesky decomposition of similarly ordered variables was also used.

However, the Cholesky identification produces spurious results for the ECB's reaction function. We find that the Taylor rule parameter estimates indicate counterintuitive monetary policy. That is, according to our estimation results (not reported to save space), the ECB would aim for lower (higher) interest rates during a high (low) inflation and output period. Thus, in our case we must exercise extreme caution regarding the results based on these exactly identified VAR models.

4.6 Conclusions

In this paper we estimated structural vector autoregressive (SVAR) models to describe the posterior distribution of impulse responses of the difference in response of inflation in the euro area from that of individual EMU member country inflation response. We acquired prior knowledge of parameters' zero restrictions from the underlying new Keynesian open-economy macro model. We found that using economic theory to specify an econometric model is crucial, since e.g. a traditional exactly identified recursive approach produced parameter estimates indicating spurious regression.

Our results indicate that the euro area monthly data does not support the claim that the consumer price inflation responses to an unanticipated common monetary policy shock are asymmetric in the EMU member countries. The result contradicts the finding of Peersman (2004), Antipin and Luoto (2005) and Antipin (2008). It seems fair to say that responses of inflation in EMU member countries to monetary policy conducted by the ECB is not likely to cause undesired real income differences between EMU member countries in consequence of unexpected, asymmetric fluctuations in demands of domestic goods.

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Appendix 1: Figures of Data and Impulse Responses

1. Figures (A-F) and Tables (1-3)

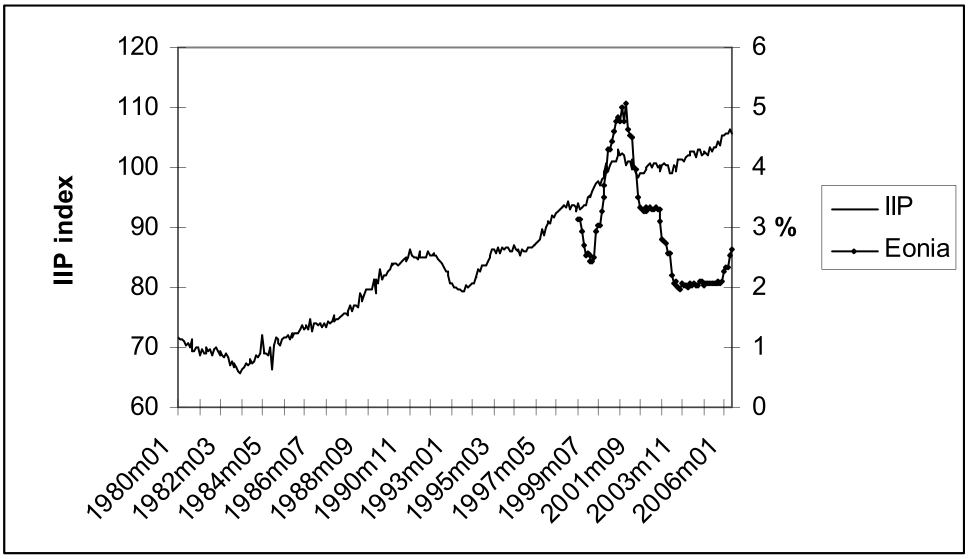
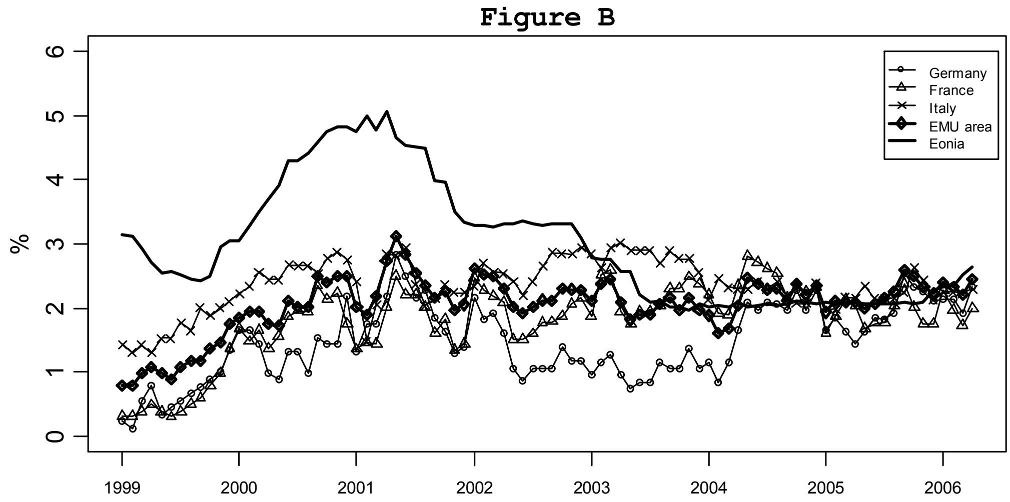
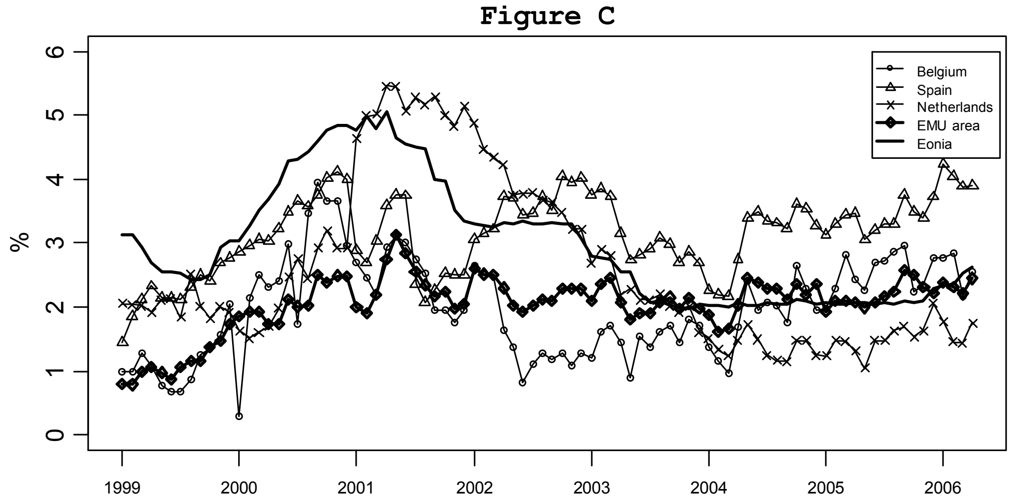


FIGURE A: Industrial Production Index (IIP) for the euro area (base year 2000) and the Eonia interest rate series.

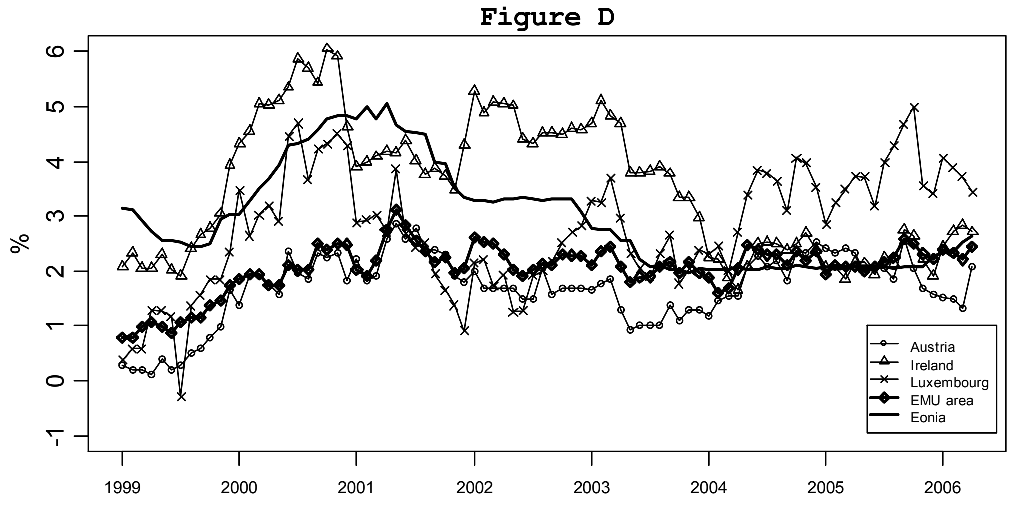
TABLE 1. Correlations between log-differences of the constructed and actual IIP series for the euro area.

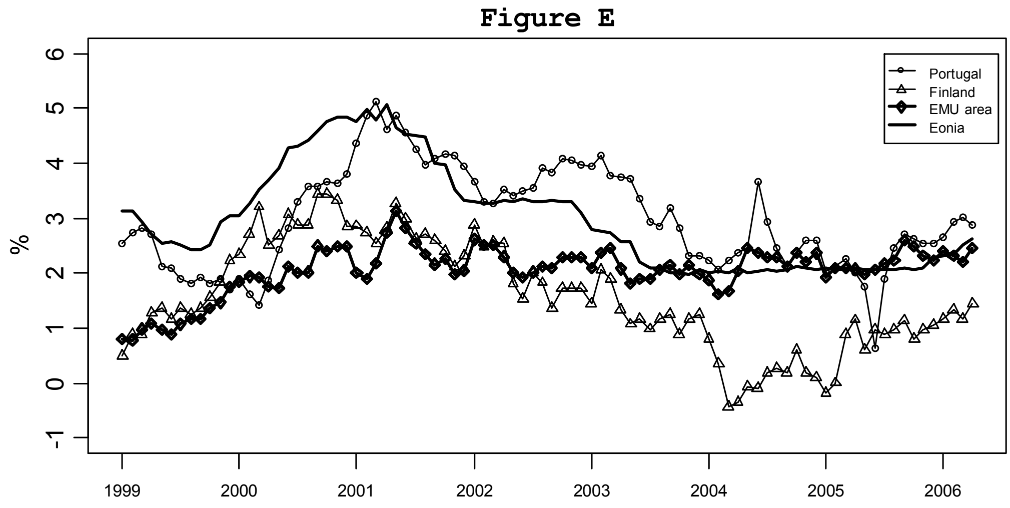
Sample 1980/m2 – 2006/m4										
BEL	GER	SPA	FRA	IRE	ITA	LUX	NETH	AUST	POR	FIN
0.80	0.67	0.77	0.75	0.79	0.78	0.79	0.78	0.79	0.78	0.79





FIGURES B-C: Actual year-on-year HICP inflations for Germany, France, Italy (Fig. B), and Belgium, Spain and the Netherlands (Fig. C) together with the euro area year-on-year HICP inflation and the Eonia interest rate series, sample period is Jan 1999 – April 2006.





FIGURES D-E: Actual year-on-year HICP inflations for Austria, Ireland, Luxembourg (Fig. D), and Portugal and Finland (Fig. E) together with the euro area year-on-year HICP inflation and the Eonia interest rate series, sample period is Jan 1999 – April 2006.

TABLE 2. Correlations between log-differences of constructed HICP and actual HICP series for the euro area.

Sample 1999/m1 – 2006/m4										
BEL	GER	SPA	FRA	IRE	ITA	LUX	NETH	AUST	POR	FIN
0.98	0.88	0.98	0.97	0.98	0.96	0.98	0.98	0.98	0.98	0.98

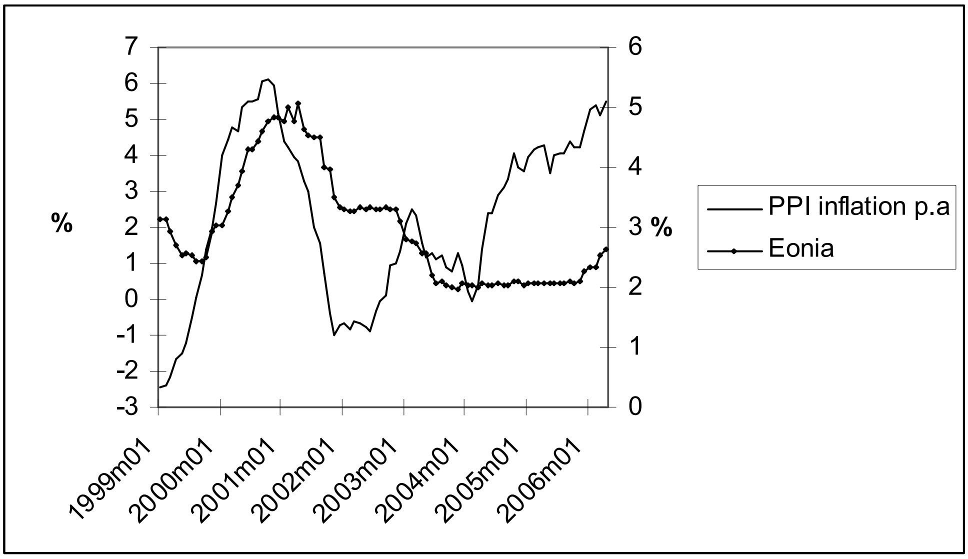


Figure F: Year-on-year Producer Price inflation for the euro area and the Eonia interest rate series (Left y-axis is for year-on-year PPI inflation values), sample period is Jan 1999 – April 2006.

TABLE 3. Correlations between log-differences of constructed PPI and actual PPI series for the euro area.

Sample 1999/m1 – 2006/m4										
BEL	GER	SPA	FRA	IRE	ITA	LUX	NETH	AUST	POR	FIN
0.99	0.97	0.85	0.84	0.88	0.83	0.88	0.85	0.87	0.87	0.88

2. Impulse responses for structural VAR model (Figures 1a and 1b)

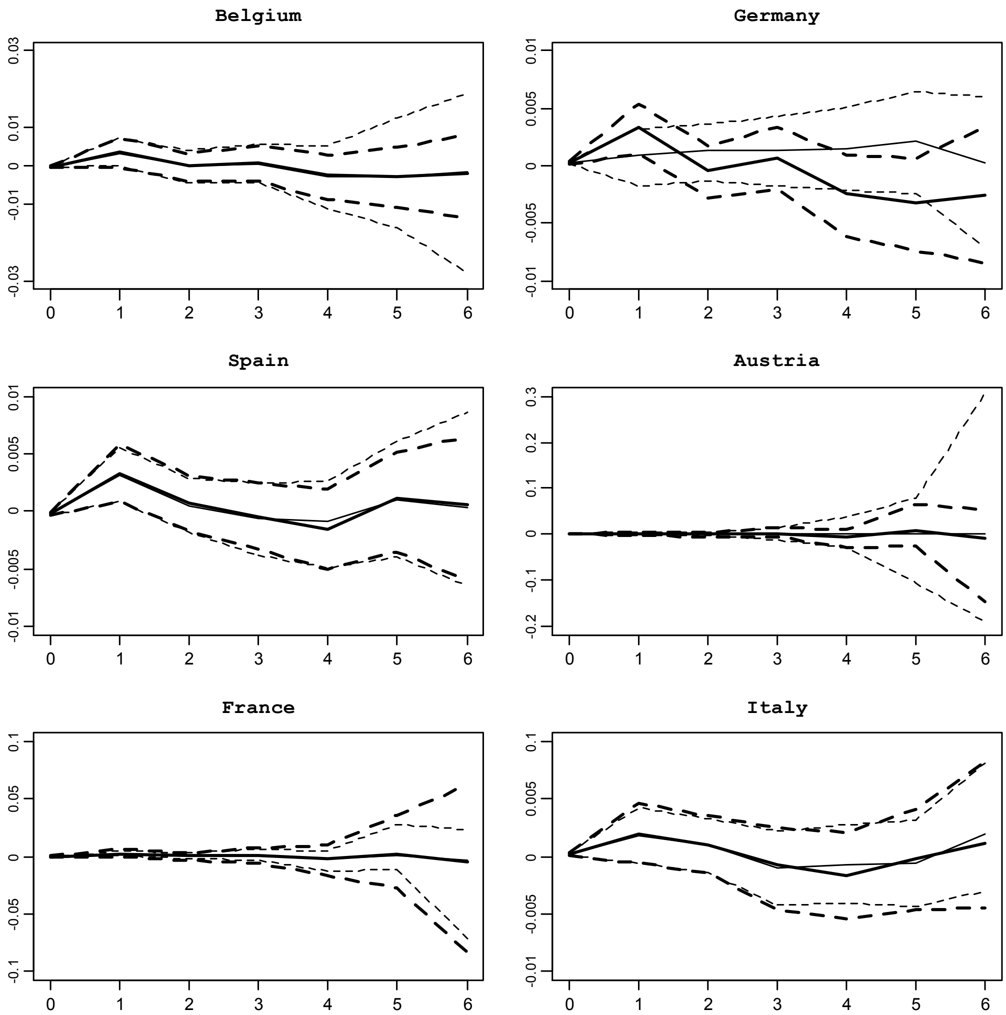


FIGURE 1A. Impulse responses of the difference in annualized HICP inflation between euro area and EMU member countries to an expansionary monetary policy shock. The time horizon of the impulse responses is 6 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals. Thick lines are for *Model 1* and thinner lines are for *Model 2*.

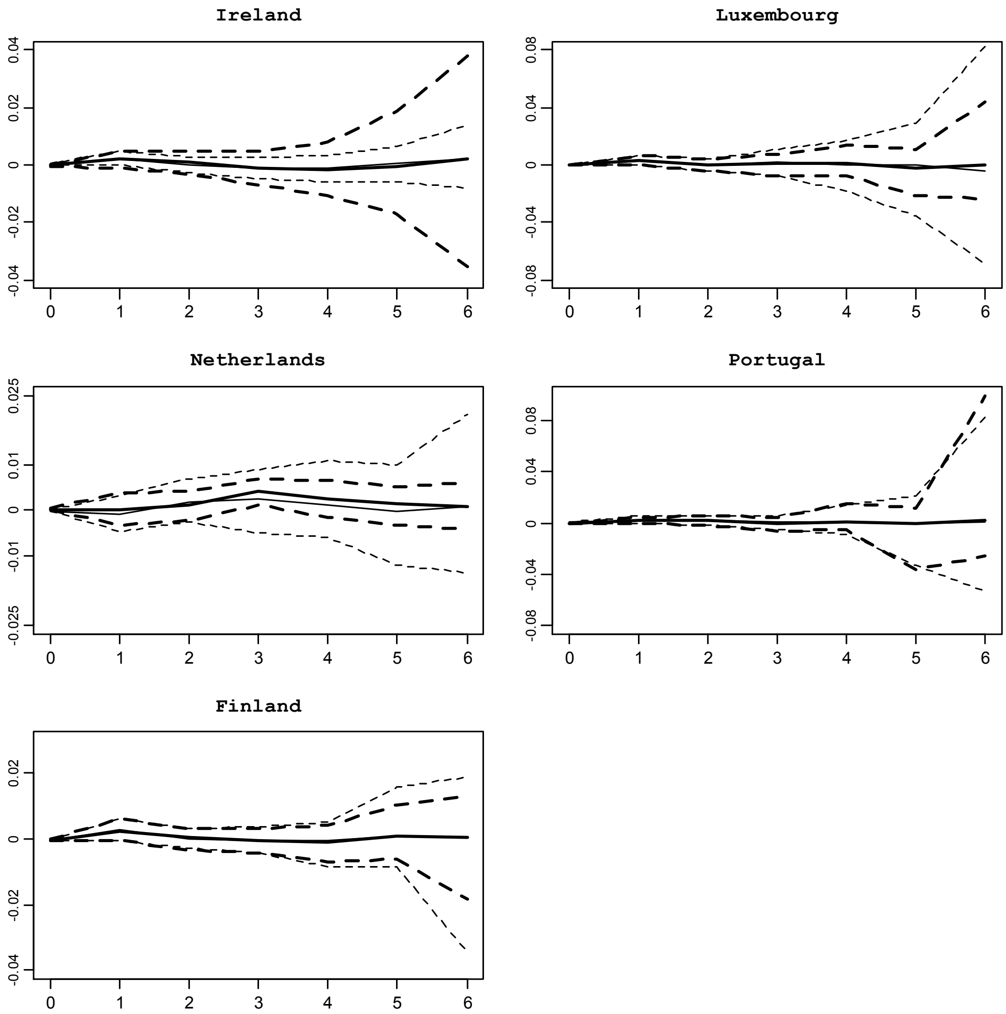


FIGURE 1B. Impulse responses of the difference in annualized HICP inflation between euro area and EMU member countries to an expansionary monetary policy shock. The time horizon of the impulse responses is 6 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals. Thick lines are for *Model 1* and thinner lines are for *Model 2*.

3. Impulse responses for VAR model identified with Cholesky factorization (Figures 2a, 2b and 2c)

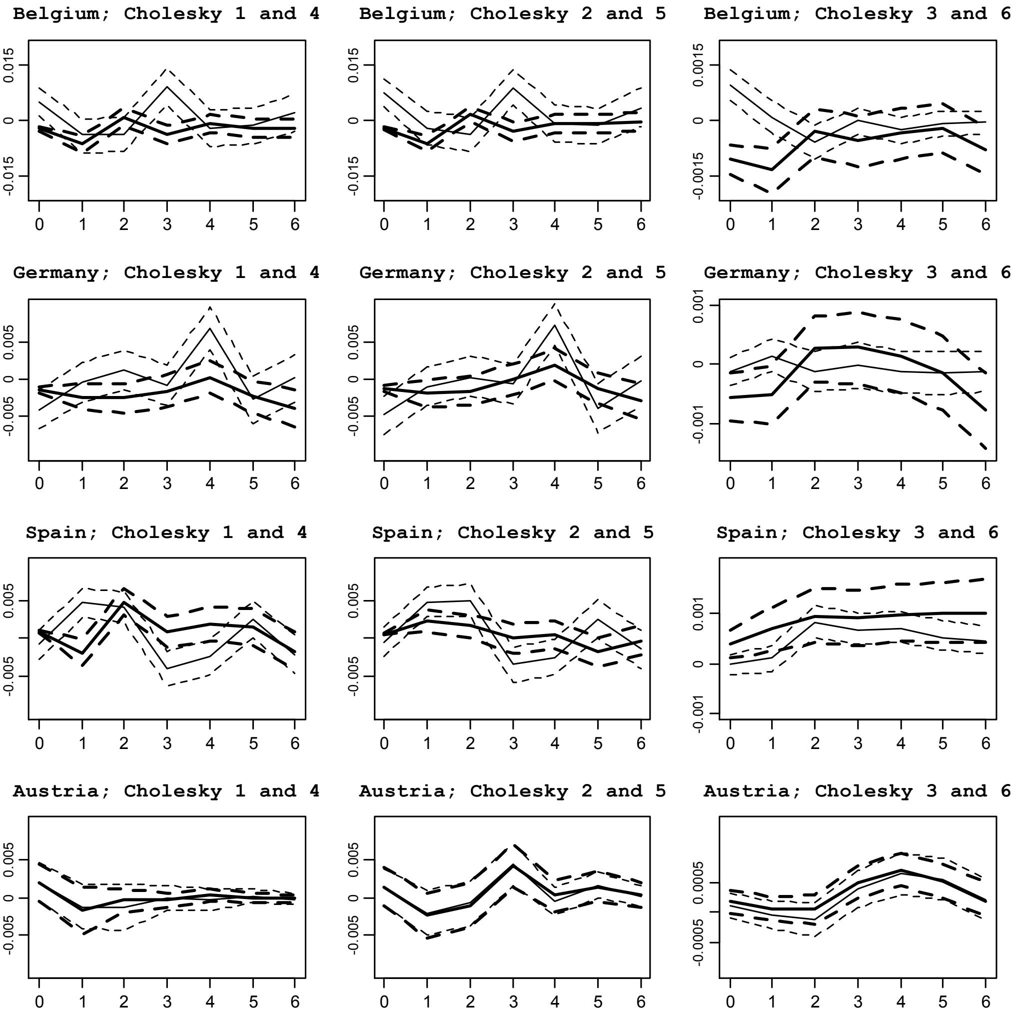


FIGURE 2A. Impulse responses of the difference in HICP inflation between euro area and EMU member countries to an expansionary monetary policy shock. The time horizon of the impulse responses is 6 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals. Each VAR model is Cholesky identified. The thick lines are for the variable ordering scheme mentioned first in the title.

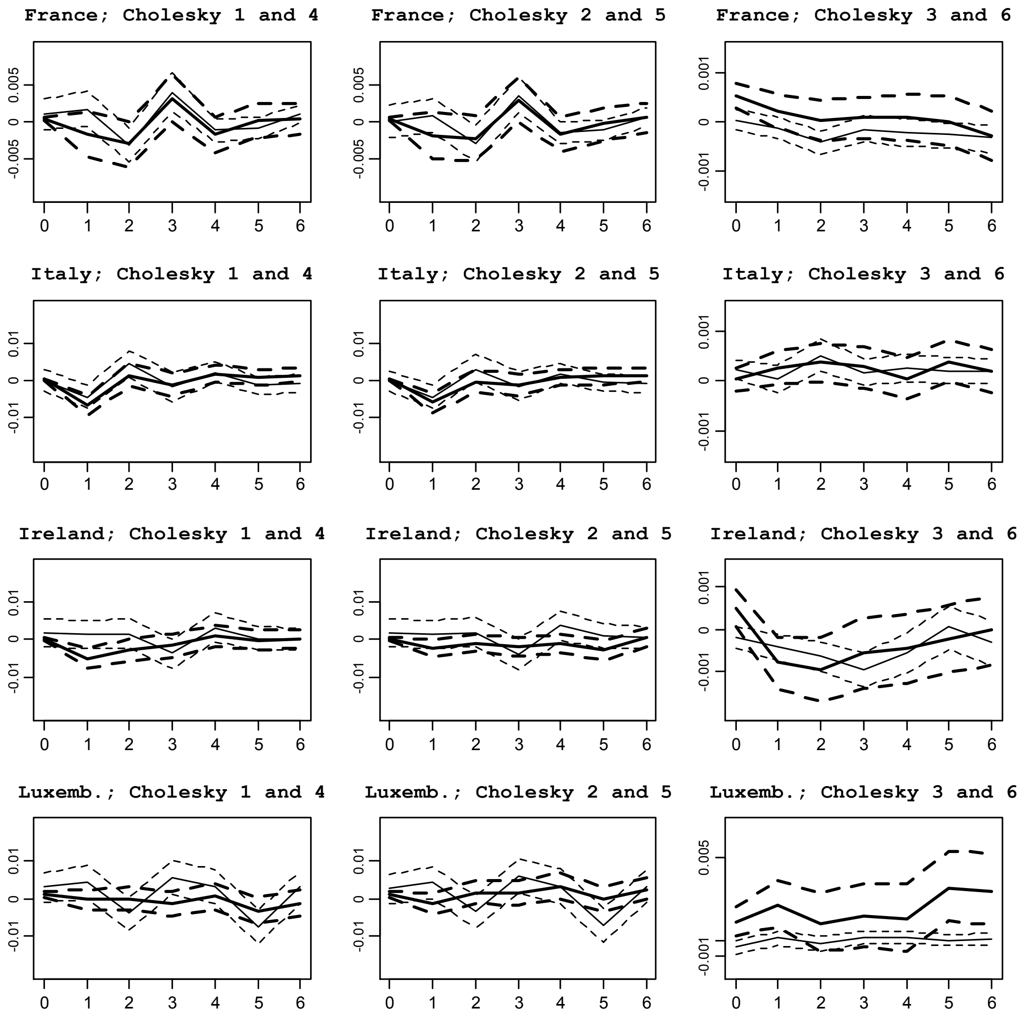


FIGURE 2B. Impulse responses of the difference in HICP inflation between euro area and EMU member countries to an expansionary monetary policy shock. The time horizon of the impulse responses is 6 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals. Each VAR model is Cholesky identified. The thick lines are for the variable ordering scheme mentioned first in the title.

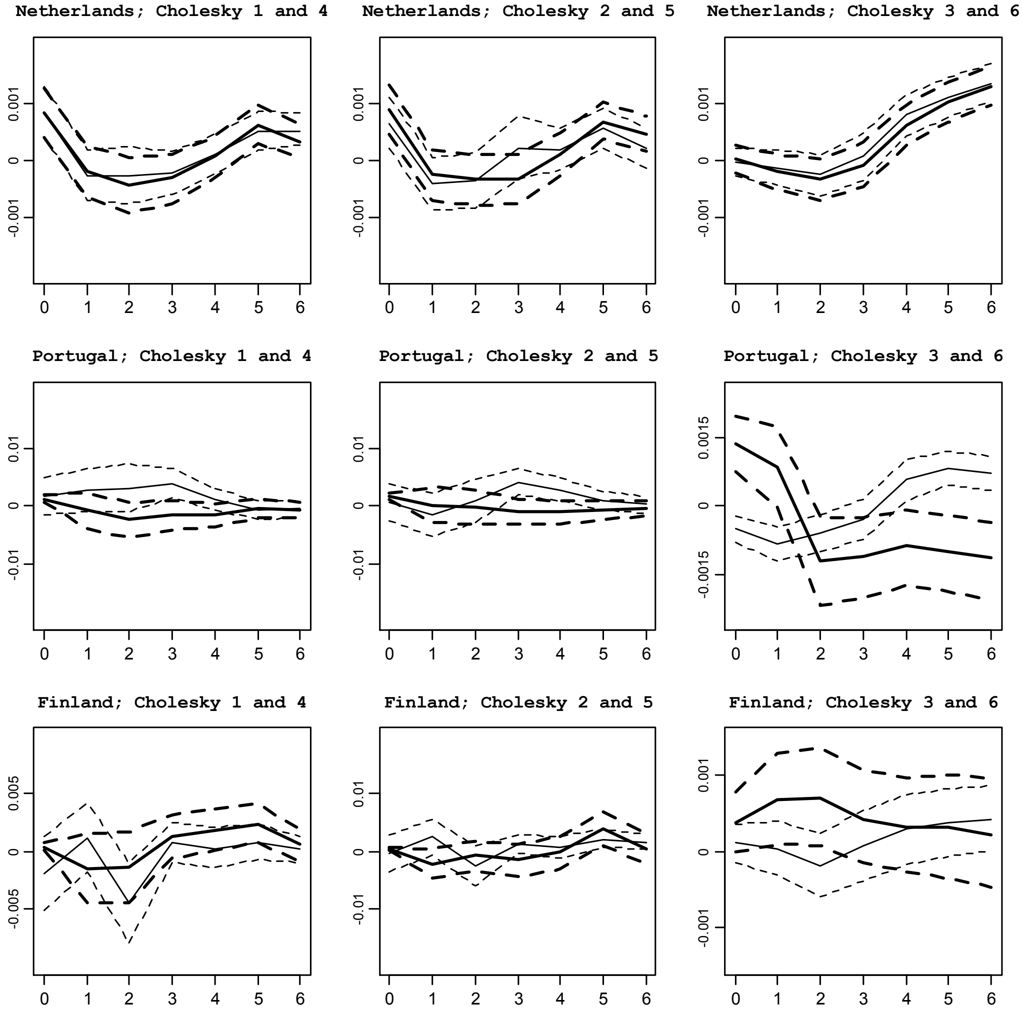


FIGURE 2C. Impulse responses of the difference in HICP inflation between euro area and EMU member countries to an expansionary monetary policy shock. The time horizon of the impulse responses is 6 months. The midmost lines are the medians and outer bands represent 68 per cent credible intervals. Each VAR model is Cholesky identified. The thick lines are for the variable ordering scheme mentioned first in the title.

Appendix 2: Cholesky VAR Decompositions and SVAR diagnostics

A. The Ordering of Variables for Cholesky identified VAR Models

In the different versions of the VAR model in Equation (26), we define the vectors of observations as

$$
{}^{1}y_t = \begin{pmatrix} \pi_t^* \\ \hat{y}_t^* \\ r_t^* \\ \pi_t \\ \hat{s}_t \end{pmatrix}, \qquad
{}^{2}y_t = \begin{pmatrix} \pi_t^* \\ \Delta \log Y_t^* \\ r_t^* \\ \pi_t \\ \hat{s}_t \end{pmatrix}, \qquad
{}^{3}y_t = \begin{pmatrix} a\pi_t^* \\ \Delta_{12} \log Y_t^* \\ r_t^* \\ a\pi_t \\ \hat{s}_t \end{pmatrix},
$$

$$
{}^{4}y_t = \begin{pmatrix} \pi_t^* \\ \hat{y}_t^* \\ r_t^* \\ \pi_t \end{pmatrix}, \qquad
{}^{5}y_t = \begin{pmatrix} \pi_t^* \\ \Delta \log Y_t^* \\ r_t^* \\ \pi_t \end{pmatrix} \quad \text{and} \quad
{}^{6}y_t = \begin{pmatrix} a\pi_t^* \\ \Delta_{12} \log Y_t^* \\ r_t^* \\ a\pi_t \end{pmatrix}.
$$

Variable $a\pi_t^*$ is year-on-year HICP inflation in the euro area and $\Delta \log Y_t^*$ and $\Delta_{12} \log Y_t^*$ are monthly and annual growth in the euro area's industrial product output (IIP), respectively. The reduced-form VAR model specified with ${}^{1}y_t$ is set to allow a direct comparison between the structural VARs. Accordingly, a reduced-form VAR of ${}^{2}y_t$ and ${}^{3}y_t$ will be estimated to have a comparison between ${}^{1}y_t$ and a structural form VAR. Models specification ${}^{4}y_t$ - ${}^{6}y_t$ are to investigate how the terms of trade (TOT = $\hat{s}_t$) adds to model dynamics.

B. Summary Statistics for SVAR models

TABLE 4. SVAR model lag lengths and convergence diagnostics of *Model 1* and *Model 2* for individual EMU member countries.

	Belgium		Germany		Spain		Austria	
	Model 1	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
lag (*p*)	6	6	7	7	8	8	2	2
Number of draws	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Acceptance ratio	25%	28%	22%	23%	21%	30%	18%	25%
Burn-in period	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Thinning interval	100	100	100	100	100	100	100	100
Geweke z-statistics								
$a_{0,11}$	1.4	0.9	-1.0	-1.5	-0.2	1.0	0.3	-1.3
$a_{0,21}$	1.3	0.8	-0.2	1.7	-1.2	1.0	-1.0	0.2
$a_{0,12}$	-1.2	-1.1	0.3	-1.2	-0.5	-0.1	-0.3	-0.8
$a_{0,22}$	0.6	0.4	-0.9	-1.5	-0.5	0.9	1.1	-1.1
$a_{0,42}$	-0.3	-0.9	0.4	0.4	0.0	0.3	1.6	-0.1
$a_{0,23}$	1.3	0.4	-0.4	-1.0	-1.4	0.2	-0.4	-0.7
$a_{0,33}$	-0.2	-0.6	0.6	-1.1	-0.3	0.9	-1.1	-1.2
$a_{0,44}$	0.4	-0.3	-0.1	0.1	0.9	0.7	-0.4	1..0
$a_{0,45}$	-0.1	-0.6	0.2	-0.6	0.7	-0.2	-1.7	0.6
$a_{0,55}$	-0.5	-1.2	0.0	1.2	-0.3	0.3	0.1	-0.6
λ_2	-0.3	NA	0.1	NA	0.0	NA	0.0	NA
Median of λ_2	46.7	NA	69.5	NA	45.0	NA	20.4	NA
Mean of λ_2	53.1	NA	76.1	NA	51.5	NA	51.5	NA

	France		Italy		Ireland		Luxembourg	
	Model 1	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
lag (*p*)	4	4	4	4	4	4	7	7
Number of draws	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
Acceptance ratio	24%	25%	20%	26%	20%	25%	24%	25%
Burn-in period	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Thinning interval	100	100	100	100	100	100	100	100
Geweke z-statistics								
$a_{0,11}$	1.5	0.7	-1.7	0.2	0.7	0.2	0.0	0.5
$a_{0,21}$	-0.6	-0.3	0.8	0.1	-0.6	-1.5	1.1	0.1
$a_{0,12}$	-1.8	0.3	-0.8	1.4	0.1	-0.7	-0.6	-0.5
$a_{0,22}$	1.3	0.9	0.0	1.2	0.5	-0.5	-0.6	0.5
$a_{0,42}$	-0.7	0.0	0.3	-1.3	1.0	-0.2	-0.7	0.8
$a_{0,23}$	-0.2	-0.4	0.5	-1.4	-1.0	0.7	-0.1	-0.5
$a_{0,33}$	-1.0	1.1	1.1	1.2	0.9	-0.4	-1.6	-0.8
$a_{0,44}$	0.2	-1.7	0.7	-0.2	0.9	0.0	0.4	0.5
$a_{0,45}$	-0.1	1.7	-0.7	0.2	1.0	0.3	0.7	-1.1
$a_{0,55}$	0.5	-0.4	-0.8	-1.66	0.8	0.9	1.2	1.6
λ_2	0.0	NA	0.1	NA	-0.7	NA	1.3	NA
Median of λ_2	87.3	NA	7.7	NA	8.23	NA	17.9	NA
Mean of λ_2	99.4	NA	11.3	NA	12.7	NA	20.3	NA

TABLE 4 - *continued*

	The Netherlands		Portugal		Finland	
	Model 1	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
lag (p)	3	3	3	3	3	3
Number of draws	50,000	50,000	50,000	50,000	50,000	50,000
Acceptance ratio	15%	18%	17%	21%	22%	25%
Burn-in period	10,000	10,000	10,000	10,000	10,000	10,000
Thinning interval	100	100	100	100	100	100
Geweke z-statistics						
$a_{0,11}$	-1.1	-0.1	-0.5	1.7	0.5	-0.1
$a_{0,21}$	1.5	0.2	-0.8	0.9	-1.4	-0.2
$a_{0,12}$	-1.4	-0.2	1.2	-0.7	-0.6	-0.2
$a_{0,22}$	-1.1	-0.1	-0.1	1.1	-0.6	-0.3
$a_{0,42}$	0.8	0.6	-0.3	-1.1	0.5	0.7
$a_{0,23}$	1.1	1.1	-0.7	-0.9	1.6	1.6
$a_{0,33}$	0.3	0.7	-0.5	1.2	-0.8	0.7
$a_{0,44}$	0.1	-0.5	-1.4	1.2	0.2	0.1
$a_{0,45}$	0.6	-1.0	-0.4	-0.4	0.1	0.1
$a_{0,55}$	-0.3	-0.5	-0.7	-0.2	0.2	0.6
λ_2	-0.2	NA	-0.8	NA	-0.2	NA
Median of λ_2	58.5	NA	49.9	NA	34.0	NA
Mean of λ_2	65.5	NA	57.6	NA	40.4	NA

TABLE 5. Information on reduced-form VAR models lag lengths.

	Estimated lag length (p)					
Country	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5	Spec 6
Belgium	6	6	9	6	6	3
Germany	7	7	10	7	7	4
Spain	8	10	3	8	8	3
Austria	2	4	7	3	4	3
France	4	4	5	4	4	5
Italy	4	4	7	4	4	3
Ireland	5	6	4	5	5	7
Luxembourg	7	6	7	6	6	3
Netherlands	3	3	4	3	4	4
Portugal	3	3	3	3	3	5
Finland	3	6	3	3	3	4

5 Essay 4: Forecasting Performance of the Small-scale Hybrid New Keynesian Model

Jan-Erik Antipin
University of Tampere,
Helsinki School of Economics
and UNU-WIDER

Jani Luoto
University of Helsinki

Abstract:

This paper uses quarterly ex post and real-time U.S. data to show that the very simple hybrid new Keynesian model of Clarida, Galí and Gertler [1999, The Science of Monetary Policy: A New Keynesian Perspective, Journal of Economic Literature, Vol. 37, pp. 1661-1707] can provide forecasts comparable to those based on Bayesian reduced-form vector autoregressive models. The issue is important since several recent papers have suggested different ways to improve the forecast performance of new Keynesian models at the cost of increasing the complexity of model mechanisms, this reducing the practicability of these approaches.

JEL Classification: C11, C32, E37, E47.

Keywords: New Keynesian model, forecasting, real-time data, Bayesian inference, vector autoregressive models.

5.1 Introduction

There is an increasing volume of literature focusing on the development of new Keynesian (NK) models suitable for forecasting and quantitative policy analysis; see Sungbae and Schorfheide (2007) and references therein. Within this literature, Smets and Wouters (2003, 2005 and 2007), Christiano *et al.* (2005), Adolfson *et al.* (2007a) and Adolfson *et al.* (2005, 2008), construct large-scale NK models aiming to find a structural macroeconomic model which has a fit comparable to that of reduced-form Bayesian vector autoregressive (VAR) models. In these studies, additional shocks, frictions and measurement errors are introduced to the NK model mechanisms until the desired fit is achieved. This approach ignores model uncertainty, leading to inferences which are over-confident and decisions which are riskier than the policy-maker believes them to be. A promising alternative strategy is provided by Del Negro and Schorfheide (2004). In their approach an NK model is used to generate a prior distribution for the parameters of the VAR to improve the forecast and policy analysis performance of these models. Although this approach is promising, it is nonetheless complicated and the numerical methods required in estimation are time-consuming. Its practicability can therefore be questioned; see also Del Negro *et al.* (2007). In the light of recent NK literature, it would thus be interesting to see whether a simple NK model, including only few shocks and standard price rigidity, can achieve a fit comparable to other forecasting methods such as the Bayesian VARs commonly used as benchmark.

This paper has two objectives. First, it provides a method for the Bayesian analysis of a simple hybrid NK model by Clarida *et al.* (1999). The method is very easy to implement and leads to savings in the CPU time required in posterior simulation, compared to the commonly used Kalman filter approach. Lindé (2005) estimates a version of the hybrid NK model by the full information maximum likelihood (FIML) method using U.S. data. We for our own part adopt a Bayesian full-information framework, since the FIML estimates turned out to be very sensitive to starting values and since Bayesian methods allow incorporation of prior information, which facilitates numerical maximization.

Our second objective is to compare the forecasting properties of the hybrid NK model against commonly used forecasting tools such as Bayesian VARs and naïve forecasts based on univariate random walks. Using quarterly U.S. data we show that the hybrid model can provide forecasts for key macroeconomic variables, inflation and short-term nominal interest rate, and a measure of the output gap comparable to forecasts based on reduced-form Bayesian VARs. Our results also indicate that the hybrid model predicts more accurately than naïve forecasts based on univariate random walks. In particular, these results hold for both ex post and real-time data, which are available to policy-makers when forecasts are being made. Our results also confirm the finding of Smets and Wouters (2007) that the cross-equation restrictions implied by NK models work especially well in forecasting at medium-term horizons (from four to twelve quarters). For policy-makers, comparisons of forecasts at horizon longer than one quarter are of interest, since policy actions typically depend on expected future developments in the economy.

Finally, we find two major reasons for the good forecasting performance of the hybrid model. Firstly, the model allows both for the endogenous persistence in inflation and output and for the persistence of exogenous shock processes. This approach is commonly used in large-scale NK models, which forecast well. Secondly, our joint prior is well designed in allowing the parameters to be estimated fairly freely, while being sufficiently informative to safeguard the posterior distribution away from economically non-meaningful values.

The remainder of the paper is organized as follows. In section 2, we discuss the model, the prior and the data and continue the analysis by reporting the posterior distributions of the parameters. In section 3, we explain the forecasting comparison methods, and present and discuss the results of a forecasting exercise. Section 4 concludes the paper.

5.2 Likelihood, Prior, Data and Posterior

In this section we introduce a hybrid NK model. Its likelihood and the joint prior density function of the structural parameters are specified. We then describe the data and continue the analysis by reporting the posterior distributions of the parameters.

5.2.1 Model Likelihood

Let us consider the following hybrid NK model for period t inflation[1], π_t, and a measure of the output gap, x_t, respectively,

[1]Price inflation is defined as the per cent change in the price level from t – 1 to t.

$$\pi_t = \alpha E_t \pi_{t+1} + (1-\alpha)\pi_{t-1} + \gamma x_t + \varepsilon_{\pi,t}, \quad (1)$$

$$x_t = \beta E_t x_{t+1} + (1-\beta)x_{t-1} - \beta_r (R_t - E_t \pi_{t+1}) + \varepsilon_{x,t}, \quad (2)$$

where parameters a and β satisfy the conditions $0 \leq a \leq 1$ and $0 \leq \beta \leq 1$. Equation (1) is the hybrid new Keynesian Phillips curve (NKPC), similar to that analyzed in Rudd and Whelan (2006), while Equation (2) is the aggregate demand equation. The model is very close to that carefully studied in Clarida *et al.* (1999).

The disturbance terms $\varepsilon_{\pi,t}$ and $\varepsilon_{x,t}$ in Equations (1) and (2) are assumed to follow univariate AR(1) processes:

$$\varepsilon_{\pi,t} = \rho_\pi \varepsilon_{\pi,t-1} + u_{\pi,t}, \quad (3)$$

$$\varepsilon_{x,t} = \rho_x \varepsilon_{x,t-1} + u_{x,t}, \quad (4)$$

where $\rho_\pi, \rho_x \in (-1, 1)$, and $u_{\pi,t}$ and $u_{x,t}$ are independently and identically distributed (i.i.d.) random variables with zero means and variances σ_π^2 and σ_x^2, respectively.

We close the model with the following Taylor rule for the nominal interest rate R_t,

$$R_t = (1-\rho)(\gamma_\pi \pi_t + \gamma_x x_t) + \rho R_{t-1} + \varepsilon_{R,t}, \quad (5)$$

where the parameter $\rho \in (0, 1)$ measures the degree of interest rate smoothing, the disturbance term $\varepsilon_{R,t}$ obeys $\varepsilon_{R,t} = \rho_R \varepsilon_{R,t-1} + u_{R,t}$, $\rho_R \in (-1, 1)$, and $u_{R,t}$ is an i.i.d. random variable with zero mean and variance σ_R^2.

The model in Equations (1)-(5) can be solved analytically by standard first-order log-linear methods. In particular, this paper follows Lindé (2005) in applying the solution algorithm of Söderlind (1999). The solution gives the equilibrium law of motion for the relevant state variables. Specifically, the state equation is given by $z_t = Cz_{t-1} + v_t$, where $z_t = (\varepsilon_{\pi,t}, \varepsilon_{x,t}, \varepsilon_{R,t}, \pi_{t-1}, x_{t-1}, R_{t-1})'$, $v_t = (u_{\pi,t}, u_{x,t}, u_{R,t}, 0, 0, 0)'$ and C is a nonlinear function of structural parameters. Given that the shocks are normally distributed and that the vector of observables $y_t = (\pi_t, x_t, R_t)'$ is a linear combination of the state variables, the common approach is to specify a recursive likelihood function for the model using the Kalman filter. The estimates of the model can then be obtained using standard non-linear optimization methods.

Alternatively, the analytical solution of the model can be written as a full information system of the vector of observables; see Lindé (2005). Specifically,

$$y_t = C_y y_{t-1} + C_\varepsilon \varepsilon_t, \tag{6}$$

where $\varepsilon_t = (\varepsilon_{\pi,t}, \varepsilon_{x,t}, \varepsilon_{R,t})'$ and C_y and C_ε are partitions of the solution matrix C conformably with y_t and ε_t, respectively.

Then denote $\varepsilon_t = P\varepsilon_{t-1}$, where P is a diagonal matrix whose diagonal entries are given by ρ_π, ρ_x and ρ_R. The likelihood function for a sample of T observations can be written as

$$L(Y;\theta) \propto |C_\varepsilon|^{-T} |\Lambda|^{-T/2} \exp\{-0.5 \times tr(U\Lambda^{-1}U')\}, \tag{7}$$

where $\theta = (\beta, a, \beta_r, \gamma, \gamma_\pi, \gamma_x, \rho, \rho_\pi, \rho_x, \rho_R, \sigma_\pi, \sigma_x, \sigma_R)'$ is a vector comprising all model parameters and Λ a diagonal covariance matrix with diagonal entries σ_π^2, σ_x^2 and σ_R^2. Furthermore, the tth rows of (Txm) matrices Y and U are given by y_t' and u_t', respectively, where m is the number of observables and

$$u_t = C_\varepsilon^{-1}\left(y_t - \left(C_y + C_\varepsilon \mathrm{P} C_\varepsilon^{-1}\right)y_{t-1} + C_\varepsilon \mathrm{P} C_\varepsilon^{-1} C_y y_{t-2}\right). \tag{8}$$

In what follows, we adopt the full-information approach of Equation (7), since the optimization algorithm based on it proved faster than the algorithm based on the recursive Kalman filter. Specifically, the Kalman filter approach requires roughly 4.5 times as much CPU time for posterior simulation as our approach (with a sample of 200 observations). Furthermore, both estimation methods were also found to produce similar results.

The model described in Equations (1)-(5) contains 13 parameters, collected in θ. Maximum likelihood (ML) estimation of the model turned out to be a challenging task. In particular, the ML estimates of the parameters were very sensitive to the starting values of maximization due to a multimodal likelihood. This problem remained even when the parameter space was restricted to an economically feasible region. To illustrate this problem we give an example from the previous literature. Lindé (2005) estimates a version of the model in Equation (1)-(5) on U.S.

data with full information maximum likelihood (FIML).[2] He finds positive and highly significant parameter estimates for the slope coefficients γ (≈ 0.05) and β_r (≈ 0.09). However, there prevails a local equilibrium in which the likelihood is higher than that in Lindé's solution. At this equilibrium the slope coefficients γ and β_r are still positive, but rather close to zero. According to Lindé (2005), the estimation can with different starting values converge to local equilibria with more or less plausible parameter values. To facilitate numerical maximization, we suggest using Bayesian methods, which allow incorporation of prior beliefs on parameters. While restricting, for example, the slope coefficients γ and β_r to be equal to some theoretical values gives an example of a very strong prior belief, other kinds of beliefs cannot easily be considered in the classical framework.

As seen in the current literature, Bayesian methods have become a standard workhorse in analysing NK models. Sungbae and Schorfheide (2007) provide an excellent review of such methods developed in recent years to estimate and evaluate this class of models (see also Adolfson *et al.*, 2007b). Rather than elaborating the details of Bayesian methods in analysing the NK models, which is already done in Sungbae and Schorfeide (2007), we discuss our choices of marginal prior distributions in the following subsection.

5.2.2 Marginal Priors

The starting-point in the Bayesian analysis is to determine the prior density function of the parameters, $p(\theta)$, which together with the likelihood function (7) yields the posterior density

$$q(\theta|Y) = \frac{p(\theta)L(Y;\theta)}{\int p(\theta)L(Y;\theta)d\theta}. \qquad (9)$$

A typical informative prior reflects the researcher's subjective beliefs, summarizes information from the data not included in the estimation sample, or is based on both. Often the underlying economic theory provides a natural starting-point for the prior elicitation. We will use a very simple structural model as the basis for our prior knowledge. The model can be obtained by log-linearizing the aggregation of individual firms' pricing decisions and the consumption Euler equation without

[2] Lindé (2005) adds additional lags in the aggregate demand equation (2) and the monetary policy rule (3) to make disturbance terms $\varepsilon_{x,t}$ and $\varepsilon_{R,t}$ white noise.

using ad hoc assumptions such as backward inflation indexation or habit formation in consumption. Specifically, the prior means of the parameters in θ are based on the following model,

$$\pi_t = bE_t\pi_{t+1} + \frac{(1-\kappa)(1-b\kappa)(1+\zeta)}{\kappa}x_t, \tag{10}$$

$$x_t = E_t x_{t+1} - (R_t - E_t\pi_{t+1}), \tag{11}$$

where b is the subjective discount factor, κ the frequency of price adjustment and ζ the elasticity of labor supply. Note that, for simplicity, a standard assumption on prior independence of parameters is used; see e.g. Zellner (1971). Del Negro and Schorfheide (2008) criticize this assumption as having the drawback that the resulting joint prior distribution may assign a non-negligible amount of probability mass to regions of the parameter space where the model is unreasonable. It is fairly easy to see this undesirable property suggested is not present in our joint prior.

Table 1 in Appendix 1 lists the marginal prior distributions of the parameters. The beta prior distributions of the parameters a and β are concentrated towards unity, but are nonetheless only weakly informative (see Equations 10 and 11 for motivation). The prior mean of the slope coefficient β_r is set at unity, while the prior mean of γ (1.00) can is obtained by setting the subjective discount factor, the elasticity of labor supply and the frequency of price adjustment at their standard calibrated values, e.g. 0.99, 2 and 0.57, respectively, in Equation (10). The prior variances of these parameters (γ, β_r) are set to be small enough to keep the posterior distribution away from economically non-meaningful values. The prior means of the policy parameters γ_π (1.50) and γ_x (0.50) are obtained from Taylor (1993).[3] However, some interest rate smoothing is also allowed a priori. That is, the prior mean of ρ is set at 0.50. With the given prior variances, the marginal prior distributions of these parameters (γ_π, γ_x, ρ) turned out to be practically uninformative.

The standard deviations σ_π, σ_x, and σ_R are assumed to follow inverse-gamma distributions with shape and scale parameters yielding fairly loose priors. Finally, the normal prior distribution with zero mean and 0.75^2 variance is used for the transformed parameters

[3] In Taylor (1993), the interest rate and the inflation rate are expressed on a yearly basis. Since we express them on a quarterly basis, the prior mean of γ_x should be set at 0.125 (0.5 divided by 4). However, the standard deviation of the measure of the output gap used in Taylor (1993) is markedly higher than that used in this paper. Thus, the prior mean of 0.5 can be seen in our case to be justified.

$$\phi_\pi = \frac{1}{2}\log\frac{1+\rho_\pi}{1-\rho_\pi}, \ \phi_x = \frac{1}{2}\log\frac{1+\rho_x}{1-\rho_x} \text{ and } \phi_R = \frac{1}{2}\log\frac{1+\rho_R}{1-\rho_R}. \quad (12)$$

These marginal priors force the posterior distributions of the autoregressive parameters ρ_π, ρ_x and ρ_R to be located in the interval (–1, 1).

The marginal priors are also particularly loose, but turned out nevertheless to improve simulation efficiency.

5.2.3 Data and Results

Throughout this study the quarterly U.S. data from 1953:2 to 2004:4 are used. In addition to the entire sample, the models are estimated for the subsample periods 1953:2-1982:2 and 1982:3-2004:4, capturing the "Great Inflation" and "Great Moderation" periods, respectively. This serves as a convenient check for robustness and parameter constancy. We are aware that the nominal interest rate, as the instrument of monetary policy, provides a reasonable description of the Federal Reserve's operating procedures only after 1964; see Clarida *et al.* (1999). However, the first ten years of data are required to have a sufficiently long out-of-sample forecasting period. We form out-of-sample forecasts from 1976:4 to 2004:4 to have a forecast series which covers a diverse spectrum of inflation volatility.

The output gap is measured as a logarithmic difference between the actual and the potential output level. Two measures of actual output are used: real gross domestic product (GDP) and non-farm business (NFB) sector output. The logarithm of the potential output is proxied by the one-sided Hodrick-Prescott filter (Hodrick and Prescott, 1997) trend estimate in the model

$$g_t = \tau_t + \eta_{1t}, \quad (13)$$

$$(1 - L)^2\tau_t = \eta_{2t}, \quad (14)$$

where g_t is the logarithm of the measure of actual output, L is a lag operator and η_{1t} and η_{2t} are mutually uncorrelated white noise sequences with the relative variance $q = \text{var}(\eta_{1t})/\text{var}(\eta_{2t})$. The value of $q = 0.67\text{x}10^{-3}$ is taken from Stock and Watson (1999). We use the previous approximation of potential output, since our focus is on forecasting and since it does not use the future values of the detrended variable, as the optimal two-sided trend extraction HP-filter for Equations (13) and (14) does.[4] Furthermore, Stock and Watson (1999) find, after experimenting with several methods suitable for forecasting, that this procedure produces plausible gap estimates which work fairly well in inflation forecasting.

Price inflation is measured as the log difference of the implicit price deflator of GDP (NFB). All the series are seasonally adjusted. The source of the final vintage data is the FREDII databank of the Federal Reserve Bank of St. Louis, while that of the real-time data is the Federal Reserve Bank of Philadelphia. The Federal Funds rate (FFR) is used as the instrument of monetary policy. The nominal interest rate and inflation rate series are measured as quarterly changes corresponding to their appearance in the structural model. Finally, the data are demeaned prior to estimation.

The estimation results[5] are presented in Table 1 in Appendix 1, in the topmost panel (A) for the entire sample and in the lower panels (B and C) for the two subsample periods. The data appear to be particularly informative in all these samples. That is, the variances of the posterior distributions are found to be systematically smaller than the prior variances. The posteriors are also relatively stable between the data sets and the subsamples with two exceptions. The variances of the stochastic error processes seem to have fallen in the second subsample period. Sims and Zha (2006) and Smets and Wouters (2007) find similar evidence in U.S. data concerning the variance of monetary policy shocks. Our results also indicate that the Federal Reserve seemed to respond to the output gap and inflation more strongly during the second subsample period. The latter result is in accordance with that of Boivin and Giannoni (2006) and Smets and Wouters (2007), while Bernanke and Mihov (1998), Leeper and Zha (2003) and Canova (2006) find a relatively stable interest rate rule for the post WW II sample.

The Taylor principle is fulfilled in all samples. This is in contrast to the findings of Clarida *et al.* (2000), who report that the Federal Reserve responded less than one-to-one to inflation during the period 1960-1979 (pre-Volcker period), thus violating the Taylor principle. In line with our

[4] We also tested for detrending linear and quadratic trend methods which are suitable for forecasting, and found that the results presented are not sensitive to use of these measures of potential output. Furthermore, we ran several regressions with the dataset used in Lindé (2005). The results of the regressions with our and his datasets were fairly similar.

[5] Appendix 1 describes in more detail the practical prodecure we applied to generate draws from the posterior distribution.

results, for example, Smets and Wouters (2007) and Rabanal and Rubio-Ramírez (2005) find that the inflation coefficient to be greater than one.

The point estimate of a (0.08) indicates a very insignificant role for forward-looking behavior in the Phillips curve. This result is in accord with those of Fuhrer (1997), Lindé (2005) and Rudd and Whelan (2006), but at odds with Smets and Wouters (2003, 2005 and 2007), Adolfson *et al.* (2005) and Galí *et al.* (2005). The latter authors obtain relatively low parameter estimates for the degree of price indexation. Our estimates were obtained using a statistical measure of the output gap. Galí and Gertler (1999) and Galí *et al.* (2005) have suggested that the key reason for the lack of success of the forward-looking NKPC is that the detrended output is not a good proxy for real marginal costs. Contrary to their finding, Rudd and Whelan (2006), who used both the output gap and labor's share as a proxy for real marginal cost, found that the evidence for forward-looking behavior in the NKPC was very weak.

The point estimates of β are high, supporting the traditional forward-looking intertemporal Euler equation. Previous studies have typically observed a high degree of habit persistence; see e.g. Christiano *et al.* (2005), and Smets and Wouters (2007). However, there seems to be a trade-off between the forward-looking behavior of the demand equation and the persistence of autoregressive demand shocks. In our paper, the high autoregressive parameter of the exogenous shock process (ρ_x = 0.79) takes into account the degree of persistence observed in the data. In Smets and Wouters (2007), the habit formation of consumption takes into account its high persistence, while the autoregressive parameter of exogenous shocks is estimated to be relatively small (0.36). Smets and Wouters (2007), however, assume a high habit parameter 0.7 (with 0.01 prior variance), a priori. Finally, the persistence of monetary policy shocks (ρ_R) is relatively low and equal to that estimated by Smets and Wouters (2007). Parameter γ in Equation 1 is updated downwards in the posterior distribution. This might suggest that a priori assumption that the elasticity of labour supply parameter ζ takes a value 2 is too high.

5.3 Forecast Comparison

In this section we first discuss the forecasting methods. We then provide some details for the forecasting comparison methods. Finally, we report the results of a forecasting exercise.

5.3.1 Measuring the Prediction Performance of Competitive Models

It is fairly easy to see that Equation (6) can be treated as a reduced-form VAR with lag-length 2 and normally distributed errors with covariance matrix $\Sigma = C_\varepsilon \Lambda C_\varepsilon'$. Thus, the conditional predictive distribution of Equation (6) for the joint lead time 1 through H, $p(y_{t+1},\ldots,y_{t+H} \mid Y, \theta)$, is multivariate normal; see Lütkepohl (1993). This facilitates straightforward simulations from $p(y_{t+1},\ldots,y_{t+H} \mid Y, \theta)$, given the posterior probability density function (p.d.f.) of θ. The method for obtaining the posterior p.d.f. of θ was explained in the previous section.[6]

The predictive performance of the hybrid NK model is compared to two Bayesian VARs and to naïve forecasts based on univariate random walks. The VAR systems consist of the same three variables, $y_t = (\pi_t, x_t, R_t)'$, as the hybrid NK model. The data are not however demeaned prior to estimation. Diffuse and Normal-Diffuse priors are used for the parameters of the VAR models; see Kadiyala and Karlsson (1997) for discussion. Parameterization of the Normal-Diffuse prior is based on the assumption that the variables behave as if they had random walk components; see Litterman (1980). That is, the prior means are set at zero except for the elements corresponding to the first own lag of each variable. The prior variances of the parameters in the ith equation of a p-lag VAR ($k = 1,\ldots, p$)[7] are given by π_1/k, $\pi_2 s_i^2/s_j^2 k$ ($i \neq j$) and $\pi_3 s_i^2$, for the parameters on own lags, foreign lags and a constant, respectively; see Litterman (1986) and Kadiyala and Karlsson (1997) for the motivation of this prior variance specification. A scale factor accounting for the different scales of the variables, s_i^2 is set at the residual standard error of equation i. The relative tightness of the prior is set at the commonly used values of hyper-parameters, $\pi_1 = 0.05$ and $\pi_2 = 0.005$; see e.g. Kadiyala and Karlsson (1997) and Litterman (1986). The tightness of the constant terms is set at $\pi_3 = 0.05$, which shrinks the processes towards a driftless univariate random walk. This prior specification provides a suitable

[6] In a rolling forecast exercise, a total of 113 chains were simulated from each model. The posterior estimates of θ are based on 30,000 draws. The first 6,000 draws were discarded as a burn-in period. To reduce the size of output files, every 12th draw was saved. The predictive likelihoods are thus computed on the basis of 2000 draws from the Markov chain. Geweke (1992) proposed a convergence diagnostic for Markov chains based on a test for the equality of means of the first and last parts of the chain (in this paper the first 10% and the last 50% of observations were used). The test statistic is a standard Z-score; the difference between the two sample means divided by its estimated standard error. The standard error is estimated from the spectral density at zero and so takes into account any autocorrelation. The hypothesis of the equality of means was not rejected for most parameters at the 5 % significance level.

[7] In our paper, p is set at 4. The fractional marginal likelihoods (FML) of Villani (2001), which were used in preliminary data analysis, supported this choice in over 99% of the estimated regressions.

description for the processes of inflation, nominal interest rate and detrended output. The posterior distributions were simulated using the Gibbs sampling algorithm[8] of Kadiyala and Karlsson (1997) for the Normal-Diffuse prior specification and the matricvariate Student's *t* distribution for the Diffuse prior specification. The predictive likelihoods were computed on the basis of 2,000 draws from the posteriors.

The forecasting performance of the models is examined using the standard rolling forecast procedure, which entails making forecasts using data dated before the forecasting period. The forecasting procedure is as follows: using data up to a given time point T all the parameters in the model are estimated and the predictive distribution over $y_{T+1},\ldots,y_{T+H}$ is computed.[9] Moving forward one period, all the parameters are re-estimated and the forecast distribution of $y_{T+2},\ldots,y_{T+H+1}$ is computed. This is continued until no more data are available to compute the one-step-ahead forecast errors. The period over which the dynamic forecast distributions are computed in this manner is 1976:4 through 2004:4. In addition to the entire forecasts sample, the forecasts are also compared for the subsample period 1990:1-2004:4 (the sample period of Smets and Wouters, 2007). This serves as a check of robustness of the results and enchances the comparability of our results to those in previous literature; especially in the paper of Smets and Wouters (2007).
Adolfson *et al.* (2007a) recommend use of several univariate and multivariate measures to determine the accuracy of the point forecasts. The two commonly used univariate measures of accuracy, the root mean squared forecast error (RMSE) and the mean absolute forecast error (MAE) are computed as

$$RMSE_i(h) = \sqrt{N_h^{-1} \sum_{t=T}^{T+N_h-1} e_{i,t}^2(h)}, \tag{15}$$

$$MAE_i(h) = N_h^{-1} \sum_{t=T}^{T+N_h-1} \left| e_{i,t}(h) \right|, \tag{16}$$

respectively, where $e_{i,t}(h) = y_{i,t+h} - \hat{y}_{i,t+h|t}$ is the ith element of the h-step-ahead forecast error, $\hat{y}_{t+h|t}$ the h-step-ahead posterior median forecast of y_{t+h} and N_h the number of the h-step-ahead forecasts (h = 1, …, H).

[8] 2,200 draws were simulated and the first 200 draws from the Markov chain were neglected as a burn-in period.

[9] Note also that when the forecasts are evaluated the data are demeaned and the gap estimates are computed using the data up to time T. Furthermore, when the analysis is based on demeaned data, the posterior median forecasts are computed and the means are added to the median forecasts.

However, only the RMSEs are reported, since these two measures were found to produce equal results.

Two multivariate accuracy measures of point forecast, the log determinant statistic and the trace statistic, are also used in addition to the univariate measures. The multivariate statistics are based on the scaled h-step-ahead mean squared error (MSE) matrix

$$T_M(h) = N_h^{-1} \sum_{t=T}^{T+N_h-1} \bar{e}_t(h)\bar{e}_t'(h) \text{ ,} \tag{17}$$

where $\bar{e}_t(h) = M^{-1}e_t(h)$ and M is a scaling matrix accounting for the different scales of the variables being forecast.[10] As discussed in Adolfson *et al.* (2007a), the forecasting performance of the least predictable dimensions, that is, those corresponding to the highest eigenvalues of the square matrix $T_M(h)$, mainly determine the trace statistic $\text{tr}[T_M(h)] = \lambda_1 + \ldots + \lambda_m$, while the log determinant statistic $\log |T_M(h)| = \log \lambda_1 + \ldots + \log \lambda_m$ also takes into account the forecasting performance of the most predictable dimensions (the lowest eigenvalues). It is also obvious that when the lowest eigenvalue of $T_M(h)$ approaches zero, the most predictable dimension determines the log determinant statistic.

Finally, in view of the increasing interest for forecast uncertainty, we also compare the prediction performance of the competitive models using the log predictive density score (LPDS), which is a measure of the accuracy of multivariate density forecasts; see Adolfson *et al.* (2007a). To be more concrete, let $\hat{y}_{t+h|t}$ and $\Omega_{t+h|t}$ denote the posterior mean and covariance matrix of the h-step-ahead forecast distribution $p_t(y_{t+h})$. Then, under the normality assumption of $p_t(y_{t+h})$, the LPDS of the h-step-ahead predictive density at time t is defined as

$$\begin{aligned} S_t(y_{t+h}) &= -2\log p_t(y_{t+h}) \\ &= m\log(2\pi) + \log\left|\Omega_{t+h|t}\right| + \left(y_{t+h} - \hat{y}_{t+h|t}\right)'\Omega_{t+h|t}^{-1}\left(y_{t+h} - \hat{y}_{t+h|t}\right). \end{aligned} \tag{18}$$

We report the averages of the LPDSs over the evaluated h-step-ahead forecasts,

$$S(h) = N_h^{-1} \sum_{t=T}^{T+N_h-1} S_t(y_{t+h}). \tag{19}$$

[10] We follow Adolfson *et al.* (2007a) and set M equal to the diagonal of the sample covariance matrix of the y_t from 1976:4 to 2004:4 (1990:1 to 2004:4).

This measure takes into account the forecasting performance of the predictive density as a whole.

5.3.2 Results

Figures 1-3 in Appendix 2 summarize the forecasting performance of the competitive models. Specifically, Figure 1 shows the RMSEs in quarterly percentage terms, Figure 2 the log determinant and the trace statistics, and Figure 3 the averages of the LPDS statistic. Figures 4-6 gives the corresponding statistics for the forecasts based on real-time data. The results based on NFB data were similar to those based on GDP data and in order to save space we report only the latter. All the statistics are reported at the 1- to 12-quarter horizons. [11] In the figures, a small value favors the model.

A few key findings emerge from the figures. Firstly, although the models are very simple they seem to forecast particularly well. According to the RMSEs, the small-scale models appear to produce more accurate point forecasts, on both inflation and the Federal Funds rate,[12] than the large-scale Bayesian VAR of Smets and Wouters (2007). In addition, the models turned out to produce real-time inflation forecasts which outperformed the naïve forecasts up to six quarters in the 1990:1-2004:4 subsample (see Figure 4). This result gives some perspective on the forecast accuracy of the hybrid model, when we take into account the finding of Atkeson and Ohanian (2001) that the one-year-ahead Federal Reserve's Greenbook inflation forecast has not been better on average than the naïve forecast since 1984.

Secondly, all the forecast comparison methods appear to yield similar conclusions. In the entire sample the forecasts of the hybrid model outperform those of the Bayesian VARs, while in the low inflation subsample (1990:1-2004:4) all the multivariate forecasting methods seem to produce equally accurate forecasts. Thus, the restrictions (stationary and cross-equation) implied by the hybrid model appear to help in forecasting especially well during high inflation periods. According to the univariate and multivariate measures of forecast accuracy, this result is most obvious at medium-term horizons. One exception is the nominal interest rate. The hybrid model forecasts this series particularly well in

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[11] We do not report the marginal likelihood, since it captures only the one-step-ahead predictive performance of the full model and is therefore too restricted for forecasting comparison.

[12] The GDP forecasts are not directly comparable to the results of Smets and Wouters (2007), since they use the log difference of GPD series, while we use the GDP gap series.

all samples and forecasting horizons (see Figure 1 and 4). In particular, all these results hold for both ex post and real-time data.

Taking a closer look at the figures we see that the hybrid model is superior to the naïve forecasts in all samples and horizons, except for the longer horizon inflation forecasts in the low inflation subsample. In this latter, the Bayesian VARs also give slightly better inflation and output gap forecasts than the hybrid model, according to the RMSEs. However, the improvement in the predictability of the variables is clearly negligible.

It would also appear that the shrinking prior does not improve the forecasting performance of VARs in terms of point forecasting accuracy. This is not surprising, since the VAR systems are particularly parsimonious and, hence, do not suffer from the over-parameterization problem. However, the LPDS statistics (see Figures 3 and 6) support a slightly better forecasting density for the Normal-Diffuse prior specification in the low inflation subsample. Over the entire sample the LPDSs support Bayesian VARs at the shorter forecasting horizons (1 to 4 quarter); however, the hybrid model again outperforms the VARs at the longer horizons.

In sum, it seems fair to say that the simple hybrid NK model captures the predictable behavior of the three U.S. key macroeconomic variables particularly well. The reason for its good forecasting performance may be that the model allows both for the endogenous persistence in inflation and output and for the persistence of the exogenous shock processes. This approach is commonly used in large-scale NK models, which forecast well. Our joint prior is also well designed in allowing the parameters to be estimated fairly freely, while being informative enough to keep the posterior distribution away from economically non-meaningful values.

5.4 Conclusions

Several recent papers have suggested different ways to improve the forecast performance of new Keynesian models. Unfortunately, improvement in fit is achieved at the cost of increasing the complexity of model mechanisms, which reduces the practicability of these approaches. This paper, in contrast, has shown that the very simple hybrid new Keynesian model of Clarida *et al.* (1999) can provide forecasts comparable to those based on commonly used benchmark models such as reduced-form Bayesian VARs and univariate random walks.

Our forecasting evidence indicates that the restrictions implied by the hybrid model work especially well in high inflation regimes. According to several univariate and multivariate measures of forecast accuracy, the forecasts of the hybrid model outperform those of the Bayesian VARs when high inflation periods are forecasted. In the low inflation forecast subsample, the methods produce equally accurate forecasts. One exception was the nominal interest rate. The hybrid model seems to forecast this series eminently well in all samples and horizons. The hybrid model also predicts more accurately than the naïve forecasts based on univariate random walks. Finally, we note that all these findings hold for both ex post and real-time data.

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Appendix 1: MCMC-procedure, Priors and Posteriors

The MCMC procedure to sample from the posterior distribution:

To generate a Monte Carlo sample from the posterior of θ we used a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MMCMC). The algorithm uses a multivariate normal distribution for the jump distribution on changes in θ. Our simulation procedure was as follows: we first simulated 10,000 draws using a diagonal covariance matrix with diagonal entries 0.00001 in the jump distribution. We then used these draws to estimate the posterior covariance matrix of θ and scale it by the factor $2.4^2/13$, to obtain an optimal covariance matrix for the jump distribution; see e.g. Gelman *et al.* (2004). We continue by simulating 10,000 draws and calculated a more accurate covariance matrix for θ. We repeated this for 2 times. We then added noise to the posterior median to obtain overdispersed starting values and simulated three chains of length 30,000. We excluded the first 5000 simulations as a burn-in period in each chain and picked out every 25th draw from the Markov chain, yielding a sample of 3000 draws, which economizes on storage space and reduces autocorrelation across draws. The convergence of the chains was checked using Gelman and Rubin's convergence diagnostic R (also called potential scale reduction factor); see Gelman and Rubin (1992). The diagnostic values close to 1 indicate approximate convergence and values smaller than 1.1 are in most cases acceptable. In our case the diagnostic was estimated to be between 1.01 and 1.03 for all parameters and all models. The multivariate version of Gelman and Rubin's diagnostic proposed by Brooks and Gelman (1998) was between 1.01 and 1.02 for each model; the convergence was thus fairly good. The frequencies of accepted jumps were roughly 0.21. Finally, the previous adaptive Metropolis algorithm is used because the covariance matrix estimate based on the local behavior of the posterior at its highest peak turned out to give too optimistic a view of precision, and thus failed to yield an efficient covariance matrix for the normal jump distribution.

TABLE 1. Priors and Posteriors of the Hybrid new Keynesian Model.

	Prior Distr.			Posterior Distr. (GDP)			Posterior Dist. (NFB)		
Panel A: Sample 1954:2 – 2004:4									
Par.	Distr.	Mean	St.Dev.	Median	5%	95%	Median	5%	95%
α	Beta	0.67	0.24	0.08	0.02	0.19	0.08	0.02	0.18
γ	Gamma	1.00	0.32	0.03	0.02	0.05	0.03	0.02	0.05
β	Beta	0.67	0.24	0.75	0.65	0.84	0.74	0.65	0.83
β_r	Gamma	1.00	0.32	0.10	0.05	0.16	0.12	0.07	0.20
γ_π	Gamma	1.5	0.61	1.82	1.50	2.32	1.82	1.46	2.34
γ_x	Gamma	0.5	0.35	0.59	0.40	0.87	0.49	0.33	0.76
ρ	Beta	0.5	0.22	0.87	0.83	0.91	0.89	0.85	0.92
ρ_π	Normal	0	0.54	-0.38	-0.46	-0.28	-0.42	-0.50	-0.33
ρ_x	Normal	0	0.54	0.79	0.67	0.87	0.78	0.66	0.86
ρ_R	Normal	0	0.54	0.12	-0.00	0.24	0.11	-0.00	0.24
σ_π	Invgam.	0.40	3.96	0.29	0.26	0.32	0.34	0.31	0.37
σ_x	Invgam.	0.40	3.96	0.16	0.12	0.20	0.21	0.16	0.28
σ_R	Invgam.	0.40	3.96	0.22	0.20	0.24	0.22	0.20	0.24
Panel B: Sample 1954:2 – 1982:2									
α	Beta	0.67	0.24	0.08	0.02	0.20	0.08	0.02	0.21
γ	Gamma	1.00	0.32	0.05	0.03	0.07	0.05	0.03	0.07
β	Beta	0.67	0.24	0.79	0.66	0.94	0.77	0.66	0.92
β_r	Gamma	1.00	0.32	0.19	0.11	0.32	0.21	0.12	0.35
γ_π	Gamma	1.5	0.61	1.86	1.46	2.46	1.81	1.41	2.47
γ_x	Gamma	0.5	0.35	0.52	0.29	0.86	0.47	0.25	0.77
ρ	Beta	0.5	0.22	0.84	0.78	0.90	0.87	0.80	0.92
ρ_π	Normal	0	0.54	-0.35	-0.48	-0.21	-0.41	-0.52	-0.28
ρ_x	Normal	0	0.54	0.77	0.60	0.87	0.76	0.60	0.87
ρ_R	Normal	0	0.54	0.11	-0.06	0.29	0.10	-0.06	0.27
σ_π	Invgam.	0.40	3.96	0.34	0.30	0.39	0.41	0.36	0.46
σ_x	Invgam.	0.40	3.96	0.24	0.17	0.34	0.32	0.22	0.43
σ_R	Invgam.	0.40	3.96	0.28	0.25	0.31	0.28	0.25	0.32
Panel C: Sample 1982:3 – 2004:4									
α	Beta	0.67	0.24	0.08	0.02	0.20	0.08	0.02	0.20
γ	Gamma	1.00	0.32	0.05	0.03	0.08	0.04	0.03	0.06
β	Beta	0.67	0.24	0.83	0.70	0.97	0.86	0.73	0.98
β_r	Gamma	1.00	0.32	0.19	0.11	0.32	0.23	0.13	0.37
γ_π	Gamma	1.5	0.61	2.65	1.93	3.64	2.63	1.88	3.75
γ_x	Gamma	0.5	0.35	0.89	0.57	1.35	0.69	0.42	1.08
ρ	Beta	0.5	0.22	0.90	0.86	0.93	0.91	0.87	0.94
ρ_π	Normal	0	0.54	-0.35	-0.50	-0.17	-0.37	-0.50	-0.22
ρ_x	Normal	0	0.54	0.88	0.79	0.94	0.88	0.80	0.94
ρ_R	Normal	0	0.54	0.29	0.11	0.47	0.34	0.16	0.52
σ_π	Invgam.	0.40	3.96	0.22	0.19	0.25	0.24	0.20	0.28
σ_x	Invgam.	0.40	3.96	0.09	0.06	0.12	0.11	0.08	0.16
σ_R	Invgam.	0.40	3.96	0.12	0.10	0.13	0.11	0.10	0.13

Appendix 2: Forecast Comparison Figures

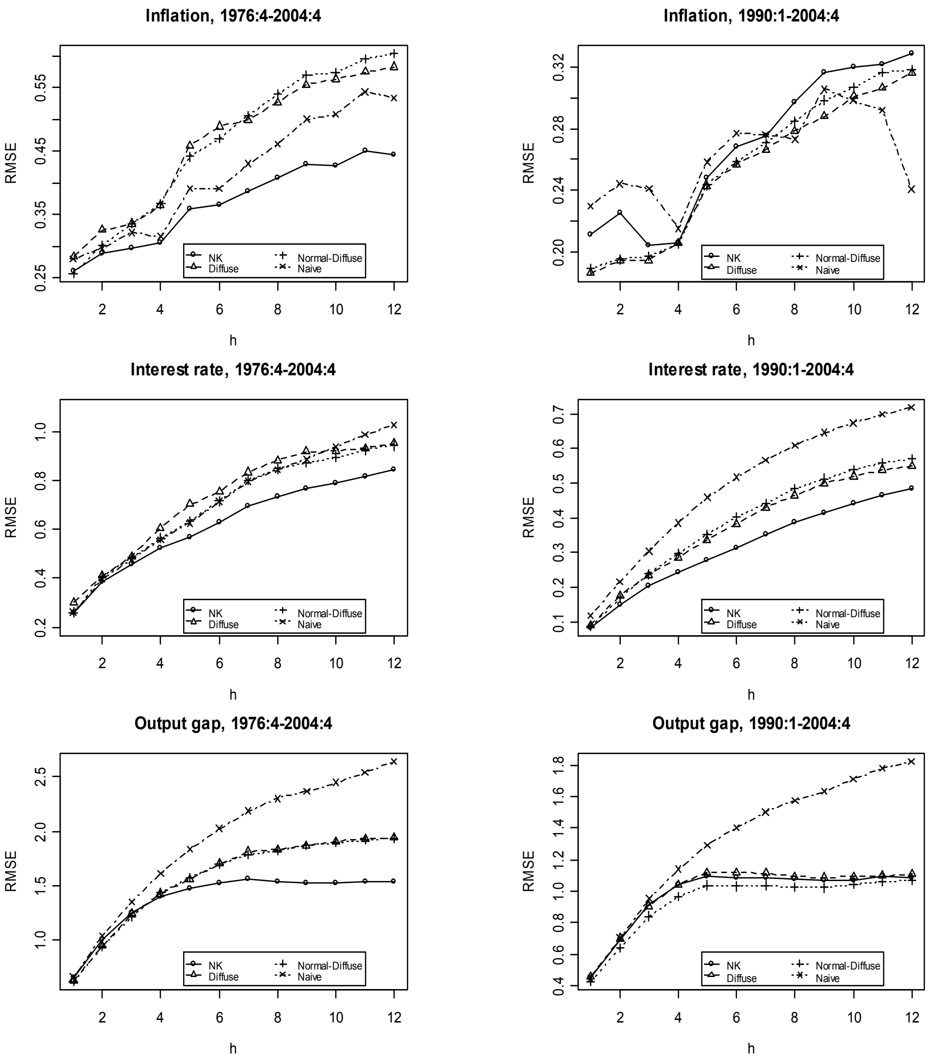

FIGURE 1. The root mean squared forecast errors for the competitive models.

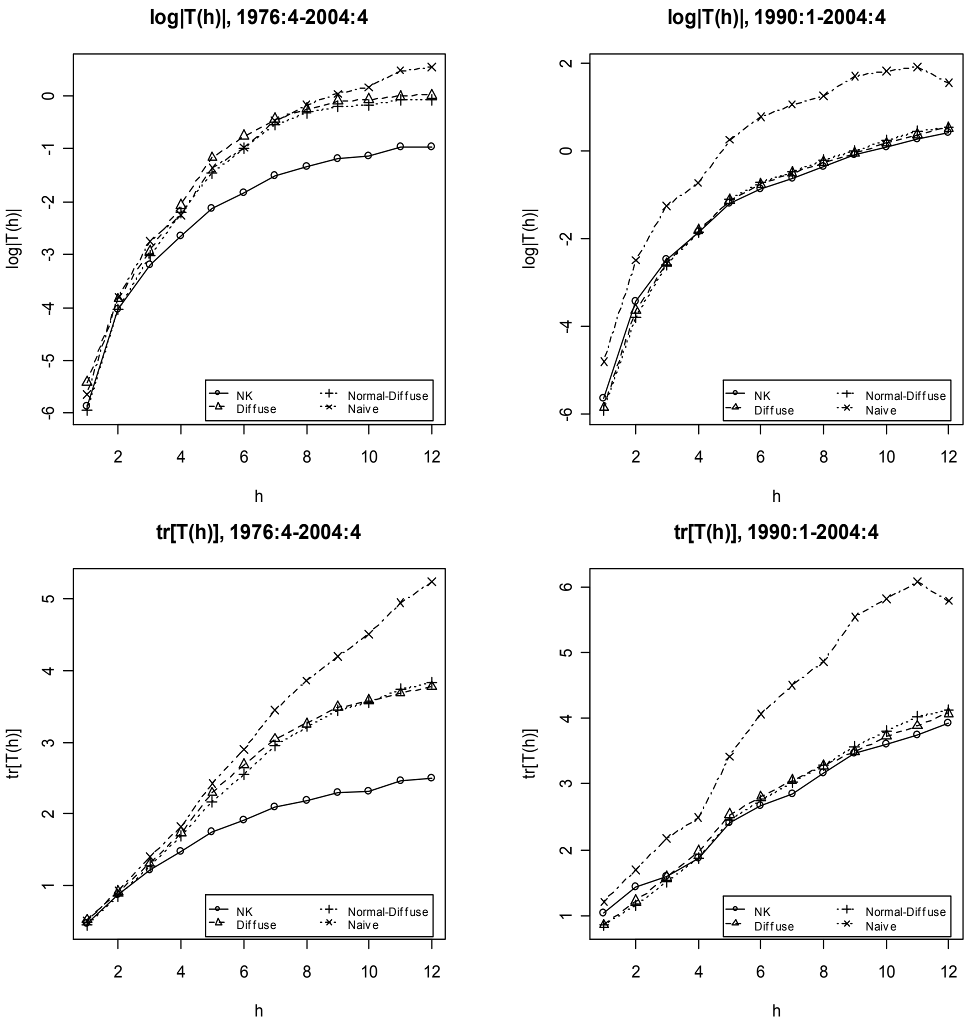

FIGURE 2. The log determinant statistics and the trace statistics for the competitive models.

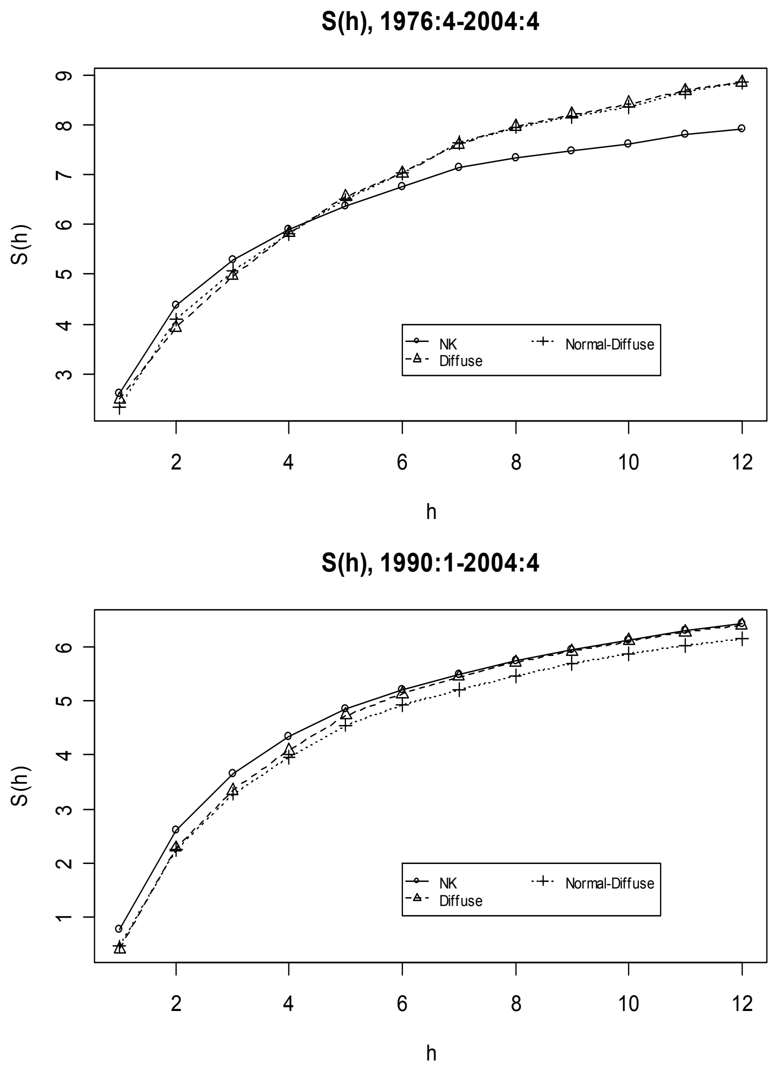

FIGURE 3. The average log predictive density scores for the competitive models.

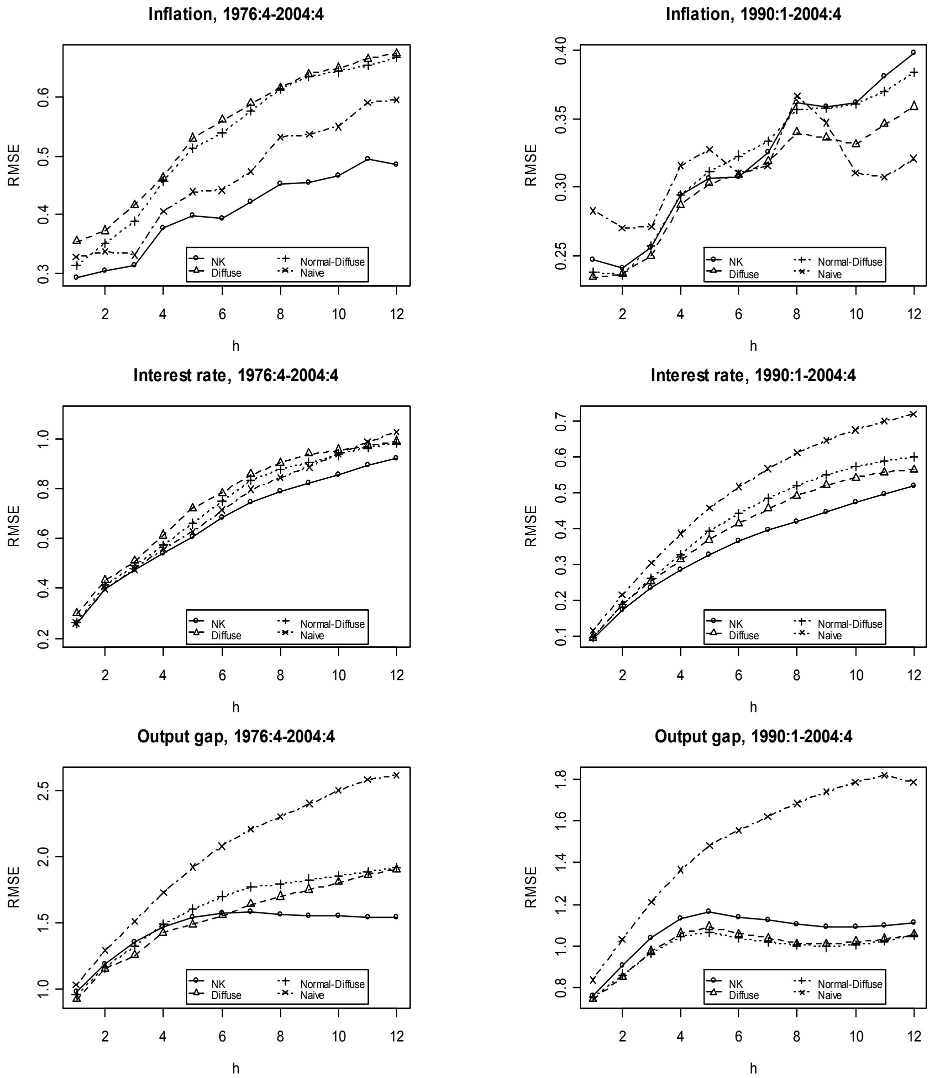

FIGURE 4. The root mean squared forecast errors for the competitive models (real-time data).

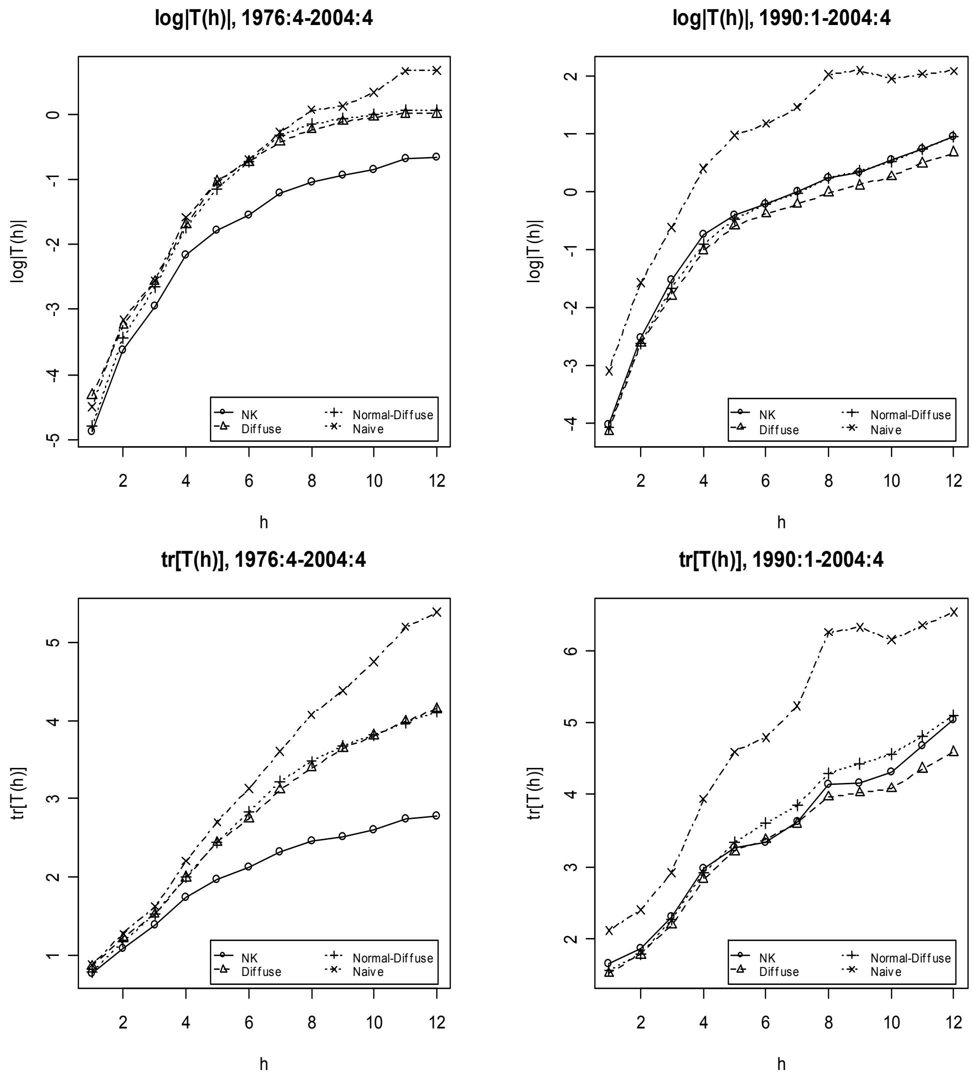

FIGURE 5. The log determinant statistics and the trace statistics for the competitive models (real-time data).

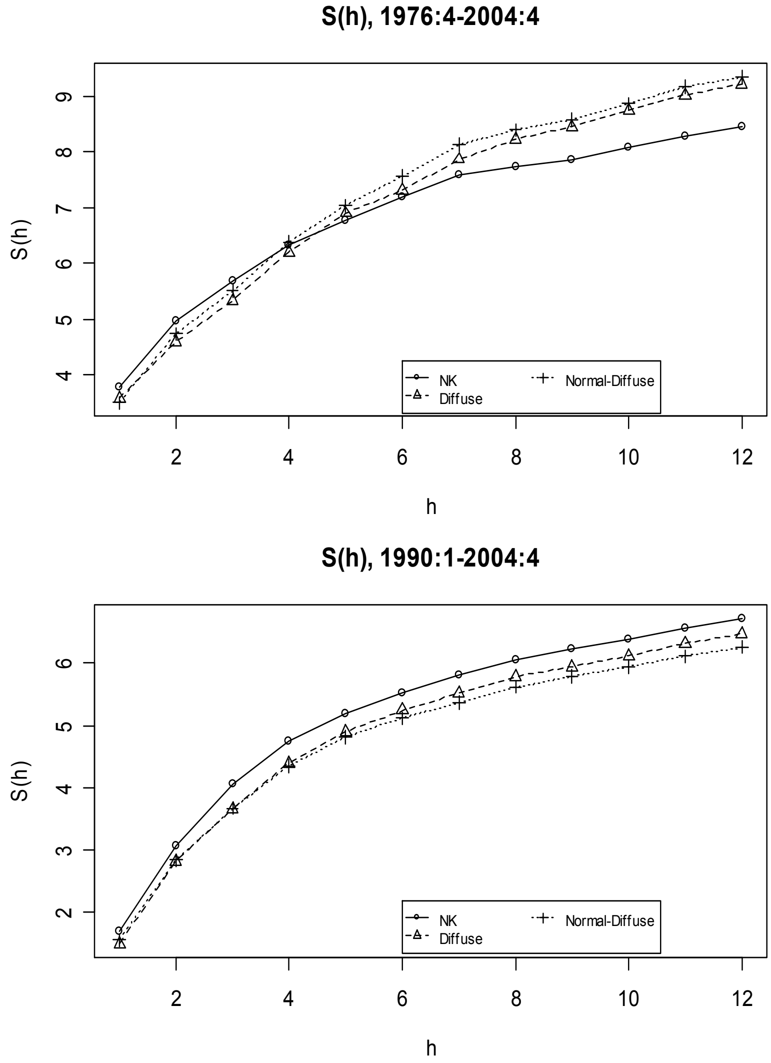

FIGURE 6. The average log predictive density scores for the competitive models (real-time data).