Business cycle analysis with structural vector autoregressions: four applications

by

Atılım Seymen

submitted in partial fulfillment of the
requirements for the degree of
Doktor der Wirtschafts- und Sozialwissenschaften (Dr. rer. pol.)
at
University of Hamburg
Edmund-Siemers-Allee 1, 20146 Hamburg
July 2009

University of Hamburg

Faculty of Economics and Social Sciences

Department of Economics

The undersigned hereby certify that they have read and recommend to the Faculty of Economics and Social Sciences for acceptance a thesis entitled "**Business cycle analysis with structural vector autoregressions: four applications**" by M.Sc. in Econ. and Mgmt. **Atılım Seymen** in partial fulfillment of the requirements for the degree of **Doktor der Wirtschafts- und Sozialwissenschaften (Dr. rer. pol.)**.

Date: October 26, 2009

Chairman: ______________________

Prof. Dr. Michael Funke

Research Supervisor: ______________________

Prof. Dr. Bernd Lucke

Examing Committee: ______________________

Prof. Dr. Bernd Lucke

____

Prof. Dr. Ulrich Fritsche

UNIVERSITY OF HAMBURG

Date: **July 2009**

Author: **Atılım Seymen**

Title: **Business cycle analysis with structural vector autoregressions: four applications**

Department: **Economics**

Degree: **Dr. rer. pol.** Convocation: **October** Year: **2009**

Acknowledgements

Many people have contributed, directly or indirectly, to the formation of this thesis throughout the years. Special thanks go to my supervisor, Bernd Lucke, for his comments and advice on the work. I have also benefited from long conversations with my second reader, Ulrich Fritsche, as well as with Beatriz Gaitan, Marcus Kappler, Olaf Posch and Hakan Yetkiner. Not all of these conversations found directly a place in this thesis, but they motivated me and contributed to my personal development enormously. Furthermore, I thank my colleagues and friends from the Institute for Growth and Business Cycles of the University of Hamburg, Angela Ebert, Karin Endrejat, Malte Knüppel, Christian Gaggermeier, Omar Feraboli, Timo Trimborn, Salam Said, Stefan Kolev, Jacopo Zotti and Thomas Haertel for their friendship. I owe many thanks to Wolfgang Franz, President of the Centre for European Economic Research (ZEW), for providiving excellent working and research conditions as well as my colleagues Claudia Busl, Jan Hogrefe, Andreas Sachs and Martin Scheffel from the Research Group "Growth and Business Cycle Analyses" of ZEW for the pleasant working environment and helpful comments on parts of this text. Many thanks also go to Barış Gök for his friendship and support. Last but not least, I have benefited a lot from participation and presentation at many international seminars, workshops and conferences in Hamburg, Izmir, Volterra, Berlin, Halle, Mannheim, Dresden, Faro, Lille, Graz, Luxemburg, Riverside, Rethymno and Vallendar.

I always felt the support and love of my parents, sister and brother-in-law, parents-in-law and many relatives throughout the years, which gave me strength. My supportive and caring wife, Burcu, whom I met after I started with my PhD studies and married not long after, often had to suffer due to my physical and mental absence. I hope this piece of work alleviates it.

Contents

Introduction

Vector autoregression (VAR) and structural vector autoregression (SVAR) models have been employed in macroeconometric analyses ever since Sims (1980) proposed in his seminal paper the VAR approach as a solution to the problems of the simultaneous equations models (SEMs), which had dominated macroeconometric research and policy analysis up to that date.[1] The VAR framework provides, on the one hand, a convenient forecasting tool without high costs in terms of model specification and estimation and allows, on the other hand, a structural analysis of macroeconomic dynamics. SVARs reflect—like the so-called dynamic stochastic general equilibrium (DSGE) models—the macroeconomic modelling philosophy that exogenous shocks and their corresponding propagation mechanisms determine the dynamics of macroeconomic variables. They are particularly suitable for business cycle analysis, to which four applications are devoted in this thesis. The SVAR framework allows macroeconomists to estimate impulse response functions and variance decompositions with respect to the structural shocks of an economy. Moreover, counterfactual analyses can be conducted, where the effects of structural shocks on macroeconomic variables are investigated in isolation from each other. A common practice is to evaluate the convenience of a theoretical model by comparing its implications with those of a SVAR model, the restrictions on which are compatible with the theoretical model of interest.

Chapter 1 of this thesis outlines the SVAR framework and establishes a general notation that is used in the applications of the later chapters. The so-called short-run and long-run restrictions are described, since these types of restrictions are used for identification in

[1]Indeed, many macroeconomic research institutes still provide forecasts based on such big models.

our applications. The structural parameters of interest are estimated by maximising the corresponding restricted maximum likelihood function in this study. Since three chapters of this study are devoted to applications on business cycle dynamics, tools of business cycle analysis in the SVAR context are reviewed as well, before closing Chapter 1 with a discussion and a review of various issues related to the SVAR methodology.

Chapter 2 motivates the empirical analysis of Chapters 3 and 4. It starts with a review of the literature on business cycle dynamics in the euro area and closes with a descriptive analysis of the data set used in the applications of Chapters 3 and 4. The main message of the literature review is that a multitude of factors affect business cycle synchronisation in both directions—convergence and divergence—across countries. The theoretical literature is not clear-cut as to whether more or less synchronised business cycles should emerge as a byproduct of globalisation and European Monetary Union (EMU) processes. The empirical literature is also not united: a number of studies report that business cycles have become more synchronised in the euro area over the course of years, whereas a multitude of studies do not obtain higher business cycle synchronisation.

Our descriptive analysis of euro area business cycles in Chapter 2 is carried out with quarterly GDP data spanning the period 1970Q1–2007Q4, which is in contrast with the majority of studies on this subject that use either annual GDP data or industrial production data. The GDP of the six largest economies of the euro area—Belgium, Germany, Spain, France, Italy and the Netherlands—is included in the data set, while other member economies are discarded since quarterly GDP data is not available for the sample period considered. We carry out our computations in sub-samples as well as in rolling windows in order to capture changes that occur in business cycle dynamics over time. We find a generally high and recently increasing synchronisation of output gaps, in terms of correlations between the output gap of each member country and the euro area, as well as in terms of the average of bilateral correlations among the six member countries of the euro area. Another important observation is the moderation of output gap volatility in the member countries—the so-called

Great Moderation—in the period preceding the recent macroeconomic turmoil.

The extent and sources of business cycle heterogeneity in the euro area are an important concern of policy makers. The common monetary policy is optimised with respect to (the business cycle of) the entire euro area economy. Therefore, it may may have destabilising effects on the member economies, cycles of which deviate to a large extent from the cycle of the entire single currency area. A sign of heterogeneity is that correlations of output gaps across member countries, as well as between each member country and the entire euro area, are typically not perfect. In order to gain more information on the dynamics of business cycle heterogeneity of the euro area, we also investigate the dynamics of output gap differentials, i.e., differentials between the output gap of each member country and the euro area output gap, in Chapters 3 and 4. An important finding of our descriptive analysis in Chapter 2 is that output gap differentials underwent a moderation as well. This result speaks for a decreasing heterogeneity in the euro area over time.

Chapters 3 and 4 investigate the properties of business cycle dynamics in the euro area by employing three different empirical approaches. Both chapters seek to answer three basic questions given the findings of Chapter 2. First, we are interested in whether member countries' output gaps are driven by a common euro area factor in addition to and/or in isolation from a global factor. The literature is not united in this respect. While Stock and Watson (2005) write about the emergence of a Euro-zone group among the G7 countries, for example, Canova, Ciccarelli, and Ortega (2007) find "little support for the idea that euro cycles are different or that a euro area cycle is emerging in the 1990s." We compute variance decompositions to measure the importance of a euro area factor in the output gap fluctuations of the member countries in an empirical framework, where both global and euro area shocks (in addition to country-specific shocks) are included as potential sources of fluctuations. Second, we ask whether differences in terms of shock transmission or rather exposure to asymmetric shocks are behind the observed heterogeneity of business cycles in the euro area. Counterfactual correlations of output gaps as well as variance decomposition of output (gap) differentials are carried out to answer this question. Third, we explore the role of two channels in the moderation of output gaps and output gap differentials—changes in size of shocks vs. changes in shock transmission.

Chapter 3 is devoted to the analysis of euro area business cycle dynamics with conventional SVAR models that comprise global, euro area and country-specific shocks over two sample-periods as the driving forces of cyclical fluctuations. The empirical framework is a modified version of the framework in Giannone and Reichlin (2006). Six trivariate SVAR models comprising the output of the US, the euro area and one of the six member countries in our sample are estimated to answer the aforementioned questions. Estimations are carried out in sub-samples as well as in 15-year rolling windows.

While the analysis of Chapter 3 is illuminating on the relationships between individual member countries and the entire euro area, its empirical approach is vulnerable to two important critiques, which are addressed in Chapter 4. First, the empirical framework of Chapter 3 does not include analysis of spillovers of country-specific shocks between pairs of member countries. A factor-structural VAR (FSVAR) model, which allows identification of global, euro area and country-specific shocks, is estimated in Chapter 4 in order to deal with this issue. Country-specific shocks are now allowed to be spilled over among all countries included in the model. The disadvantage of this model is, however, that the euro area output is no longer included so that the relationships between individual countries and the entire euro area cannot be explored.

The second vulnerability of the empirical framework of Chapter 3, which applies to the FSVAR model as well, is that the break date for splitting the sample into two sub-periods is chosen somewhat arbitrarily. Rolling window estimations provide more dynamics and are useful for getting an idea about changing business cycle dynamics over time, yet they may also lead to biased estimations, in particular, when the break date belongs to but is not dealt with in a rolling window. Therefore, we also estimate time-varying coefficients SVAR (TVC-SVAR) models in Chapter 4, which stand for the time-varying coefficients version of the fixed-coefficient SVAR models of Chapter 3. Breaks in the data are included naturally in this type of an empirical framework via time-varying VAR coefficient matrices as well as time-varying covariance matrices of structural shocks.

The three empirical models employed in the estimations of Chapters 3 and 4 are complementary to each other. Despite differences across these models, the answers given by them to the three questions posed above are broadly in line. First, it is found that both global and euro area shocks play non-negligible roles in output fluctuations. However, it is not clear-cut whether the share of euro area shocks in output gap variance has increased or decreased in the euro area recently. Second, business cycle heterogeneity is driven to a large extent by exposure to asymmetric shocks in the euro area. However, this picture is changing in some countries recently, while the heterogeneity is becoming weaker. Finally, the moderation of output and output differential dynamics corresponding to business cycle frequencies is found to be mainly due to a decline in the size of shocks rather than changes in shock transmission.

The application in Chapter 5 deals with the role of *structural* common and country-specific shocks in the business cycle dynamics of the G7 countries. The point of departure for the investigation is the estimation of country-specific VAR models of the G7 countries comprising real and nominal variables, which are modified versions of the benchmark model of Beaudry and Lucke (2009). An important difference to the previous chapters is that the estimated shocks are given an interpretation based on macroeconomic theory in Chapter 5, while the interpretation of shocks in Chapters 3 and 4 are based solely on the geographical origin of shocks. The most recent views on the sources of business cycle fluctuations are embedded into the SVAR model underlying the analysis. For each G7 country, neutral technology, news, preference and monetary shocks are estimated. The most important finding is that neutral technology and news shocks (shocks about future technological developments) drive the output fluctuations of all G7 countries, whereas smaller roles are attributed to preference and monetary shocks.

In Chapter 5, we also use maximum likelihood techniques in order to estimate common and country-specific factors that drive the structural shocks of the individual countries, as well as the corresponding dynamic multipliers (the transmission channels of these shocks). Particular attention is paid to the weight of structural-international common shocks in the cyclical fluctuations of macroeconomic variables. Again with the exception of Japan, international news shocks are found to be an important source of output fluctuations, especially in recent periods. Hence, both the country-specific and international models of Chapter 5 suggest including news shocks in theoretical models as a stochastic source of fluctuations.

Chapter 1

Structural vector autoregressions

This chapter sets the general framework and notation used throughout the study. It starts by describing the relationship between reduced-form and structural VARs which is followed by a discussion of different approaches to identification and estimation of structural parameters. Subsequently, a review of two techniques that can be employed for business cycle analysis in the SVAR framework is provided. The chapter closes with the discussion of various issues on SVAR methodology and remarks.

1.1 VARs and SVARs

1.1.1 Reduced form

A VAR refers to a so-called reduced-form VAR throughout this study. It establishes a relationship between current and past values of a vector of variables. Let Y_t be a vector of K stationary variables at period t. The subject of interest is the VAR model of order p, which is given by

$$Y_t = bd_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + u_t, \qquad (1.1)$$

where Y_t is a $K \times 1$ vector of endogenous variables, b is a $K \times M$ coefficient matrix loading the $M \times 1$ vector of M deterministic terms and/or exogenous variables d_t, B_i for $i = 1, \ldots p$ is the i^{th} $K \times K$ VAR coefficient matrix, and u_t is a $K \times 1$ vector of Gaussian innovations with the covariance matrix Σ_u. The VAR model in (1.1) has the so-called moving average (MA) representation given by

$$Y_t = fd_t + \sum_{i=0}^{\infty} \phi_i u_{t-i}, \tag{1.2}$$

where ϕ_i for $i = 0, 1, \ldots$ stand for $K \times K$ moving average coefficient matrices with $\phi_0 = I_K$, where I_K is the $K \times K$ identity matrix, and $f = B(1)^{-1} b$ with $B(1) = I_K - B_1 - \cdots - B_p$. The MA coefficient matrices ϕ_i for $i > 0$ can be computed from the relationships

$$0 = \phi_i - \phi_{i-1} B_1 - \cdots - \phi_0 B_i \text{ for } i > 0, \tag{1.3}$$

with $B_i = 0$ for $i > p$.[1]

When Y_t comprises K nonstationary variables, this implies that

$$0 \leq rk(\Pi) = r < K, \tag{1.4}$$

with $\Pi = B(1)$. Note that $r = K$ would imply stationarity of all variables in (1.1). When $r = 0$ (and hence $\Pi = 0$), it is appropiate to estimate (1.1) in first differences, i.e.,

$$\Delta Y_t = bd_t + D_1 \Delta Y_{t-1} + \cdots + D_{p-1} \Delta Y_{t-p+1} + u_t \tag{1.5}$$

with $D_i = -\sum_{j=i+1}^{p} B_j$ for $i = 1, ..., p-1$.[2] Simple ordinary least squares (OLS) techniques can be employed for the estimation of the coefficients in (1.5).

If $0 < r < K$ holds, the variables are said to be cointegrated, i.e., there are r distinct linear combinations of them which all follow stationary processes. In such a case, it is appropriate to rewrite (1.1) as a vector error correction model (VECM) given by

$$\Delta Y_t = bd_t + \Pi Y_{t-1} + D_1 \Delta Y_{t-1} + \cdots + D_{p-1} \Delta Y_{t-p+1} + u_t. \tag{1.6}$$

The coefficient matrices D_i for $i = 1, \ldots, p-1$ in (1.6) can be derived in the same way as for (1.5) with respect to the representation in (1.1). Although the OLS estimator of the

[1] See the first chapter in Lütkepohl (2007).

[2] Note that coefficient matrix B_1 of the representation in (1.1) is not included in any of D_i for $i = 1, \ldots, p-1$, but is given by $B_1 = I_K - \sum_{i=2}^{p} B_i$, since $\Pi = 0$ for the system in (1.5).

coefficients in (1.1) in case of cointegrated variables has asymptotically the same properties as the maximum likelihood (ML) estimator subject to the constraint (1.4), the ML estimator is more suitable and widely employed for small sample estimations. Moreover, the ML approach provides the estimators of the so-called loading and cointegration matrices, α and β, such that $\Pi = \alpha\beta'$, α and β being of order $K \times r$.

The moving average representation corresponding to the VAR model in first-differences in (1.5) and the VECM in (1.6) is given by

$$\Delta Y_t = cd_t + \sum_{i=0}^{\infty} C_i u_{t-i}, \tag{1.7}$$

where C_i for $i = 0, 1, \ldots$ stand for $K \times K$ moving average coefficient matrices with $C_0 = I_K$, and $c = D\,(1)^{-1}\,b$ with $D\,(1) = I_K - D_1 - \cdots - D_{p-1}$ for (1.5), and $c = \beta_\perp\,(\alpha'_\perp D\,(1)\,\beta_\perp)^{-1}\,\alpha'_\perp b$ for (1.6), where $\alpha_\perp$ and $\beta_\perp$ are $K \times (K - r)$ orthogonal complements such that $\alpha'\alpha_\perp = \beta'\beta_\perp = 0_{r\times(K-r)}$. The MA coefficient matrices C_i for $i > 0$ corresponding to (1.5) can be computed, similar to (1.3), from the relationships

$$0 = C_i - C_{i-1}D_1 - \cdots - C_0 D_i \text{ for } i > 0, \tag{1.8}$$

where $D_i = 0$ for $i > p-1$. The existence of an MA representation (1.7) of (1.6) is not obvious at first glance. The Granger representation theorem states that an MA representation exists. The MA coefficient matrices are, however, different than the ones described by (1.8), namely

$$C_0 = I,\ C_1 = C_0\,(\alpha\beta' + D_1)\,, \tag{1.9a}$$

$$C_i = C_{i-1}\,(I + \alpha\beta' + D_1) + \sum_{j=2}^{p-1} C_{i-j}\Delta D_j \text{ for } i > 1, \tag{1.9b}$$

where $C_{-1} = \cdots = C_{-p+3} = 0$.

1.1.2 Structural form

In econometrics, reduced form is a representation of endogenous variables as a function of exogenous and predetermined variables in a system. Reduced form follows from original structural relationships, which are typically not directly observable. A certain number of restrictions are usually imposed on relationships among variables and/or shocks for estimating structural relationships. Equation (1.1) is in reduced form, which could equivalently be written as

$$AY_t = ad_t + A_1 Y_{t-1} + \cdots A_p Y_{t-p} + B\varepsilon_t, \tag{1.10}$$

with $a = Ab$, $A_i = AB_i$, and

$$Au_t = B\varepsilon_t. \tag{1.11}$$

a and A_i are structural coefficient matrices, while ε_t demonstrates structural innovations with the covariance matrix Σ_ε. Moreover, A and B are non-singular matrices. (1.10) is said to be the structural representation of (1.1) , where the term "structural" refers to the fact that A_i and ε_t can (partially or totally) be given a meaningful economic interpretation depending on the restrictions imposed on A, B and/or Σ_ε. ε_t comprise structural shocks that are typically labelled as supply, demand, monetary, fiscal policy, etc. in reference to macroeconomic theory, while A_i contain the so-called dynamic multipliers that determine the effects of structural shocks on the variables of the VAR over time.

Note that the error terms in (1.1) stand for linear combinations of the structural innovations following from (1.10). The so-called identification problem is the determination of the (non-singular) $K \times K$ matrices A and B of structural parameters. Obviously, the knowledge of A and B is sufficient for computing all structural coefficient matrices and shocks. The coefficient matrices and the residuals in (1.10) can be estimated using one of the well-established methods.

We write the structural MA representation corresponding to (1.2) and (1.7) as

$$Y_t = fd_t + \sum_{i=0}^{\infty} \Phi_i \varepsilon_{t-i}, \tag{1.12}$$

and

$$\Delta Y_t = cd_t + \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i}, \tag{1.13}$$

with $\Phi_i = \phi_i A^{-1} B$ and $\Theta_i = C_i A^{-1} B$ for $i \geq 0$, respectively. Moreover, (1.13) can be rewritten such that

$$Y_t = Y_0 + c \sum_{j=1}^{t} d_j + \sum_{i=0}^{t-1} \Theta_i^* \varepsilon_{t-i}, \tag{1.14}$$

with $\Theta_i^* = \sum_{j=0}^{i} \Theta_j$. The representations in (1.12) and (1.14) underlie the impulse-response and variance decomposition computations in the forthcoming chapters of this study.

1.2 Identification

Different strategies have been proposed in the SVAR literature for dealing with the aforementioned identification problem. These differ in particular with respect to how the dynamic response of variables to structural shocks is modelled. Assumptions on the short-term or long-term responses of variables to structural shocks lie at the heart of the identification schemes discussed in the following. Common to almost all identification strategies is the assumption that the structural shocks are orthogonal to each other, i.e., Σ_ε is typically assumed to be a diagonal matrix. Given (1.11), it thus can be written as

$$\Sigma_\varepsilon = B^{-1} A \Sigma_u A' B'^{-1}. \tag{1.15}$$

In practice, Σ_u is estimated using the estimated residuals of the reduced form. Given that covariance matrices are always symmetric, (1.15) provides $K(K-1)/2$ restrictions for identifying the elements of A and B. Since there are $2K^2$ unknowns in A and B, $2K^2 - K(K-1)/2$ more restrictions are needed for an exact identification.[3] These additional restrictions are typically imposed using implications of macroeconomic theories. Three general strategies for imposing restrictions have been suggested in the literature. The first is either to model instantaneous relationships among endogenous variables and/or to model impact effects of structural shocks on endogenous variables. The second possibility is to impose restrictions

[3] The number of theoretical restrictions cannot be less than $2K^2 - K(K-1)/2$ for identification, while it is possible to use more than $2K^2 - K(K-1)/2$ restrictions. In the latter case, the system is said to be overidentified.

on the long-run effects of structural shocks on macroeconomic variables. We use both types of restrictions in our empirical applications. A third possibility is to restrict the sign of variables' responses to structural shocks, which is, however, not applied in this study. Therefore, we do not describe this latter possibility.

1.2.1 Short-run restrictions

The framework given in (1.10) and (1.11) is called the AB-model. It allows econometricians to set restrictions on both instantaneous relationships of endogenous variables and impact effects of shocks on endogenous variables at the same time. An example, where restrictions on both A and B are imposed, can be found in Blanchard (1989). The author justifies his theoretical identification restrictions with a traditional Keynesian model. His main interest lies in detecting whether the findings from the SVAR support the implications of "traditional", i.e. Keynesian, models.

A special case of the AB-model is the A-model, where only the instantaneous relationships among the endogenous variables are modelled by imposing restrictions on A and setting $B = I_K$. An example of such an approach can be found in Christiano, Eichenbaum, and Evans (1999), who review the literature on the response of macroeconomic variables to monetary policy shocks. The authors assume in their first benchmark model a causal ordering of variables such that A is lower triangular and the policy variable in the model, the Fed funds rate, which is assumed to be the policy instrument, is always ordered before and after the same variables regardless of the orderings of those in their subgroups. Their seven-variable model can be summarised by

$$Y_t = \begin{bmatrix} y_t \\ p_t \\ pcom_t \\ ff_t \\ tr_t \\ nbr_t \\ m_t \end{bmatrix}, \; A = \begin{bmatrix} * & 0 & 0 & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 & 0 \\ * & * & * & * & 0 & 0 & 0 \\ * & * & * & * & * & 0 & 0 \\ * & * & * & * & * & * & 0 \\ * & * & * & * & * & * & * \end{bmatrix} \text{ and } \Sigma_\varepsilon = I_7 \tag{1.16}$$

where $y_t, p_t, pcom_t, ff_t, tr_t, nbr_t$ and m_t stand for the log of real GDP, the log of implicit GDP deflator, the smoothed change in an index of sensitive commodity prices, the federal funds rate, the log of total reserves, the log of non-borrowed reserves plus extended credit, and the log of money supply (either M1 or M2) at period t, respectively. This structure implies that the monetary authority observes the economic activity variables y_t, p_t and $pcom_t$ before setting the policy rate, whereas the realisation of tr_t, nbr_t and m_t does not take place before the policy rate is set at each period. Note that other shocks are not given an economic interpretation in the framework of Christiano, Eichenbaum, and Evans (1999).

The other special case of the AB-model is the B-model, in which innovations in u_t are modelled as a special linear combination of structural innovations, and instantaneous relationships among endogenous variables are not touched directly by imposing restrictions on B and setting $A = I_K$. An example of such a model can be found in Evans (1989), where a bivariate VAR with first-differenced output and unemployment rate is estimated. Formally, the SVAR can be summarised by

$$Y_t = \begin{bmatrix} \Delta y_t \\ U_t \end{bmatrix}, \; B = \begin{bmatrix} * & 0 \\ * & * \end{bmatrix}, \; \varepsilon_t = \begin{bmatrix} \varepsilon_t^d \\ \varepsilon_t^s \end{bmatrix} \text{ and } \Sigma_\varepsilon = I_2. \tag{1.17}$$

Evans (1989) labels the two shocks in his model output and unemployment shocks (which we interpret here as demand and supply shocks following Blanchard and Quah (1989)) and argues that that supply disturbances do not have a contemporaneous effect on output. This restriction is reflected in the lower-triangular matrix B in (1.17). We estimate B-models in Chapters 3 and 4 of this study.

1.2.2 Long-run restrictions

In SVARs with long-run restrictions, the cumulative effect of a certain shock is usually constrained to bear a certain value, typically zero. This restriction is particularly meaningful when it is imposed to constrain the impact of a structural shock on the long-run behavior of a nonstationary variable. A prominent example of long-run restrictions can be found in Blanchard and Quah (1989). The authors impose such a restriction in a VAR comprising first-differenced log output and the level of the unemployment rate. Formally, their model can be summarised by

$$Y_t = \begin{bmatrix} \Delta y_t \\ U_t \end{bmatrix}, \Phi(1) = \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \text{ and } \Sigma_\varepsilon = I_2 \tag{1.18}$$

where Δy_t and U_t stand for the first-differenced log output and the unemployment rate, and $\Phi(1) = \sum_{i=0}^{\infty} \Phi_i$ in terms of (1.12) is the matrix of the long-run multipliers of the shocks. Blanchard and Quah label the second shock a demand shock (represented by the money-supply shock in the theoretical model they use to motivate their empirical approach) since it has no long-run impact on output, and the first shock a supply shock (represented by shocks to productivity) with a long-run impact on output. This model structure implies that only supply shocks are behind the non-stationarity of log output.

In another seminal study employing long-run restrictions for identification, King, Plosser, Stock, and Watson (1991) use the cointegration property to distinguish between the effects of permanent and transitory structural shocks on the variables of a cointegrated VAR comprising only $I(1)$ variables.[4] Transitory shocks are defined as the shocks with zero long-run effects on the variables of a cointegrated VAR. The general model with a cointegration rank of r can be summarised by

$$\Theta(1) = \begin{bmatrix} \tilde{\Theta}_{K\times(K-r)} & 0_{K\times r} \end{bmatrix}, \tag{1.19}$$

where $\Theta(1) = \sum_{i=0}^{\infty} \Theta_i$ in terms of (1.13) is the structural matrix of long-run multipliers, of

[4]See Chapter 9 in Lütkepohl (2007) for a more general description of SVECMs. Pagan and Pesaran (2007) also study systems with permanent and transitory shocks.

which first $K-r$ columns show the long-run effects of the permanent shocks. Such structural models are usually estimated as a B-model such that

$$\Theta(1) := C(1)\,B, \tag{1.20}$$

where $C(1) = \sum_{i=0}^{\infty} C_i$ in terms of (1.7) is known to have a rank of $K-r$ for a VAR with r cointegrating variables.[5] In general, when r cointegrating relationships exist, at most r transitory shocks can be allowed in the system, since more than r transitory shocks would imply that the cointegration rank must be less than r.

It is known from the Granger representation theorem that the $r \times K$ matrix containing the cointegrating vectors (β') is orthogonal to the matrix of long-run multipliers: $\beta' C(1) = 0_{r\times K}$. Hence,

$$\beta' \Theta(1) = 0_{r\times K} \tag{1.21}$$

according to (1.20). Since $\Theta(1)$ has a cointegration of rank $K-r$, i.e., $K-r$ independent elements in each of its columns, (1.21) amounts to only $r(K-r)$ restrictions on each row of $\Theta(1)$.

It is seen from (1.19) and (1.20) that the first $K-r$ columns of the matrix B must be known in order to compute the dynamic multipliers of the permanent shocks. Similarly, the knowledge of the first $K-r$ rows of the matrix B^{-1} is necessary for computing the variances of the permanent shocks. As will be clear in the following, the knowledge of either the first $K-r$ columns of B or the first $K-r$ rows of B^{-1} is enough for computing the other one. Thus, when the interest lies in computing the dynamics related to the permanent shocks, $K(K-r)$ elements have to be estimated in either B or B^{-1}. When the covariance matrix of structural shocks (Σ_ε) is a diagonal matrix, this imposes $(K-r)((K-r)-1)/2$ restrictions to this end. Recall from above that $r(K-r)$ additional restrictions come from the cointegration property of the model. Hence,

$$K(K-r) - \frac{(K-r)((K-r)-1)}{2} - r(K-r) = \frac{(K-r)((K-r)+1)}{2}$$

[5] See Lütkepohl (2007), p. 252, on the rank of $C(1)$.

more restrictions are needed for computing the variances and dynamic multipliers of the permanent shocks. Since B has K^2 unknown elements,

$$K^2 - \frac{K(K-1)}{2} - r(K-r) - \frac{(K-r)((K-r)+1)}{2} = \frac{r(r+1)}{2}$$

more restrictions are needed for identifying the transitory shocks, when the covariance matrix of structural shocks (Σ_ε) is a diagonal matrix.

King, Plosser, Stock, and Watson (1991) estimate a trivariate model, given by

$$\Delta Y_t = \begin{bmatrix} \Delta y_t \\ \Delta c_t \\ \Delta i_t \end{bmatrix}, \ \Theta(1) = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \text{ and } \Sigma_\varepsilon = \begin{bmatrix} * & 0 & 0 \\ 0 & * & 0 \\ 0 & 0 & * \end{bmatrix} \tag{1.22}$$

where y_t, c_t and i_t stand for the logs of output, consumption and investment. The authors assume (and confirm by applying statistical tests) a cointegration rank of 2 in their model, which implies a rank of 1 for $\Theta(1)$ in (1.22). Obviously, the first shock in the system is the permanent shock, and the last two shocks are the transitory shocks. The corresponding cointegration matrix is restricted such that

$$\beta' = \begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \end{bmatrix}, \tag{1.23}$$

with which the condition in (1.21) is fulfilled. Note that if, for example, the $(1,1)$ element of $\Theta(1)$ in (1.22) is set to one, the $(1,2)$ and $(1,3)$ elements must also be one. Similarly, when, for example, $(1,2)$ and $(1,3)$ elements of $\Theta(1)$ are set to zero in (1.22), the $(2,2), (3,2), (2,3)$ and $(3,3)$ elements also have to be zero given (1.23). Rewriting (1.20) as

$$\Theta(1) B^{-1} = C(1) \tag{1.24}$$

the first row of B^{-1} is identified. Note that the variance of the only permanent shock, which is given by the $(1,1)$ element of Σ_ε, follows from the relationship

$$\Sigma_\varepsilon = B^{-1} \Sigma_u B'^{-1} \tag{1.25}$$

when the first row of B^{-1} is known and Σ_u, the covariance matrix of reduced form error terms, is estimated. Finally, the first column of B must be available for computing the dynamic multipliers of the permanent structural shocks, Θ_i for $i \geq 0$, where $\Theta_i = C_i B$. It can be computed by rewriting (1.25) as

$$B\Sigma_\varepsilon = \Sigma_u B'^{-1}. \tag{1.26}$$

Notice that (only) the first column of the matrix on the right-hand-side as well as the $(1,1)$ element of the diagonal matrix Σ_ε on the left-hand-side are identified, which gives three restrictions for the three unknown elements of the first row of B.

1.3 Estimation of structural parameters

The estimation of a structural VAR consists of two steps. The first step is the estimation of the reduced form, while the second step provides the estimates of the structural parameters. Since the techniques are rather standard, we do not go into any detail regarding the estimation of the reduced form but refer the reader to Hamilton (1994) and Lütkepohl (2007). Instead, we focus on the estimation of structural parameters in the following.

Cholesky decomposition can be implemented with both short-run restrictions and long-run restrictions when a recursive ordering of the variables/shocks in a VAR can be justified on a theoretical basis. The benchmark A-model of Christiano, Eichenbaum, and Evans (1999), described above, is an example, where Cholesky decomposition can be implemented to impose short-run restrictions such that the matrix A is lower triangular. In another example, Blanchard and Quah (1989) employ the Cholesky decomposition to impose the restriction that the structural matrix of long-run multipliers $\Theta(1)$ is lower triangular in their VAR model. Finally, Cholesky decomposition can also be employed in a SVECM framework, as described by King, Plosser, Stock, and Watson (1991) in the appendix to their study. While these authors are interested in the estimation of permanent structural shocks only, transitory structural shocks can also be estimated analogously in their system.

The instrumental variables (IV) approach is an alternative to Cholesky decomposition, but both approaches yield the same result. The approach of Shapiro and Watson (1989) is, for example, equivalent to the long-run identification scheme of Gali (1999), which is based on a Cholesky decomposition.

The maximum likelihood method provides a less restrictive way of estimating the structural parameters than the Cholesky decomposition or the IV estimation and is employed in the applications of this thesis. Once the reduced form parameters are estimated, the concentrated log-likelihood function for a SVAR in AB-form can be written as

$$\ln l_c (A, B) = \text{constant} + \frac{T}{2} \ln |A|^2 - \frac{T}{2} \ln \left|B^2\right| - \frac{T}{2} tr \left(A' B'^{-1} B^{-1} A \hat{\Sigma}_u \right), \tag{1.27}$$

where T stands for the number of observations in the sample and $\hat{\Sigma}_u$ for the estimate of Σ_u. A and B together have $2K^2$ parameters, the estimates of which follow from the maximisation of the log-likelihood function in (1.27) subject to the constraints

$$\Sigma_u = A^{-1} B \Sigma_\varepsilon B' A^{-1\prime} \tag{1.28}$$

and

$$vec(A) = R_A \gamma_A + r_A \qquad \text{and} \qquad vec(B) = R_B \gamma_B + r_B, \tag{1.29}$$

where (1.28) provides $K(K-1)/2$ restrictions, and γ_A and γ_B are respectively K_A-dimensional and K_B-dimensional column vectors containing $K_A + K_B = K(K+1)/2$ free parameters and $2K^2 - K(K+1)/2$ restricted parameters. R_A and R_B are accordingly of order $K^2 \times K_A$ and $K^2 \times K_B$, respectively, and r_A and r_B are both K^2-dimensional column vectors. This maximisation problem has analytic solutions only for special cases. Otherwise, numerical techniques must be applied to find a solution. The scoring algorithm is typically used in the literature to this end, see, e.g., Chapter 4 in Amisano and Giannini (1997) or Chapter 9 in Lütkepohl (2007).

1.4 Business cycle analysis with SVARs

Various tools are available for conducting business cycle analysis with SVARs. Since the main applications of this study deal with the sources of business cycle fluctuations, we review in the following two of these tools that are central to the analyses of the forthcoming chapters.

1.4.1 Forecast error variance decomposition

Forecast error variance decomposition (FEVD) is based on the representation Y_t in (1.12) or (1.14).[6] We can write the h-step forecast error for that process as

$$Y_{t+h} - Y_t\left(h\right) = \sum_{i=0}^{h-1} \Theta_i^* \varepsilon_{t+h-i}, \tag{1.30}$$

with $Y_t\left(h\right)$ being the optimal h-step forecast at period t for Y_{t+h}. The total forecast error variance of the variables in Y_t under the aforementioned restrictions and assumptions are given by the diagonal elements of

$$E\left[\left(Y_{t+h} - Y_t\left(h\right)\right)\left(Y_{t+h} - Y_t\left(h\right)\right)'\right] = \sum_{i=0}^{h-1} \Theta_i^* \Sigma_\varepsilon \Theta_i^{*\prime}. \tag{1.31}$$

When decomposing forecast error variances, it is assumed that the structural innovations do not exhibit any autocorrelation or correlation among their leads/lags. The contribution of the k^{th} structural shock to the forecast error variance of the j^{th} variable for a given forecast horizon is then computed by

$$\sum_{i=0}^{h-1} \left(e_j' \Theta_i^* e_k\right)^2 \sigma_k^2, \tag{1.32}$$

where e_k is the k^{th} column of the K-order identity matrix, and σ_k is the standard deviation of the k^{th} structural shock. Given (1.31) and (1.32), it is straightforward to compute the share of a structural shock in the fluctuations of a variable, see the first chapter in Lütkepohl (2007).

What is done in the literature is to set h such that the computation is made for the business cycle horizon. This means setting $6 \leq h \leq 32$, if one works with quarterly data following the business cycle definition widely used by macroeconomists.

[6]Our following demonstration is based on (1.14).

1.4.2 Variance decomposition of filtered processes

Macroeconomists often employ filters to extract the cyclical component of macroeconomic time series. Statistics of interest such as the second moments of the data are then computed using the filtered time series. Another common practice is to simulate macroeconomic time series using a theoretical model, of which structural parameters are calibrated to match empirical observations. Such artificial data is then filtered using a filter in the same manner as the real data. Such simulations are carried out for a large number of times, and the statistics of interest are computed for each realisation. Finally, the mean of the computed statistics is used as the estimate of the particular statistic by the theoretical model.[7] In this thesis, we apply the same logic to our SVAR models by assuming that they represent the true process generating the macroeconomic data of interest. However, we do not simulate our models many times and then filter the artificial data before computing the statistic of interest, but we apply a filter directly on the process governing the motion of each variable of our SVAR models.

Two widely-used filters are the ones suggested by Baxter and King (1999) and Christiano and Fitzgerald (2003).[8] Both filters belong to the class of linear filters that eliminate "very slow-moving ('trend') components and very high-frequency ('irregular') components while retaining intermediate ('business-cycle') components", quoting Baxter and King. An important property of these filters is that they are both approximations of an ideal band-pass filter following from a frequency-domain analysis, but can be applied in the time domain by applying moving averages. The cyclical component of a macroeconomic variable, say x_t, is given, for example, by

$$x_t^c = \sum_{m=-\kappa}^{\kappa} a_m x_{t-m}, \tag{1.33}$$

where a_k are moving average weights such that $a_m = a_{-m}$ and $\sum_{m=-\kappa}^{\kappa} a_m = 0$, and x_t^c stands for the cyclical component of x_t. Such a filter can be applied to each individual process in

[7]See, e.g., Prescott (1986).

[8]We call these BK-filter and CF-filter in the following.

Y_t of, for example, (1.14). Note that each process in Y_t is the sum of a deterministic term and/or an exogenous component and sub-components corresponding to structural shocks. In the applications of Chapters 3 and 4, the only deterministic term is a constant in the VAR, and no exogenous variables are included. The BK-filter and the (symmetric) CF-filter both attribute the constant to the trend component of the process. Hence, the cyclical component of the i^{th} variable in the VAR consists of only sub-components corresponding to each structural shock in the VAR,

$$Y_{j,t}^c \approx \sum_{k=1}^{K} \sum_{m=-\kappa}^{\kappa} \Psi_{jk,m} \varepsilon_{k,t-m}, \tag{1.34}$$

where $Y_{j,t}^c$ stands for the cyclical component of the j^{th} variable at period t, $\Psi_{jk,m}$ are functions of $\Theta_{jk,m}^*$ and a_m, and $\varepsilon_{k,t-m}$ is the k^{th} structural shock at period $t-m$.[9] Although (1.34) is an approximation, the quality of the approximation is very good in practice for $\kappa = 60$ with quarterly data. Statistics of interest can be computed based on this formula. The mean of $Y_{j,t}^c$ is, for example, given by

$$E\left[Y_{j,t}^c\right] = \sum_{k=1}^{K} \sum_{m=-\kappa}^{\kappa} \Psi_{jk,m} E\left[\varepsilon_{k,t-m}\right] = 0, \tag{1.35}$$

since $E\left[\varepsilon_{k,t-m}\right] = 0$. Furthermore, its variance is given by

$$E\left[\left(Y_{j,t}^c\right)^2\right] = \sum_{k=1}^{K} \sum_{m=-\kappa}^{\kappa} \Psi_{jk,m}^2 \sigma_{\varepsilon_k}^2, \tag{1.36}$$

where $\sigma_{\varepsilon_k}^2$ stands for the variance of the shock ε_k. Note that (1.36) gives the same result as (i) computing a large number of, say 10000, realisations of $Y_{j,t}^c$ by simulating $\varepsilon_{k,t-m}$ for the sample length of interest; (ii) computing the variance of $Y_{j,t}^c$ using each artificial sample of $\varepsilon_{k,t-m}$; and (iii) then taking the mean of the 10000 variances. The variance of $Y_{j,t}^c$ conditional on the k^{th} structural shock is, similar to (1.36), given by

$$E\left[\left(Y_{jk,t}^c\right)^2\right] = \sum_{m=-\kappa}^{\kappa} \Psi_{jk,m}^2 \sigma_{\varepsilon_k}^2. \tag{1.37}$$

[9]See the appendix to this chapter for the derivation of $\Psi_{jk,m}$ coefficients in (1.34).

Hence,

$$E\left[\left(Y_{jk,t}^{c}\right)^{2}\right]/E\left[\left(Y_{j,t}^{c}\right)^{2}\right] \tag{1.38}$$

is the share of the k^{th} structural shock in the variance of the cyclical variable $Y_{j,t}^{c}$.

As we already mentioned above, the BK-filter and the CF-filter, are both approximations of an ideal band-pass filter following from a frequency-domain analysis. Let the spectral density matrix of the variables in ΔY_t in (1.13) be given by

$$S_{YY}(\omega) = \Theta\left(e^{-i\omega}\right)^{-1}\Sigma_{\varepsilon}\left[\Theta\left(e^{-i\omega}\right)^{-1}\right]', \tag{1.39}$$

where $\Theta(L) = \sum_{i=0}^{\infty}\Theta_i L^i$, and L being the conventional lag operator.[10] Note that $S_{YY}(\omega)$ corresponds here to first-differenced series. The spectral density of the filtered (level) series, using the filter f, is then given by the diagonal elements of

$$S_{YY}^{c} = \left|\frac{f\left(e^{i\omega}\right)}{\left(1-e^{i\omega}\right)}\right|^{2} S_{YY}(\omega), \tag{1.40}$$

where $\left|f\left(e^{i\omega}\right)\right|^{2}$ stands for the transfer function of the underlying filter such that $\left|f\left(e^{i\omega}\right)\right|^{2} = 1$ for $\omega_1 \leq \omega \leq \omega_2$ and $\left|f\left(e^{i\omega}\right)\right|^{2} = 0$ otherwise. The frequencies, ω_1 and ω_2 are typically set to $\omega_1 = \frac{2\pi}{32}$ and $\omega_2 = \frac{2\pi}{6}$ so that the filter extracts the components of the data corresponding to the business cycle periodicities of 6 to 32 quarters and does not include other components of the data corresponding to higher and lower frequencies. The spectral density of the cyclical component of Y_t conditional on the k^{th} structural shock is similarly given by

$$S_{k,YY}^{c} = \left|\frac{f\left(e^{i\omega}\right)}{\left(1-e^{i\omega}\right)}\right|^{2} S_{k,YY}(\omega), \tag{1.41}$$

with

$$S_{k,YY}(\omega) = \Theta\left(e^{-i\omega}\right)^{-1}\Sigma_{\varepsilon_k}\left[\Theta\left(e^{-i\omega}\right)^{-1}\right]', \tag{1.42}$$

where Σ_{ε_k} is the covariance matrix of the structural shocks, of which k^{th} column remains as it is and all other columns are set to zero. The variances of $Y_{j,t}^{c}$ and $Y_{jk,t}^{c}$ are given by the

[10] See Hamilton (1994), Chapter 10.

diagonal elements of

$$\int_{-\pi}^{\pi} \left| \frac{f\left(e^{i\omega}\right)}{\left(1-e^{i\omega}\right)} \right|^2 S_{YY}\left(\omega\right) d\omega \text{ and } \int_{-\pi}^{\pi} \left| \frac{f\left(e^{i\omega}\right)}{\left(1-e^{i\omega}\right)} \right|^2 S_{j,YY}\left(\omega\right) d\omega, \tag{1.43}$$

respectively.[11]

Note that the variance formulas in (1.43) are equivalent to the formulas in (1.36) and (1.37), when all correspond to the same filter. We use the latter formulas in the forthcoming chapters, since their linear structure is easier to follow and allows us to decompose the channels that led to the moderation in business cycle dynamics.

Filtering is known to have an important impact on the statistical properties of the underlying data. Therefore, it is not surprising that results from FEVD at the business cycle horizon often deviate from variance decomposition results of filtered processes. In Chapter 2, which serves as a motivation for the analyses of Chapters 3 and 4, we provide a description of the business cycle dynamics in the euro area based on CF-filtered output.[12] Therefore, we find it appropriate to report findings based on both CF-filtered processes as well as FEVD findings in Chapters 3 and 4, where we investigate the dynamics of euro area business cycles by employing three different types of SVARs. We report only FEVD results in Chapter 5 in order to confine this study to a convenient size.

1.5 Remarks

The SVAR methodology provides a valuable tool for macroeconomic analysis, but SVAR models are also subject to vulnerabilities as every empirical model is. Before closing this chapter, we mention some important issues in order to make the reader aware of potential problems related to the applied methodology.

[11] See, e.g., Baxter and King (1999). See also Altig, Christiano, Eichenbaum, and Linde (2005a), Altig, Christiano, Eichenbaum, and Linde (2005b) and Stock and Watson (2005) for examples, where this technique is used to compute the variance of the cyclical component of data.

[12] Note that we label CF-filtered output as *output gap*, the gap between the originial series and its long-run trend, throughout this study.

The lack of robustness of results with respect to model specification is an issue that is sometimes raised in the literature. It should be noted that this critique is not specific to SVARs and applies to all empirical models. In the VAR context, model specification concerns in particular decisions on which variables should be included in the VAR, if a variable transformation is necessary before the estimation is carried out, which lag order should be chosen, and whether nonstationarity and cointegration exist. We provide robustness analyses in this study whenever our conclusions may be sensitive to model specification.

Structural VAR models are typically only locally identified, and this only up certain sign restrictions with respect to the sign of the response of a variable to a certain shock at some horizon. Christiano, Eichenbaum, and Evans (1999) discuss this issue nicely. The identification scheme proposed by Uhlig (2005) is based on multiple sign restrictions on the response of various variables in a VAR at a certain forecast horizon. Examination of signs of impulse response functions may provide help when uncertainty exists concerning the specification of a SVAR model. In Chapter 5, we check the sign of the response of labor productivity and stock prices to news shocks when determining the number of cointegrating relationships to be included in the SVECM of that chapter. We deal with the discrepancy between data and macroeconomic theory with respect to the rank of cointegration in our SVECM by referring to the sign of these impulse response functions.

Lippi and Reichlin (1993), among others, point to the possibility of the existence of various non-fundamental moving average (MA) representations of a VAR model, which are compatible with certain macroeconomic theories. The conventional SVAR analysis is based on the so-called fundamental (Wold) representation, for which the MA polynomial of the representation has no roots on or inside the unit circle, while there is an infinite number of non-fundemantal representations that do not fulfill this property. Lippi and Reichlin (1993) argue that there are economic theories which favor a non-fundemantal representation. In a reply to Lippi and Reichlin (1993), Blanchard and Quah (1993) acknowledge the problem, but state that it "is an issue whenever a researcher wishes to give an economic interpretation to time series." There may be dynamics of interest for which non-fundamental representations can be dismissed, whereas fundamental representations may also be unsuitable for certain analyses. The way this issue is handled depends on the assumptions of the user. While non-fundamental representations, as alternatives to the fundamental representation in (1.2) or (1.7), may represent a further source of lack of robustness, this does not necessarily imply that results depending on a fundamental representation are less reliable.

Since a SVAR reflects a simplification of the real world, like every model does, whether it provides a good approximation depends on the properties of the data generation mechanism. SVARs are often employed to test the validity of theoretical models. Altig, Christiano, Eichenbaum, and Linde (2005a) even make use of impulse response functions stemming from an estimated SVAR when calibrating their model. The authors calibrate their theoretical model such that the distance between the theoretical and empirical impulse responses are minimised according to a statistical measure. In other words, findings based on SVARs are often treated as stylised facts that the theoretical models should generate. Many econometricians are, however, at best reserved about such exercises and prefer to check the reliability of SVARs based on artificial data generated using theoretical macroeconomic models. The common practice in the literature is to compare the "true" dynamic responses of variables which result from a theoretical model economy with the empirical ones coming from SVARs that are estimated using artificial data generated by the same theoretical model, see, e.g., Cooley and Dwyer (1998), Erceg, Guerrieri, and Gust (2005), Chari, Kehoe, and McGrattan (2005) and Christiano, Eichenbaum, and Vigfusson (2006). With the exception of Christiano, Eichenbaum, and Vigfusson (2006), all these studies evaluate SVARs with long-run restrictions. An important caveat of this literature is that the quality of an SVAR identification scheme depends a lot on the true data generating process, which is unfortunately not known in reality. While sampling uncertainty is typically not small, particularly when long-run restrictions are employed for identification regardless of by which model the artificial data is generated, Christiano, Eichenbaum, and Vigfusson (2006) find that models with short-run restrictions perform quite well in this respect.

The matrix of long-run multipliers can be only imprecisely estimated in a SVAR with nonstationary variables, a critique which is also related to the findings of the aforementioned simulation exercises. Faust and Leeper (1997) discuss in one of the relevant studies the imprecise estimation of long-run effects of shocks, which may lead to badly biased impulse responses. The problem is related to the difficulty of having a good estimate of the matrix of long-run multipliers $C(1)$. It occurs since errors corresponding to an infinite number of coefficients in $C(L)$ are accumulated in $C(1)$. One solution Faust and Leeper suggest is using further restrictions to guarantee a more reliable inference. The lag order p in finite order VARs is typically an approximation for an infinite lag order. Faust and Leeper argue that setting the lag order with the help of simulations can help improve the performance regarding the problem of large confidence intervals. The authors also propose strengthening the identification scheme by imposing overidentifying restrictions such that the original restriction is stated as a finite-horizon restriction. The issue is relevant only in the application of Chapter 5 in this thesis. However, the number of long-run restrictions is only two in the four-variable SVECMs of that chapter, whereas four short-run restrictions are also imposed. Therefore, the conclusions from the estimations are probably more reliable in comparison to identification schemes where only long-run restrictions are employed. We use only short-run restrictions in our applications in Chapters 3 and 4.

Arbitrariness is attributed to SVAR models because of the "atheoretical" restrictions used for identification. Cooley and Dwyer (1998) distinguish between two types of restrictions in SVARs. They call the first group of restrictions *atheoretical* or *auxiliary* which comprise the restrictions imposed on the variance-covariance matrix of the structural shocks as well as the choices related to model specification. The second group of restrictions are *theoretical*. Cooley and Dwyer (1998) do not particularly favor the substitution of atheoretical restrictions for theoretical ones, since such a substitution does not result in more robustness according to their view. Although more theoretical restrictions do also not lead to more robustness, they can at least be based on "fully articulated" theoretical models according to these authors. A critical atheoretical restriction mentioned in their simulation study is that structural innovations are contemporaneously uncorrelated, which applies to the majority of SVAR models in the literature. Although this is just a theoretical construct, the restriction has at least two uses for econometricians. First, it allows a healthy impulse response analysis of orthogonal shocks. Second, it provides a comparable framework for competing SVAR and theoretical models. Since every theoretical or SVAR model consists of typically different identified (and sometimes non-identified) structural shocks depending on the model specification, only the assumption of orthogonality of the structural shocks can guarantee a minimum requirement for a reasonable comparison of the impulse response functions.

"It is unclear" according to Cooley and Dwyer (1998), "why shocks would be uncorrelated since monetary shocks may well react to productivity shocks if the Fed pursues activist policies." However, this is just a matter of definition. We may well pose the question, why we should see the reaction of monetary authorities to a technology shock as a monetary shock. Gali (1999) assumes, for example, in the theoretical model he uses to motivate his identification scheme that the quantity of money M_t^s evolves according to

$$M_t^s = M_{t-1}^s \exp\left(\xi_t + \gamma\eta_t\right), \tag{1.44}$$

where η_t is an i.i.d. process that hits the growth rate of the aggregate technology index, i.e., the process governing the technology shocks, and ξ_t is a white noise process and orthogonal to η_t at all leads and lags.[13] Thus, the monetary authority is assumed to respond to technology shocks systematically when $\gamma \neq 0$.

According to Cooley and Dwyer (1998), "conclusions about the importance of technology and other shocks based on simple SVARs are certainly not invariant to the identifying assumptions and may not be very reliable as vehicles for identifying the relative importance of shocks". Although this critique cannot be rejected for SVARs, it must be noted that it applies to almost every empirical or theoretical model investigating similar questions. Robustness

[13]This is the equation (9) in Gali. We stick to his notation for easier comparability.

of empirical results, if available, makes us surely more confident about our conclusions in an empirical or a theoretical study. If it is not possible to check robustness directly, we can attribute a certain amount of reliability to our conclusions only when we are sure about the relevance of the assumptions for the investigated issue in our models.

Chapter 2

Business cycle dynamics in the euro area: review*

Properties of business cycles in the euro area countries have been the subject of a large literature since the initiation of the European Monetary Union (EMU) process which led to using a common currency—the Euro—in meanwhile 16 countries. The subject is interesting not least because of the fact that common currency and common monetary policy may have not only positive impacts but also adverse effects on some of the member countries of a monetary union when their business cycles are not sufficiently synchronised. In particular, the member countries do not pursue own exchange rate and monetary policies in a monetary union and may hence lack flexibility when confronted with shocks.[1] Since central banks optimise and set the monetary policy with respect to the business cycle of an entire zone that shares a common currency, common monetary policy may have destabilizing effects on member countries, of which business cycles deviate to a large extent from the one of the entire single currency area. This is why an important concern of the member countries' policy-makers in the pre-EMU and post-EMU periods has been the extent and sources of

*The literature review in this chapter is based on Kappler, Sachs, Seymen, van Aarle, and Weyerstrass (2008), "Study on Economic Integration and Business Cycle Synchronisation" with the reference number BEPA-01/2007-PO, presented to the European Commission Bureau of European Policy Advisers (BEPA). Financial support by BEPA is gratefully acknowledged. The descriptive analysis in the chapter is based on Seymen (2009).

[1] The optimum currency area theory sets some guidelines on the conditions that should be fulfilled for a successful monetary union. See Mundell (1961) and McKinnon (1963) for the first contributions to the theory.

business cycle heterogeneity in the euro area, a subject that also triggered extensive academic research.

The driving forces of business cycle fluctuations as well as the extent and sources of business cycle heterogeneity in the euro area are also at the core of the forthcoming two chapters of this thesis. The aim of the current chapter is to give the reader an overview of the literature on international business cycle synchronisation as well as to provide a description of the business cycle dynamics in the euro area, based on the data set that is used for the empirical analyses of Chapters 3 and 4. In this context, we often refer to *output gaps*, as the measure of the business cycle, which we computed by applying the symmetric filter suggested by Christiano and Fitzgerald (2003) to this end.

The most popular tool employed in the literature to assess the synchronisation and heterogeneity in the euro area countries' business cycles is the unconditional Pearson correlation.[2] It has been shown in many studies that business cycles of the euro area countries are positively correlated. However, that the correlations are typically not perfect reflects the fact that there is some heterogeneity involved. Furthermore, macroeconomic theory is not united about the effects of monetary unions on business cycle synchronisation. While there are theoretical arguments that suggest higher business cycle synchronisation (and hence less heterogeneity) follows among member countries due to establishment of a monetary union, theoretical arguments have also been put forward that monetary unions might lead to a divergence of the member countries' business cycles as we discuss below. We review these arguments and the corresponding empirical findings in this chapter.

In addition to conventional Pearson correlations, we also consider a second measure of heterogeneity in this study, which is the differential between the euro area business cycle and the business cycle of a member country. The analysis of differentials brings additional insights on the extent of business cycle heterogeneity. The ideal case for the members of a monetary union is clearly that the cycle of the entire euro area and each member country

[2]See, e.g, Artis and Zhang (1999), Gayer (2007), Afonso and Furceri (2007) and Stock and Watson (2005). Note that this list is by no means exhaustive.

overlap exactly. Note, however, that there may be differences between the euro area business cycle and the cycle of a member country, even when they are perfectly correlated. In reality, of course, cycles do not move symmetrically around turning points, their amplitude, phase and other characteristics change over time due to shocks that hit economies. This is why we do not content only with a correlation analysis of cycles in this study, but also investigate the driving forces of differentials.

The so-called Great Moderation has been the subject of a large empirical (and theoretical) literature that covers the sample period, which underlies the descriptive statistics presented in this chapter as well as the empirical estimation of the following two chapters. It refers to the decline in volatility of business cycles in industrialised countries after roughly the second half of the 1980s until a short time ago.[3] Note that a moderation in output gaps must not necessarily imply a moderation of output gap differential. In principle, a moderation of output gaps can even be accompanied by growing differentials, while a moderation of output gap differentials would clearly signal decreasing heterogeneity of business cycles. In this chapter, we present statistics on changing volatility of output gaps and output gap differentials in the euro area as well. The moderation of output fluctuations is another subject that we address in the forthcoming two chapters.

In the following, we review the literature on the properties of euro area business cycles, which is followed by the presentation of some descriptive statistics derived from the data set that underlies the empirical applications of Chapters 3 and 4. The chapter closes with a discussion of the research questions that are dealt with in the empirical applications.

[3]See, e.g, Cabanillas and Ruscher (2008), on the Great Moderation in the euro area.

2.1 Related literature

Our review starts with a summary of the literature on six potential determinants of business cycle synchronisation, which have been the subject of a large literature.[4] Those are trade, being member of currency unions, fiscal policy, sectoral structure and financial market integration. We also review the so-called gravity variables that are often included in the empirical studies on the determinants of business cycle co-movement. The review of the literature shows that it is not clear-cut whether these factors lead to more or less synchronised business cycles over time. The second part of the literature review summarises the hitherto findings on business cycle synchronisation in the euro area.

2.1.1 Determinants of business cycle synchronisation

Trade integration

Trade is one of the major channels through which economic activity is transmitted across countries. It is therefore seen as a prime candidate variable for driving business cycle synchronisation across countries. Empirical consensus is that there is a strong positive relationship between trade intensity and business cycle synchronisation. Baxter and Kouparitsas (2005) and Böwer and Guillemineau (2006), who apply extreme bounds analyses to check the robustness of a number potential determinants of (positive) business cycle correlations, find that trade belongs to the class of robust determinants, although the latter authors also report a relative decline in the importance of this factor since the introduction of the euro in 1999.

Theory is, however, not so clear-cut as to whether stronger or weaker correlations of national cycles should result from tighter trade links between countries. The standard Ricardian or Heckscher-Ohlin arguments would predict, for example, a higher specialisation of countries due to comparative advantages and economies of scale, when they are engaged

[4] While this classification is arbitrary, it reflects the factors that have most often been considered in the related literature.

in more trade. When a country is highly dependent on a specific industry, being hit by a sector-specific shock may drive away the output cycle of that country from its trade partners' cycles, for which that specific industry does not play a major role. However, if demand shocks predominate or if intra-industry trade accounts for most of trade, cycles can become more synchronised as countries trade more intensively with each other. Increasing trade would result in higher output gap correlations also when it induces technological and knowledge spillovers.

Frankel and Rose (1998) find an economically and statistically strong positive relationship between bilateral trade intensity and cycle synchronisation. Their finding suggests that bilateral trade integration is driven mostly by increasing intra-industry, rather than inter-industry, trade. Similar findings are also reported in, e.g., Gruben, Koo, and Millis (2002), Calderón, Chong, and Stein (2002) and Imbs (2004). The latter author finds only weak evidence of trade-induced specialisation affecting cycle synchronisation and shows that the large share of the measured effect of trade on synchronisation works through intra-industry trade. This finding is also supported by Akin (2007), who reports a significant increase in the amount of this kind of trade.

The role of currency unions and monetary integration

The effect of a common currency and monetary integration on the business cycle synchronisation of the participating nations is ambiguous. Common monetary policy within a currency union implies, on the one hand, better coordination of response to common shocks. By stripping the participating nations of a means for buffering asymmetric shocks through exchange rate adjustments, however, monetary union may, on the other hand, exacerbate the business cycle differences of the participating nations. Empirical findings mirror this theoretic ambiguity.

Artis and Zhang (1999) investigate whether the functioning of the Exchange Rate Mechanism (ERM) of the European Monetary System has produced similar cycles for its member countries and find that a higher degree of synchronisation of business cycles is associated with lower volatility in exchange rates. Frankel and Rose (2002) find that a currency union strengthens the bilateral trade between the members and hence contributes to higher synchronisation. However, other studies produce results on the subject that are not in accordance with these findings. Clark and van Wincoop (2001) and also Baxter and Kouparitsas (2005) find that similar monetary policy is not among the important determinants of business cycle correlation. By analysing bilateral growth correlations in a sample of OECD countries, Otto, Voss, and Willard (2001) come to a similar conclusion. de Haan, Inklaar, and Sleijpen (2002) find for the US States, German states and 18 OECD countries that although trade seems to have fostered convergence, stable exchange rates countervail this development: integration can be both a stabilising and a decoupling factor for synchronisation.

Fiscal policy

An important determinant of business cycle synchronisation, especially in the context of the European Union, is the coordination of fiscal policy across nations. On the one hand, the Stability and Growth Pact (SGP) reduces the risk of asymmetric policy shocks by imposing constraints on national fiscal policies. On the other hand, by obeying the criteria of the SGP, nations are stripped of the ability to counteract country-specific shocks with, say, expansive fiscal policies. These two implications of the SGP may have different effects on business cycle synchronisation in the euro area.

Empirical studies analysing fiscal policy and cycle synchronisation typically measure similarities in or coordination of fiscal policies by the differences in ratios of government spending to GDP and differences in national budget balances. Darvas, Rose, and Szapáry (2005) find that complementary fiscal policies have a positive effect on synchronisation in a panel of OECD countries. Morever, output correlation is found to be higher in phases with lower budget deficits by these authors. The low-budget-deficit requirement of the SGP may similarly also have a positive effect on synchronisation. The findings of Akin (2007) also show that output synchronisation is fostered by similar fiscal policies.

Böwer and Guillemineau (2006) find a lower bilateral discrepancy of output fluctuations to be related to lower differentials of budget deficits in the period from 1980 to 1996, but not in the later term from 1997 to 2006. Clark and van Wincoop (2001) apply OLS and IV techniques to a sample of 14 EU countries and find no evidence of either higher or lower business cycle synchronisation due to more coordinated policies. However, they also conclude that their finding does not rule out an indirect—trade, for instance—channel through which institutional similarity could have an effect on business cycle co-movement. To summarise, the net effect of fiscal policy similarity on business cycle synchronisation can be small since country-specific fiscal policy can both be a source and a stabiliser of business cycles.

Sectoral structure

Economies with similar industrial structures should respond to common shocks similarly. In such a case, the similarities of the business cycles depend on the share of common shocks in the total variation of the countries' business cycles. If countries have, however, only few common industries, their business cycles should be less synchronised in the face of common shocks. By constructing an index that measures the distance between industry structures of two countries, Otto, Voss, and Willard (2001) investigate whether similar industry structures are positively correlated with output co-movement. The results do unfortunately not have statistical significance in their general model with all relevant variables included. Testing for robustness confirms the fragility of this determinant as an important factor which is in line with the findings of Baxter and Kouparitsas (2005) and Böwer and Guillemineau (2006). The striking findings of Imbs (2004) and Garcia-Herrero and Ruiz (2008) point, on the other hand, to a reduction of bilateral output fluctuation correlations when countries have similar production structures. All in all, the role of sectoral structure similarity on business cycle synchronisation is ambigious.

Financial market integration

Empirical consensus for positive and robust effects of trade openness and integration on the synchronisation of business cycle activity across countries overwhelms the theoretic ambiguity regarding the direction of these effects. Yet, despite the equally prominent role financial market integration has played in economic integration between countries, it remains one of the least researched determinants of business cycle synchronisation in the existing literature. This can, however, mainly be attributed to methodological problems, rather than lack of interest in the matter itself. From a theoretical point of view, financial integration, just as trade integration, induces sectoral specialisation, but the overall effect of trade in assets on business cycle synchronisation remains ambiguous due to the potentially complex interaction of its positive and negative effects on cycle comovement.

Imbs (2004), among others, addresses these complex interactions. Strong financial linkages between countries can easily propagate financial disturbances and crises of one to the rest and dampen demand through the income channel and supply through the investment channel in all affected countries. Several indirect ways also exist, through which financial integration influences business cycle synchronisation. For example, financial integration provides an incentive to specialise, since it allows better international risk sharing and insures countries against their idiosyncratic shocks. Specialisation can, as mentioned above, lead to less synchronised cycles, since sector-specific idiosyncratic shocks can not easily cross borders if countries are specialised in different industries. On the other hand, economies exploit their comparative advantages better through sectoral specialisation and engage in international trade, which in turn results in a higher degree of business cycle synchronisation.

For researchers, it is a challenge to estimate the direct and indirect effects of financial market integration simultaneously. A common practice in the existing literature has been to employ a simultaneous equations approach that uses a three-stage least squares estimation technique with instrumental variables.[5] The advantage of this approach is its ability to

[5] See, e.g., Imbs (2004, 2006), Akin (2007), and Garcia-Herrero and Ruiz (2008).

treat a multitude of potential determinants of international business cycle co-movements, such as trade, sectoral specialisation and financial integration, as endogenous variables, thus allowing for interdependencies between them and enabling distinction between direct and indirect effects.

The measurement of the degree of financial integration is another methodological problem that is often faced in the literature. It is not easy to measure financial integration as, for example, trade integration. Return spreads in equity and debt markets across countries are used, for instance, when data on bilateral flows and/or stocks are missing. However, return spreads are merely crude measures of financial integration, since they may be driven by a number of idiosyncratic factors rather than low arbitrage opportunities due to a low degree of integration of financial markets.

Given these problems, it is not surprising that empirical findings on the effects of financial integration on business cycle synchronisation are ambigious. Imbs (2004) concludes that despite the unambiguous positive effect of financial integration on sectoral specialisation, its total effect on cycle synchronisation is significantly positive. This overall positive relationship is supported by Imbs (2006), who uses bilateral portfolio investment data among other variables to identify a strong residual effect on cycle synchronisation over and above indirect channels via goods trade and specialisation. Akin (2007) finds that average global financial integration of country pairs has a positive but weak effect on cycle synchronisation of the two countries, with synchronisation increasing for country pairs with high degrees of financial openness. Bordo and Helbling (2003) argue that their inconclusive results are due to data problems and do not reject the general idea that financial integration plays a role in determining synchronisation. Böwer and Guillemineau (2006) fail to qualify the asset flows among euro area countries as a robust determinant of business cycle synchronisation in the euro area. Kalemli-Ozcan, Sorensen, and Yosha (2004) focus on the interdependence of financial integration and sectoral specialisation. Their finding is a negative indirect effect of financial integration on business cycle synchronisation through increasing sectoral specialisation.

To summarise, findings for the literature on the overall effects of financial integration on business cycle synchronisation are ambigious. Further research, especially employing better data, is needed to shed more light on the issue.

Gravity variables and other indicators

Gravity variables that characterise "natural" similarities between economies are widely found to account for correlation of business cycle activity across countries, either by reinforcing similarities in transmission channels or increasing the susceptibility of these countries to common economic shocks. Typical gravity variables include common border and language dummies, geographical distance, relative country size in terms of population or economy, etc. Otto, Voss, and Willard (2001) identify a number of characteristics that, if shared, might lead countries to a similar response to economic shocks, such as legal origin, accounting standards, the extent of structural economic reforms, and the speed of technology adoption. Common legal origins, identified following the classification of Porta, de Silanes, Shleifer, and Vishny (1998), can give rise to similarities in economic characteristics by affecting the degree of financial and institutional integration between countries and their systems of corporate governance, as well as forms of labour market organisation. Bilateral differences in the amount of structural economic reforms are calculated using the country index developed by Lehman Brothers that rates countries on the scale of 0 to 10 on their structural economic policies. Results of the authors' estimations that also include common language and border variables show that, in particular, good accounting standards, similar legal systems, common language, and openness to new technology are important determinants of bilateral cycle correlation.

Akin (2007) considers—in addition to standard transmission mechanism variables—membership in a free trade area (FTA) and finds no statistically significant effect of such membership on business cycle similarity when similarities in macroeconomic policies are accounted for. She therefore concludes that formation of free trade areas does not guarantee higher level of cycle synchronisation if member countries are not integrated financially or through trade, lack policy coordination, and have divergent macroeconomic fundamentals. Baxter and Kouparitsas (2005) find significant but not robust effects both for similarity in export and import baskets and in factor intensities, while the geographical distance is found to be a robust determinant of cycle comovement. Böwer and Guillemineau (2006) test the robustness of a broad set of explanatory variables for business cycle correlation across euro area countries. Difference in cross-country competitiveness as well as difference in labour market flexibility is found to be negatively related to business cycle synchronisation according to their findings, but the latter finding is neither significant nor robust. Finally, while the gravity variable of distance is significant and has the expected negative sign (i.e., the lower the distance, the higher the business cycle synchronisation), the gravity variable of relative population does not have a significant effect on synchronisation.

2.1.2 Business cycle synchronisation in the EU

The introduction of a common currency in the EU and the likely expansion of its membership has fuelled the political and economic significance of analysing business cycle behaviour across EU nations. In the substantial literature that has developed in recent years on cycle synchronisation within the euro area, an important contribution has been made by Artis and Zhang (1999), who find that the correlation of business activity in the euro area has increased substantially over time. They conclude that the functioning of the European Exchange Rate Mechanism (ERM) has produced a group-specific European cycle, which has become more synchronised with the German cycle and less synchronised with the US cycle. This finding is challenged by Inklaar and de Haan (2001), who find that correlations of euro area countries with Germany are higher in the decade preceding the creation of the ERM than in the one following. Massmann and Mitchell (2004) re-examine these contrasting results to find that there have been periods of convergence and periods of divergence, with the mean correlation of 12 examined European cycles trending upwards until the mid-1970s then falling to zero in the mid to late 1980s, supporting the view against a monotone movement towards the emergence of a distinctly European business cycle.

The literature shows also mixed findings with regard to the effects of the European Monetary Union (EMU) on cycle synchronisation in the euro area, reflecting the general theoretical ambiguity of the effects of a currency union on cycle synchronisation of its members. While Afonso and Furceri (2007) find evidence that the introduction of the euro was followed by substantially more synchronised cycles among the member countries except for Germany, de Haan, Inklaar, and Sleijpen (2002) do not find a clear evidence that the single currency has a positive effect on cycle synchronisation. A recent study by Gayer (2007) observes that the level of synchronisation of euro-area business cycles has been high since the beginning of the 1990s but did not change with the introduction of the euro in 1999. Using correlation-based measures of business cycle synchronisation, Gayer (2007) finds no evidence of higher correlation after the launch of the euro in 1999.

Of substantial empirical interest is also the question as to what extent evolution of cycle synchronisation in the euro area is attributable to global shocks. Stock and Watson (2005) find no evidence of rising business cycle synchronisation in the G7 countries from 1960 to 2002, but observe the emergence of a European cycle within the G7. In general , the literature suggests that synchronisation of business cycles among the industrial countries has experienced a change during the last three to four decades; however mixed results are obtained regarding the question of whether country-specific or global impacts gained in importance.

2.2 Data

The bottom line of the foregoing literature review is that many factors play a role in international business cycle dynamics. While trade is a robust determinant of international business cycle synchronisation according to a majority of empirical studies, the effect of other factors seems to be less unambiguous. Moreover, the literature on business cycle synchronisation is also vulnerable to the wide variety of methods used to extract cycles so that there are considerable differences in the outcomes and conclusions of the studies on this topic. The results differ also across countries as groups of countries are quite heterogeneous, and general conclusions are hard to draw. Another drawback has been the practice to often use Germany as a reference country instead of using the aggregate euro area business cycle. Finally, many studies concentrate on industrial production since data on it are often more reliable and available for a longer time period. On the other hand, a robustness check concerning the results, using, e.g., GDP data seems desirable since industrial production represents only a certain fraction of the total economy and conclusions based exclusively on this variable are potentially biased.

In this sub-section, we turn our attention to descriptive statistics of output gaps and output gap differentials in the euro area. The output gaps are computed by employing the asymmetric filter suggested by Christiano and Fitzgerald (2003) in this chapter. This linear filter brings the advantage that we do not lose observations at both ends of the sample when we employ it. We specify the filter such that it eliminates the trend and irregular components of time series that do not correspond to the conventional range of 1.5 to 8 years.[6]

Our data set contains the real GDP data of only six member countries—Belgium (bel), Germany (deu), Spain (esp), France (fra), Italy (ita) and the Netherlands (nld)—as well as the GDP data of the euro area corresponding to the first 12 countries. The data set is retrieved from Datastream, the original source being the OECD. Some of the other member countries are discarded from the sample, since they do not have a long enough history to

[6]We carried out a robustness check with respect to the underlying business cycle definition, since our conclusions may depend on the definition we choose. See, for example, Canova (1998) who reports that "stylised facts" of business cycles vary across different filtering methods. Artis, Krolzig, and Toro (2004) also mention some studies on business cycle synchronisation in the euro area that come to different conclusions due to disagreement on the used detrending method. Our finding is that results following from CF-filter, BK-filter, HP-filter and year-on-year growth rates are in line with each other, while results based on quarterly report are sometimes different. The measure of business cycle is the CF-filter in the benchmark models of Chapters 3 and 4.

show an ERM/EMU effect in large parts of our sample. For some others, reliable quarterly data are not available over the entire sample period we consider, which spans the time from 1970Q1 (the first quarter of 1970) to 2007Q4. Note that this is the data set which underlies the empirical analyses of Chapters 3 and 4.

We report statistics from two sub-periods, 1970Q1–1990Q2 and 1990Q3–2007Q4, in this as well as coming chapters on business cycle dynamics in the euro area. Splitting the entire sample into two sub-periods allows us to capture changes in business cycle dynamics over time. Although a significant moderation of business cycles can be observed for each country in the sample, it can be said even without referring to a statistical test that the countries do not share a common structural break (see Figure 2.1 which shows the output gap of the entire euro area together with the output gap of each member country). The most important reason for splitting the sample at 1990Q2 is that it corresponds to the official kick-off of the EMU process, as suggested by the so-called Delors report—"Report on Economic and Monetary Union in the European Community" prepared by the "Committee for the Study of Economic and Monetary Union" headed by the then president of the European Community Jacques Delors. The report foresaw three stages leading to the euro area, the first of which was started on July 1, 1990. Note that this period also coincides roughly with the collapse of the Iron Curtain and a new wave in globalisation. It is also the quarter immediately before the reunification of Germany, the country with the highest economic weight in the euro area.

Note that other break dates could also have been chosen. Perez, Osborn, and Artis (2006) split their sample, for example, in 1979, the year of the commencement of the European Monetary System (EMS). Another candidate is 1984, which many studies date as the start of the Great Moderation. A later date might also make sense due to the fact that the EMU process got on its way in a more accelerated pace after the SGP was signed in 1993 or started to be implemented in 1997. Yet, besides being also arbitrary, all these choices would imply the length of sub-periods be quite unbalanced. In order to capture the sensitivity with respect to our choice of the break date, we also present statistics from rolling windows

Table 2.1: Output gap correlation of member countries with the euro area aggregate

	bel	deu	esp	fra	ita	nld
1970Q1–1990Q2	0.80	0.89	0.53	0.86	0.83	0.77
1990Q3–2007Q4	0.88	0.94	0.81	0.85	0.88	0.76

Abbreviations: bel: Belgium, deu: Germany, esp: Spain, fra: France, ita: Italy, nld: the Netherlands.

covering 60 quarters from the beginning of the sample until the end in order to capture changing business cycle dynamics over time throughout this study.

2.2.1 Output gaps

Looking at Figure 2.1, it immediately catches one's eye that output gaps of member countries are generally strongly correlated with the output gap of the entire euro area, although the correlation is typically not perfect. Table 2.1 quantifies this observation. All reported correlations exceed 0.5 for both sub-periods. The Spanish cycle is related to the euro area cycle much less in the first sub-period than in the second sub-period. This is not very surprising given the change Spain underwent in its political system in the 1970s and given that its EU membership started at a later date than the other five countries considered in this study. However, following an initial adjustment process after the EU membership in 1986, Spain seems to have caught up with the core countries of the EU in terms of synchronicity of its cycle with the entire euro area.

Figure 2.2 shows the output gap correlations of each member country with the output gap of the entire euro area over 15-year rolling windows. With the exception of the Netherlands, it is possible to say that correlations are slightly higher in more recent rolling windows. The correlation of the Dutch output gap with the euro area output gap seems to have decreased over rolling estimation windows recently. Yet, the most recent correlation coefficient is still around 0.7 for the relationship between the Netherlands and the euro area.

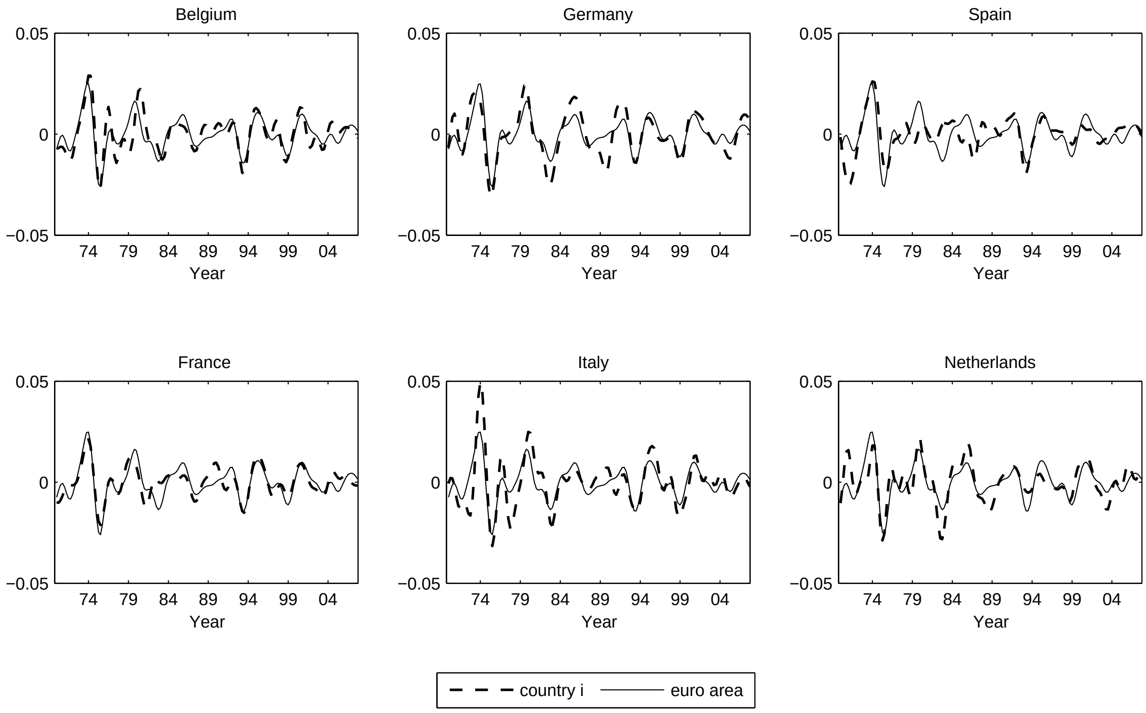


Figure 2.1: Output gap of individual countries and euro area

An interesting observation that follows from Figure 2.2 is that the rolling window correlations start to decrease sharply around 1982 for four countries—Belgium, Spain, France and Italy—and reach the bottom around 1983, after which they gradually catch up to the end of the sample period. The decline is most severe for the correlation corresponding to Spain, the cycle of which is virtually uncorrelated with the euro area cycle over some rolling windows. The decline is less severe for Belgium and France and least severe for the correlation corresponding to Italy. Also striking is the absence of such a pattern for Germany and the Netherlands. The 15-year rolling window correlations corresponding to Germany are generally high. Yet, a slight decrease is observable corresponding to rolling windows after roughly 1987, which may be traced back to the German reunification. The correlations recover again recently.

The hitherto reported correlations addressed the relationship between the entire euro area output gap and the output gap of a member country, where the euro area was meant to be

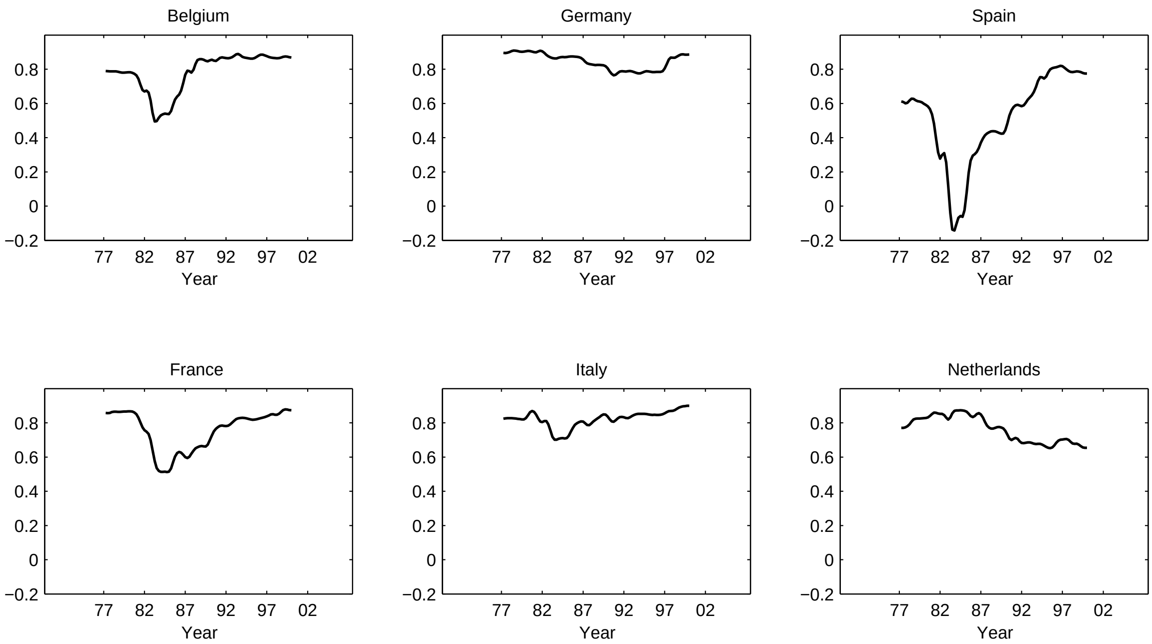


Figure 2.2: Output gap correlation with the euro area over 15-year rolling windows

the single currency area of the first 12 members. However, we find it useful to compute also descriptive statistics that correspond to member country pairs. Output data of six individual countries are included in our sample, which means that we can compute correlations for 15 distinct country pairs. Since it becomes quite cumbersome to report and comment the relationship between each pair, we compute only the mean and the standard deviation of these 15 correlations over 15-year rolling windows which can be seen in Figure 2.3. Note that an increase in the mean correlation is meaningful when it is not accompanied by an increase in the corresponding standard deviation. The latter condition is fulfilled in our sample period. The mean correlation is roughly 0.6 in the early rolling windows with a standard deviation below 0.2. It starts to decrease around 1982, as was the case for Belgium, Spain, France and Italy in Figure 2.2, reaches the bottom around 1983 and recovers gradually after this date until finally reaching the highest mean correlations of about 0.7 in most recent rolling windows, while the standard deviation at the same time gradually decreases to levels about 0.15. The overall finding is an increase in the business cycle synchronisation of the

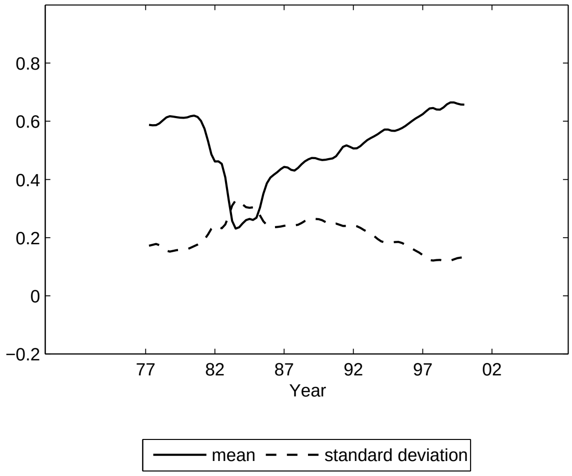


Figure 2.3: Mean and standard deviation of bilateral correlations of 6 euro area member countries over 15-year rolling windows

six member countries we consider over time.

Table 2.2 reports the standard deviation of output gaps in the euro area in the two sub-periods. The first and second rows respectively show the standard deviation of the output gap of the selected countries. Like in Figure 2.1, the volatility of output gaps decreases in each member country in the second half of the sample, and the standard deviations in Table 2.2 confirm this result. The third row of Table 2.2 shows the change in volatility, i.e., the standard deviation in the second sub-period subtracted by its counterpart in the first sub-period for each country. The relative decline in output gap volatility is lowest in France, where the output gap standard deviation in the second sub-period is 0.75 times the standard deviation in the first sub-period.

Given the previous finding of changing dynamics in terms of correlation over rolling sample windows, we have also computed the standard deviation of the member countries' output gaps over 15-year rolling windows, which are illustrated in Figure 2.4. A similarity to the foregoing findings deserves attention: the standard deviations corresponding to Belgium, Spain, France and Italy decrease sharply around 1982, reach a lower level roughly about 1983, and stay roughly constant afterwards. In Germany and the Netherlands, on the other hand,

Table 2.2: Output gap volatility

	bel	deu	esp	fra	ita	nld
1970Q1–1990Q2	1.12	1.22	1.14	0.80	1.50	1.13
1990Q3–2007Q4	0.73	0.80	0.64	0.60	0.74	0.56
change	-0.39	-0.42	-0.50	-0.20	-0.76	-0.57

Notes: The third row shows the difference between the second and first sub-period values for each country. See Table 2.1 for abbreviations.

a gradual decline over the rolling windows can be observed from the beginning until the end of the entire sample period.

Overall, the hitherto analysis of output gap correlations points to generally high and recently increasing correlations in the euro area. Rolling window computations imply that the business cycle dynamics have changed over time. The change in the statistics over time motivates our sub-sample and rolling window as well as time-varying coefficient estimations in Chapters 3 and 4, when investigating the driving forces of output fluctuations, structural sources of business cycle heterogeneity and the channels that led to the moderation of output dynamics.

2.2.2 Output gap differentials

We had mentioned in the introduction that investigation of output gap differentials provides additional valuable information on business cycle heterogeneity in the euro area. Differentials are computed by subtracting the realisation of the cyclical measure—the output gap computed with the Christiano-Fitzgerald filter—in the euro area from its counterpart in a member country. Hence, the output gap differential shows what should happen in a member country so that its business cycle position coincides exactly with the business cycle position of the entire euro area at a certain time point.

There is no a priori reason for the moderation in output gaps to lead to a decline in output

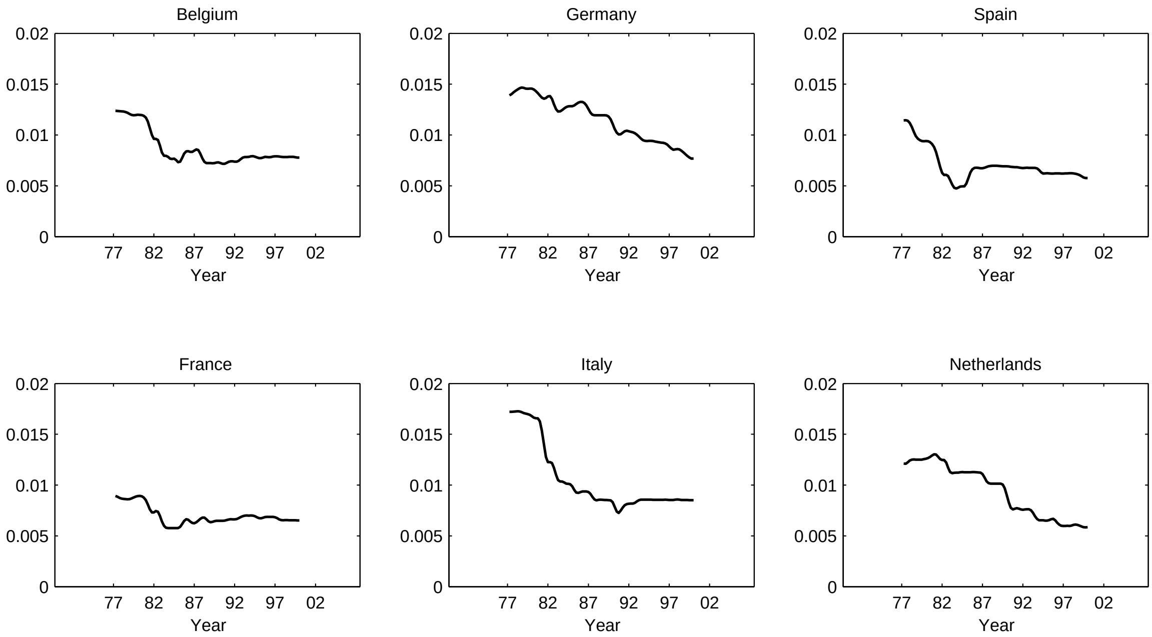


Figure 2.4: Standard deviation of output gaps over 15-year rolling windows

gap differential volatility. There can be given hypothetical examples such that the volatility of output gap differentials are higher or lower than the volatility of the underlying output gaps. Output gap differentials of the selected member countries are shown in Figure 2.5. The first observation is that amplitude and shape of differentials differs across countries. So, the member countries have clearly distinct relationships with the entire euro area.[7] Second, the volatility of an output gap differential is always lower than the volatility of the corresponding member country's output gap, which is a byproduct of positive correlations of output gaps. Finally, output gap differentials also underwent a moderation like output gaps, which speaks for decreasing heterogeneity among euro area business cycles. The latter observation is quantified in Table 2.3. Moreover, the standard deviation of output gap differentials over 15-year rolling windows, illustrated in Figure 2.6, also decline most recently. While this decline is rather gradual in Spain, Italy and the Netherlands, the volatility of output gap

[7]This assessment is supported by correlations of output gap differentials of the chosen countries, which are often negative or insignificantly different from zero, and positive in only three cases. We do not further report these correlations here.

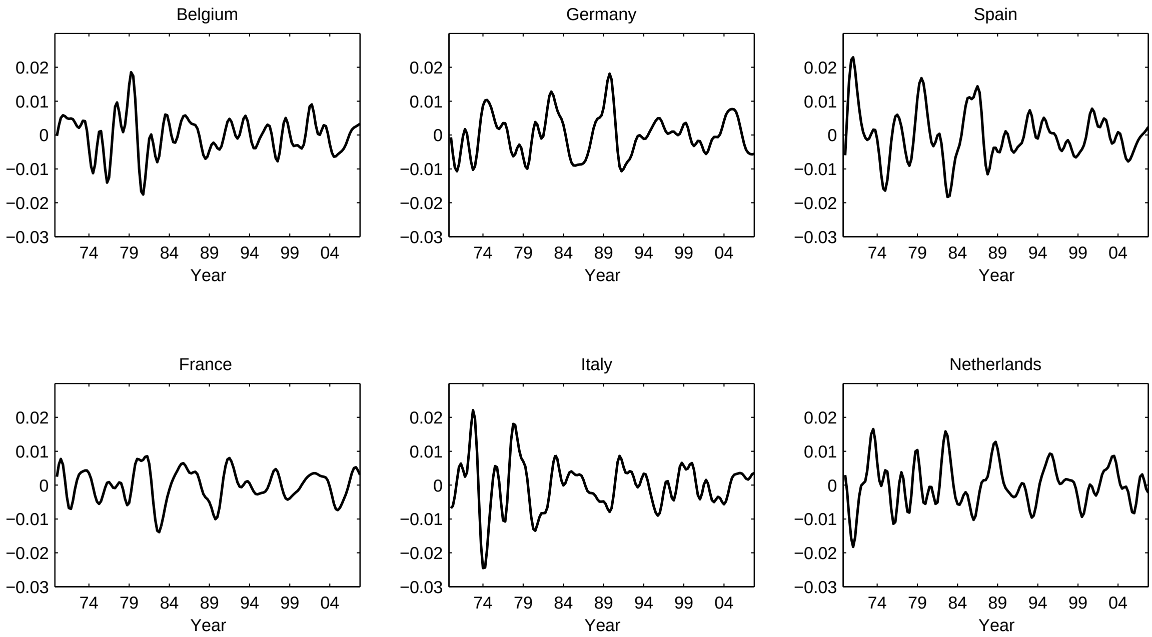


Figure 2.5: Output gap differentials in the euro area

differentials of Belgium, Germany and France is roughly constant and relatively high over the rolling windows corresponding to the first half of the entire sample and declines afterwards.

2.3 Remarks and outlook

A prerequisite for a successful monetary union is that the business cycles of its members are driven by common factors. Therefore, one question of interest in the following chapters is the

Table 2.3: Output gap differential volatility

	bel	deu	esp	fra	ita	nld
1970Q1–1990Q2	0.68	0.57	1.02	0.49	0.88	0.73
1990Q3–2007Q4	0.35	0.31	0.39	0.33	0.35	0.41
relative volatility	0.52	0.54	0.38	0.66	0.40	0.56

Notes: The third row shows the relative difference between the second and first sub-period values for each country. See Table 2.1 for abbreviations.

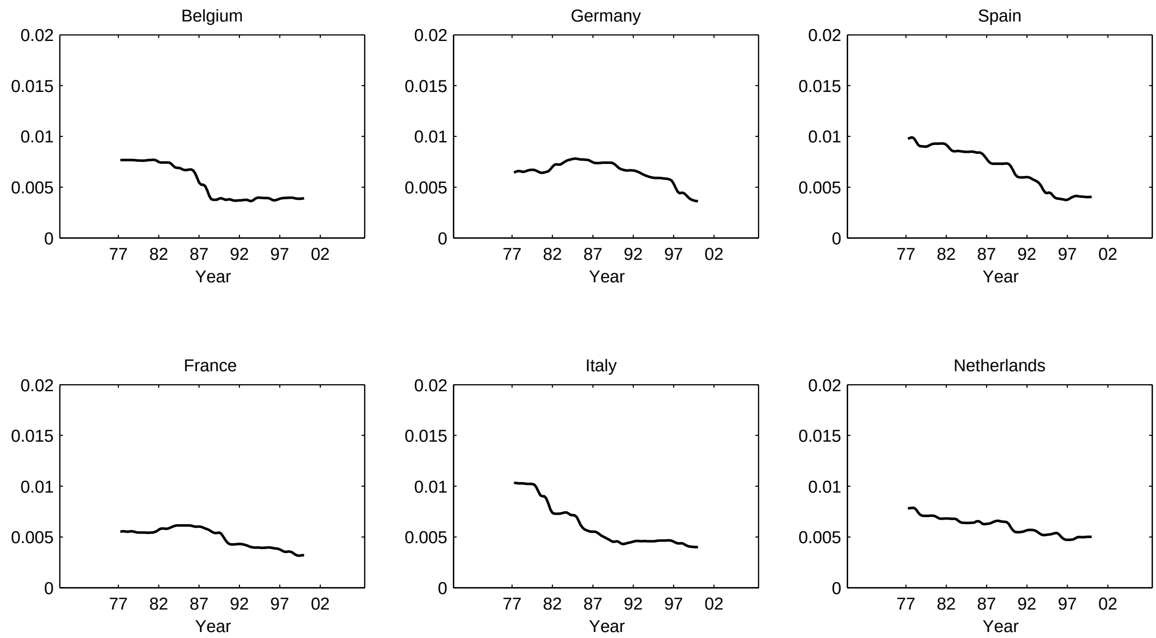


Figure 2.6: Standard deviation of output gap differentials over 15-year rolling windows

extent to which the business cycles of the euro area countries have been driven by common factors. One should differentiate between global and euro-area-specific common factors when dealing with this question, since the EMU process has been taking place concurrently with the globalisation phenomenon, and since both are similarly characterised by features such as a substantial increase in international capital flows and trade relative to former times, stronger financial market integration, higher mobility of labor, etc. The presumption of a large body of macroeconomic theory suggests that both the EMU process and the globalisation should lead to a stronger integration of the euro area economies. This should imply in turn a higher synchronisation of the member countries' business cycles due to the increasing impact of common factors they are subject to. While our descriptive analysis above points in general to a high and recently increasing synchronisation of the euro area business cycles, a challenge is to isolate the effects of the EMU process and the globalisation on these dynamics, which requires the measurement of a euro area factor in addition to a global factor as a potential driving force of business cycle fluctuations. We measure both factors with the aid of a conventional SVAR model in Chapter 3 and factor-structural VAR (FSVAR) and time-varying coefficient SVAR (TVC-SVAR) models in Chapter 4. In each of these chapters, we investigate the role of global and euro area factors in cyclical fluctuations of member countries' output by employing variance decompositions.

Another aim of us in the coming chapters is to assess the sources of business cycle heterogeneity, of which dynamics have been shown to have changed over time in this chapter. In theory, two extreme situations can be the driving force of business cycle heterogeneity. On the one hand, countries may be subject to common shocks, but their response to those shocks may differ substantially. Such a case can be seen as reflection of differences between countries in terms of economic structure. The term economic structure refers here to the entire economic environment covering aspects like fiscal policy, natural and human resources, sectoral structure and specialisation, labor market regulation, etc. On the other hand, countries may be sharing similar economic structures, but may be hit by asymmetric shocks. Both mechanisms are likely to play some role in reality, and our analysis helps shed light on the extent to which these mechanisms explain the observed heterogeneity in the euro area.

We employ two different measures of heterogeneity. The first measure is the simple correlation coefficient between each member country's cycle and the entire euro area cycle. In this context, we compute true and counterfactual correlations. True correlations are generated when all types of shocks are allowed to take place in an empirical model, while counterfactual correlations refer to correlations that would have been observed if at least one source of shocks were set to zero. High and positive counterfactual correlations in the face of common shocks—global or euro area shocks—are interpreted to be reflective of structural similarity of an individual country to the entire euro area. The other measure of heterogeneity is the output gap differential mentioned in this chapter. We employ variance decompositions in order to detect the driving forces of output gap differential variance corresponding to each member country.

Our findings in this chapter also document the moderation of output gaps as well as of output gap differentials in the euro area. While different explanations of the moderation in output gap volatility have been suggested in the literature, the concurrence of the decline in business cycle volatility in many countries makes the question interesting whether it is related to changes in international factors. Our empirical framework in the coming chapters allows us to investigate the extent to which the moderation can be attributed to changes related to global, euro area and country-specific shocks in the euro area. Furthermore, we explore whether the decline in output gap volatility has its roots in changes in shock propagation mechanisms or in changes in size of shocks. If the declining size of shocks plays the main role in this phenomenon, the Great Moderation can be interpreted to be related to good luck as well as good policy, while a dominant role of changes in shock propagation suggests that structural changes in economies is the main driving force of the Great Moderation.

To summarise, dynamics of both output gaps and output gap differentials underwent changes over time in the euro area. While a large literature reviewed in this chapter suggests that the change could be in one of two directions, i.e., increasing or decreasing synchronisation of business cycles, our descriptive analysis also pointed to the fact that each member country has its own peculiar relationship with the entire euro area. In Chapters 3 and 4, we follow different empirical approaches to investigate how the developments summarised in this chapter are related to global, euro area and country-specific factors.

Chapter 3

Business cycle dynamics in the euro area: SVAR approach*

In this chapter and the next, we employ three different empirical approaches to address the issues that have been brought forward in the the previous chapter. As our literature review points out, applying different methodologies is one of the reasons behind disagreements on the nature of business cycle dynamics in the euro area. Our results should therefore be complementary to the existing literature, while handling the issues at hand with the same data set but three different empirical approaches should give the reader a sense about the robustness of the findings. In Chapters 3 and 4, we address three basic questions: (i) To what extent are the business cycles of the euro area countries driven by common (global and euro area) factors? (ii) What are the extent and sources of heterogeneity in the euro area in terms of business cycles? (iii) If the moderation of business cycles and business cycle differentials were statistically significant, which mechanisms led to it in the euro area?

3.1 Econometric methodology

The econometric analysis of this chapter builds on a modified framework of Giannone and Reichlin (2006), who investigate the level of business cycle heterogeneity with the aid of

*This chapter is based on a strongly revised version of Seymen (2009). Most of the estimations and calculations in this chapter are carried out using MATLAB codes written by the author. JMulTi is used for model specification. The MATLAB code included in the Spatial Econometrics Toolbox of James P. LeSage is used for the estimation of the structural parameters in the VAR.

bivariate VAR models comprising the euro area output and the output of a member country of the euro area. Using an approach similar to that of Stock and Watson (2005), Giannone and Reichlin distinguish between euro area and country-specific shocks. The euro area shocks are defined as shocks that affect the entire euro area as well as individual member countries in the period they occur, while country-specific shocks are labelled as such since they are spilled over from a certain country of origin to the rest of the euro area with a time lag. An important methodological handicap of this approach is that it takes into account only two sources of shocks—euro area and country-specific. However, we want to assess the role of both global and euro area shocks in business cycle dynamics of the euro area. If global shocks have indeed a significant explanatory power for the dynamics, a model without global shocks may suffer from omitted-variables bias. In order to overcome this potential shortcoming, we augment the bivariate framework of Giannone and Reichlin (2006) with US output following Giannone and Reichlin (2005, 2006) and Perez, Osborn, and Artis (2006). Three types of shocks—global, euro area and country-specific shocks—are estimated. Global shocks are identified as shocks that influence both the output in the US and the euro area, as well as individual euro area countries, immediately in the period they take place. The euro area and country-specific shocks are defined in the same manner as described above.

3.1.1 Bivariate models

The first bivariate model of Giannone and Reichlin (2006) follows from a simpler version of the strategy followed by Stock and Watson (2005). The moving average representation of the B-model underlying the empirical analysis is given by

$$\begin{bmatrix} y_{EA,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} \mu_{EA} \\ \mu_i \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \Phi_{11,j} & \Phi_{12,j} \\ \Phi_{21,j} & \Phi_{22,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{EA,t} \\ \varepsilon_{i,t} \end{bmatrix}, \tag{3.1}$$

where $y_{EA,.t}$ and $y_{i,t}$ stand respectively for the log output of the euro area and country i at period t, μ_{EA} and μ_i stand for constant terms, $\Phi_{kl,j}$ is the (k,l) element of the j^{th} moving average coefficient matrix, and $\varepsilon_{EA,t}$ and $\varepsilon_{i,t}$ are defined as euro area and country-i

shocks, respectively. The crucial identification restriction in this system is that country-specific shocks affect the euro area aggregate only with a lag of one quarter. Therefore, the immediate effect of a country-specific shock on the euro area output in the period it occurs is limited to the population share of the country the shock stems from. Formally,

$$\Phi_0 = \begin{bmatrix} \Phi_{0,11} & p_i \Phi_{0,22} \\ \Phi_{0,21} & \Phi_{0,22} \end{bmatrix}, \tag{3.2}$$

where p_i is the population share of country i in the euro area.

Three important differences to the study of Giannone and Reichlin in our application are that (i) we work with quarterly data (at the cost of losing some countries in the sample) as is typical in studies dealing with business cycles, while Giannone and Reichlin use annual data; (ii) we estimate the model also in sub-periods in order to capture potential changes in the size of shocks as well as their transmission so that changes due to, e.g., the EMU process and the globalisation as well as the moderation in macroeconomic fluctuations can be addressed; and (iii) we compare output gaps in the euro area computed with the Christiano-Fitzgerald filter in line with the descriptive analysis of the previous chapter, while Giannone and Reichlin concentrate on output level or quarterly growth.

In a similar model to the first one, Giannone and Reichlin (2005, 2006) also investigate the business cycle relationship between the US and the euro area. The model reads

$$\begin{bmatrix} y_{US,t} \\ y_{EA,t} \end{bmatrix} = \begin{bmatrix} \mu_{US} \\ \mu_{EA} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \Phi_{11,j} & \Phi_{12,j} \\ \Phi_{21,j} & \Phi_{22,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{US,t} \\ \varepsilon_{EA,t} \end{bmatrix} \tag{3.3}$$

with

$$\Phi_0 = \begin{bmatrix} \Phi_{0,11} & 0 \\ \Phi_{0,21} & \Phi_{0,22} \end{bmatrix}, \tag{3.4}$$

so that euro area shocks are spilled over to the US after a one-quarter lag, while US shocks affect both the US and the euro area in the period they occur. Giannone and Reichlin motivate this type of framework with Granger causality tests (among others). According to their findings, it is not rejected that the log output growth of the US and the euro area do not Granger-cause the log output differential (in levels) between the US and the euro area. The hypothesis that the output differential does not Granger-cause the US output growth is also not rejected, whereas the hypothesis that the output differential does not Granger-cause the euro area output growth is rejected by Granger causality tests. Giannone and Reichlin (2005) conclude from this picture that “the euro area rate of growth adjusts itself to the US growth while the US does not respond to shocks specific to the euro area”. Granger-causality tests based on our sample, of which results we do not report here, are also in accordance with this picture. Moreover, euro area shocks play virtually no role in US output fluctuations according to all of our country-specific models. Finally, Perez, Osborn, and Artis (2006) order the US output before the EU15 output within a similar VAR structure due to “the important role of the US in the international economy during the postwar period”.

3.1.2 Trivariate model

The bivariate model in (3.1) does not allow us to distinguish between global and euro area shocks which may bias our results. We find it useful to augment it with another variable—the US output—in the way the model in (3.3) suggests. This enables us to isolate the effects of US, euro area and country-specific shocks for each member country. We deem the US shocks to be standing for global shocks in the following.

The trivariate model we work with is a natural extension of the strategy followed by Giannone and Reichlin (2006). It combines the aforementioned two models that these authors work with. Furthermore, the model resembles the model employed by Perez, Osborn, and Artis (2006), who work with trivariate VARs containing the first-differenced log output of the US, EU15 and one of the G7 countries except the US. Our innovation is (i) to consider the euro area instead of the EU15, since the euro area is a more coherent group in terms of being subject to common policy and is our subject of interest; and (ii) to take into account the population shares of the member countries in the identification scheme in the way Giannone and Reichlin (2006) do, which is a more reasonable restriction than the zero restriction used by Perez, Osborn, and Artis (2006) for the impact of German, French and Italian shocks on

EU15 output.

The trivariate model is given by

$$\begin{bmatrix} y_{US,t} \\ y_{EA,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} \mu_{US} \\ \mu_{EA} \\ \mu_i \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \Phi_{11,j} & \Phi_{12,j} & \Phi_{13,j} \\ \Phi_{21,j} & \Phi_{22,j} & \Phi_{23,j} \\ \Phi_{31,j} & \Phi_{31,j} & \Phi_{33,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{US,t} \\ \varepsilon_{EA,t} \\ \varepsilon_{i,t} \end{bmatrix}, \tag{3.5}$$

which is analogous to (3.1), the only difference being that the US output, the corresponding coefficients and a US shock, which we assume to represent a global shock, are now a part of the VAR as well. In this case, the impact effect of shocks on the output of the US, the euro area and country i is given by

$$\Phi_0 = \begin{bmatrix} \Phi_{11,0} & 0 & 0 \\ \Phi_{21,0} & \Phi_{22,0} & p_i \Phi_{33,0} \\ \Phi_{31,0} & \Phi_{32,0} & \Phi_{33,0} \end{bmatrix}. \tag{3.6}$$

The zero entries in the first row of Φ_0 imply that euro area and country-specific shocks do not influence the US economy in the period they occur.

Stock and Watson (2005) and Perez, Osborn, and Artis (2006), among others, estimate their models in the first difference of log output. This may be, however, problematic in case log outputs of the countries included in the analysis are cointegrated. Therefore, we estimate the country-specific models in levels of log output following Giannone and Reichlin (2006). Note that OLS estimation of cointegrated systems in levels is asymptotically consistent. Estimating in levels helps us avoiding problems related to model specification with respect to unit root and cointegration issues.

3.1.3 Output gap generating process

Our empirical results all follow from estimated processes that generate the output gaps of the US, the euro area and each member country included in our data set, where the output gap measure is the symmetric CF-filter. We apply the symmetric Christiano-Fitzgerald filter to each sub-component of each variable in (3.5) as described for Equation (1.34) of Section

1.4.2. The approximate process generating the output gap of country j for $j = US, EA, i$, can be written as

$$\tilde{y}_{j,t} \approx \sum_{m=-\kappa}^{\kappa} \Psi_{j,US,m}\varepsilon_{US,t+m} + \sum_{m=-\kappa}^{\kappa} \Psi_{j,EA,m}\varepsilon_{EA,t+m} \sum_{m=-\kappa}^{\kappa} \Psi_{j,i,m}\varepsilon_{i,t+m}, \tag{3.7}$$

where $\Psi_{jk,m}$ for $k = US, EA, i$ stand for coefficients of the output gap generating process of country j, with respect to structural shocks, and $\varepsilon_{k,t+m}$ stand for shocks at period $t + m$. Based on the output gap processes, counterfactual correlations can be computed, and variance decompositions or decompositions of changes in cyclical dynamics can be carried out.

3.2 Results from discrete samples

3.2.1 Model specification

Since the output dynamics of each country are unique, we apply conventional information criteria to determine the optimal number of lags for each country-specific model and test for cointegration in each country-specific model for each period considered. The results, reported in Table 3.1 for three different sample periods, differ across country-specific models and over different periods. For the sake of comparability, we carry out Johansen cointegration tests for each country-specific model with two lags of variables (in levels), since information criteria often suggest this lag order. Moreover, the trend in the data is assumed to be orthogonal to the cointegration relations. Johansen test results in Table 3.1 often point to a cointegration rank of either zero or one. The only exception to this rule is Spain in the second sub-period. We have also tested for cointegration in a bivariate model comprising only the output of the US and the euro area, results of which are not on Table 3.1. While a rank of zero is rejected for the full sample and the second sub-sample at the 5-percent significance level, it is rejected at the 10-percent significance level for the first sub-sample.

Table 3.1: Johansen cointegration rank tests

		70Q1–07Q4		70Q1–90Q2		90Q3–07Q4	
	rank	statistic	p-value	statistic	p-value	statistic	p-value
bel	0	34.22	0.01	32.55	0.02	32.88	0.02
	1	14.38	0.07	9.75	0.31	11.36	0.19
deu	0	31.32	0.03	21.40	0.34	20.40	0.41
	1	5.38	0.77	4.92	0.82	4.23	0.88
esp	0	30.17	0.05	20.44	0.40	35.73	0.01
	1	3.20	0.95	1.96	0.99	16.91	0.03
fra	0	35.84	0.01	36.14	0.01	26.27	0.12
	1	11.28	0.20	11.65	0.18	5.95	0.70
ita	0	26.74	0.11	31.91	0.03	29.65	0.05
	1	3.20	0.95	13.59	0.09	8.08	0.46
nld	0	26.76	0.11	23.21	0.24	26.38	0.12
	1	4.09	0.89	9.54	0.32	4.31	0.87

Notes: Two lags are included in each model. See Table 2.1 for abbreviations.

3.2.2 Comparison of country-specific models

An important drawback of the empirical approach of this chapter is that six different trivariate models are estimated for the same phenomenon—global and euro area shocks and their dynamic multipliers. In case these differ significantly across the estimated models, the effects of those shocks on the individual countries can no longer be compared consistently. In order to get an idea on this issue, we first summarise the correlation among them over the two sub-periods in Table 3.2. Global shocks of the country-specific models show a higher correlation than euro area shocks over both sub-periods. However, the euro area shocks' correlations across the country-specific models are still strong, most of them being above 0.75.

Moreover, the estimated country-specific shocks must be orthogonal to each other. Non-zero correlations among them would suggest that they are not really country-specific. Most of the country-specific shock correlations given in the bottom panel of Table 3.2 are statistically

Table 3.2: Correlations of estimated shocks

Global shock correlations

	Sample: 1970Q1–1990Q2					Sample: 1990Q3–2007Q4				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	0.91					0.96				
	(0.03)					(0.01)				
esp	0.96	0.94				0.88	0.85			
	(0.02)	(0.02)				(0.04)	(0.04)			
fra	0.89	0.94	0.93			0.91	0.91	0.77		
	(0.03)	(0.02)	(0.02)			(0.02)	(0.03)	(0.05)		
ita	0.91	0.91	0.95	0.88		0.96	0.90	0.89	0.88	
	(0.02)	(0.02)	(0.01)	(0.04)		(0.01)	(0.03)	(0.03)	(0.03)	
nld	0.93	0.92	0.96	0.90	0.91	0.94	0.91	0.84	0.88	0.93
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)

Euro area shock correlations

	Sample: 1970Q1–1990Q2					Sample: 1990Q3–2007Q4				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	0.77					0.71				
	(0.06)					(0.07)				
esp	0.91	0.80				0.88	0.78			
	(0.03)	(0.06)				(0.04)	(0.06)			
fra	0.84	0.75	0.90			0.90	0.79	0.92		
	(0.05)	(0.06)	(0.03)			(0.03)	(0.07)	(0.03)		
ita	0.82	0.67	0.80	0.77		0.86	0.76	0.81	0.86	
	(0.05)	(0.08)	(0.06)	(0.06)		(0.05)	(0.06)	(0.06)	(0.04)	
nld	0.90	0.77	0.94	0.93	0.82	0.91	0.79	0.94	0.92	0.88
	(0.03)	(0.07)	(0.02)	(0.02)	(0.05)	(0.03)	(0.06)	(0.02)	(0.03)	(0.03)

Country-specific shock correlations

	Sample: 1970Q1–1990Q2					Sample: 1990Q3–2007Q4				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	-0.24					-0.07				
	(0.13)					(0.15)				
esp	0.09	-0.19				0.00	-0.16			
	(0.13)	(0.12)				(0.12)	(0.13)			
fra	0.04	-0.31	-0.05			-0.07	-0.41	0.12		
	(0.11)	(0.11)	(0.12)			(0.13)	(0.17)	(0.11)		
ita	0.09	-0.37	0.02	0.02		0.08	-0.37	-0.10	0.15	
	(0.12)	(0.13)	(0.12)	(0.13)		(0.14)	(0.14)	(0.13)	(0.13)	
nld	0.17	-0.04	0.11	-0.15	0.07	0.03	0.08	-0.01	-0.16	-0.21
	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.14)	(0.14)	(0.13)	(0.15)

Notes: Standard errors in parentheses. See Table 2.1 for abbreviations.

insignificant. The only exceptions to this rule are the correlations of German-French and German-Italian shocks in both sub-periods, for which significant negative correlations are observed.

Next, we show in Figure 3.1 the response of the US and euro area outputs to global and euro area shocks in the six trivariate models. Again, in the ideal case all impulse response functions coincide. Unsurprisingly, the ideal case does not hold, but the impulse response functions of both variables with respect to both shocks are quite similar across the second sub-period estimations of the country-specific models. However, more discrepancies exist in the estimations for the first sub-period, particularly with respect to the response of the US and euro area outputs to euro area shocks.

3.2.3 Driving forces of business cycles

Variance decomposition of output gaps

In this sub-section, we shed light on the role global, euro area and country-specific shocks play in the cyclical fluctuations of the member countries. A variance decomposition analysis is employed to this end. The variance of the output gap, $var\left(\tilde{y}_{j,t}\right)$ for $j = US, EA, i$, is given by

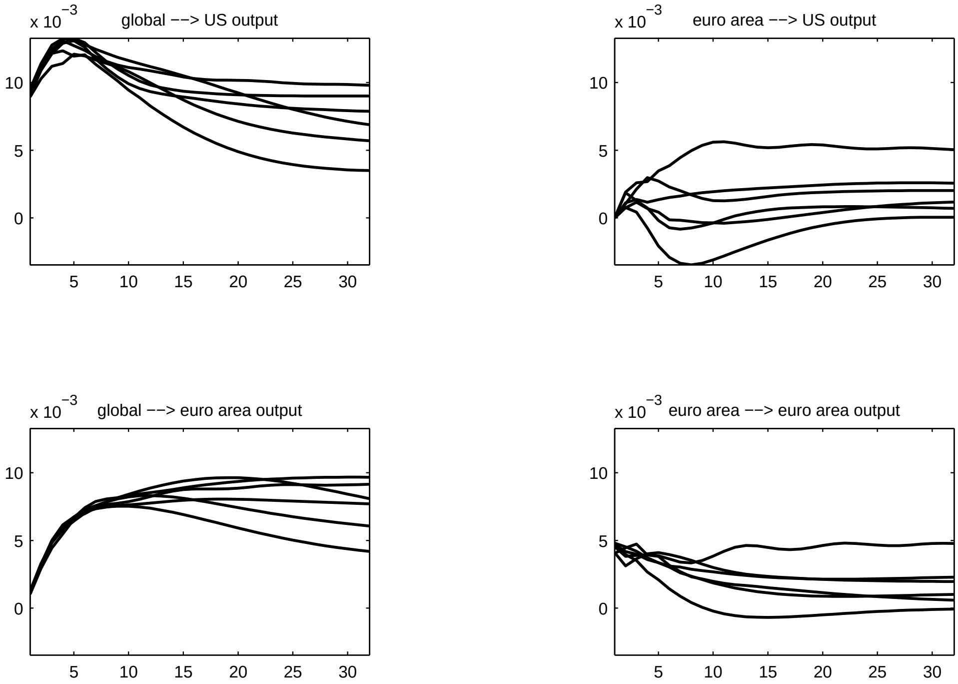
$$var\left(\tilde{y}_{j,t}\right) = \sum_{k} \left[\left(\sum_{m=-\kappa}^{m} \Psi_{jk,m}^{2} \right) \sigma_{k}^{2} \right], \tag{3.8}$$

where σ_k for $k = US, EA, i$ stands for the standard deviation of the global, euro area or country-specific shock in the corresponding model, which follows from (3.7). Hence, the share of the structural shock k on the variance of the output cycles of country j for $j = US, EA, i$ is simply

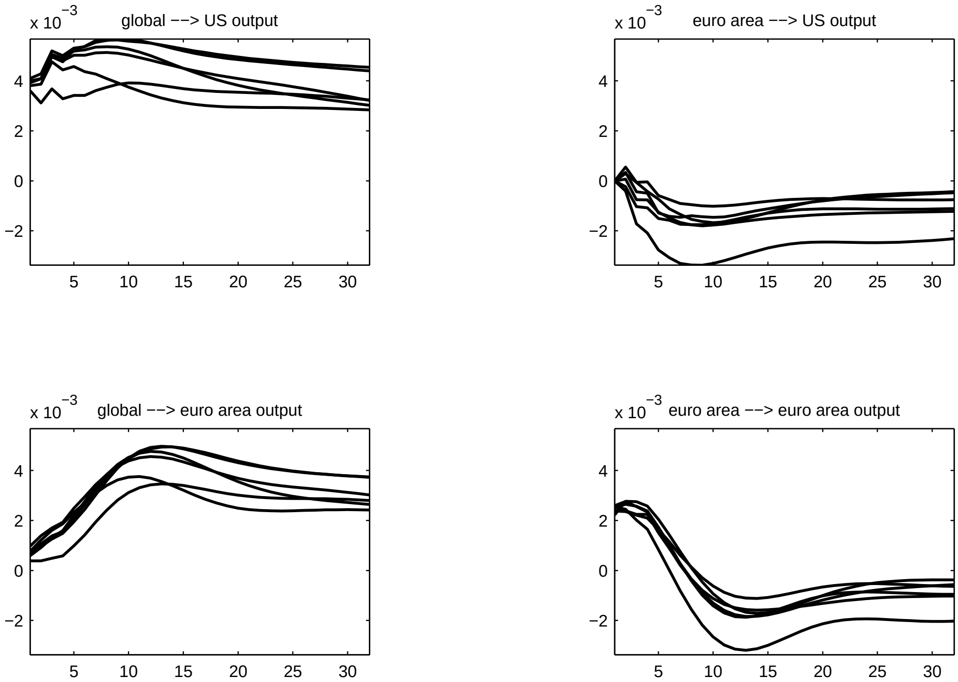
$$s_{jk}^{i} = \left[\left(\sum_{m=-\kappa}^{\kappa} \Psi_{jk,m}^{2} \right) \sigma_{k}^{2} \right] / \sum_{k} \left[\left(\sum_{m=-\kappa}^{m} \Psi_{jk,m}^{2} \right) \sigma_{k}^{2} \right], \tag{3.9}$$

which follows from the country-specific trivariate model of country i.

The first panel of Table 3.3 shows the shares of shocks in the output gap variance of the euro area countries over the full sample period. The importance of adding a global factor



(a) Sample: 1970Q1–1990Q2



(b) Sample: 1990Q3–2007Q4

Figure 3.1: Response of US and euro area output to common shocks in trivariate models

to the bivariate model becomes clear immediately, since the global shock has a statistically significant and non-negligible share in each member country considered. Euro area shocks also have significant and non-negligible shares in Belgium, Germany, France and the Netherlands according to the full-sample estimates. Country-specific shocks dominate the output gap fluctuations of Belgium, Spain and Italy with shares above 0.50, while their share is also quite high in the other member countries.

In the second and third panels of Table 3.1, the shares of shocks in the output gap variance of the euro area countries in the two sub-periods of interest are reported. The estimates corresponding to the first sub-period are generally in line with the full-sample estimates for Belgium, Spain, Italy and the Netherlands. Some discrepancy is observed, however, for Germany and France. The first sub-period estimate of the global shock share is 0.62 for Germany, whereas it is 0.28 according to the full-sample estimation. The point estimates of the shares of euro area and own shocks is accordingly somewhat lower in the first sub-sample than in the full sample for this country. A higher estimate of the share of euro area shocks in the first sub-sample than in the full sample is registered for France, which is roughly compensated by a lower own-shock estimate in the first sub-period.

The point estimates of the shares of shocks corresponding to the second sub-period differ from the point estimates corresponding to the full sample period as well as the first sub-period. Global shocks have only statistically insignificant shares in all member countries except the Netherlands, whereas they were found to be significant according to the estimations of the other sample periods (except in Spain in the first sub-period). The point estimates of euro area shocks are either higher in the second sub-period than in the first sub-period or are in the second sub-period as high as in the first sub-period. They are all significant at the 5-percent significance level (except for Italy, where the significance is obtained only at the 10-percent level) in the second sub-period, which does not apply to the full-sample and first sub-period estimates. Country-specific shocks have significant shares in all member countries except the Netherlands in the second sub-period.

Table 3.3: Shares of shocks in output gap variance of euro area countries

	Sample: 1970Q1–2007Q4					
	bel	deu	esp	fra	ita	nld
global shock	0.22	0.28	0.23	0.31	0.25	0.30
	(0.09)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)
euro area shock	0.24	0.34	0.09	0.32	0.13	0.28
	(0.09)	(0.09)	(0.06)	(0.11)	(0.08)	(0.10)
country shock	0.54	0.37	0.68	0.36	0.61	0.42
	(0.11)	(0.10)	(0.13)	(0.12)	(0.11)	(0.10)

	Sample: 1970Q1–1990Q2					
	bel	deu	esp	fra	ita	nld
global shock	0.23	0.62	0.29	0.35	0.31	0.29
	(0.13)	(0.13)	(0.18)	(0.15)	(0.14)	(0.15)
euro area shock	0.23	0.20	0.06	0.42	0.13	0.30
	(0.12)	(0.11)	(0.09)	(0.14)	(0.09)	(0.12)
country shock	0.55	0.18	0.65	0.22	0.55	0.42
	(0.14)	(0.09)	(0.18)	(0.12)	(0.14)	(0.13)

	Sample: 1990Q3–2007Q4					
	bel	deu	esp	fra	ita	nld
global shock	0.18	0.21	0.24	0.21	0.11	0.40
	(0.12)	(0.14)	(0.13)	(0.12)	(0.13)	(0.15)
euro area shock	0.27	0.49	0.41	0.41	0.24	0.41
	(0.13)	(0.15)	(0.16)	(0.16)	(0.14)	(0.16)
country shock	0.55	0.29	0.34	0.38	0.65	0.18
	(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.13)

	Change in the share of shocks over time					
	bel	deu	esp	fra	ita	nld
global shock	-0.04	-0.41	-0.05	-0.15	-0.20	0.12
	(0.17)	(0.19)	(0.23)	(0.20)	(0.18)	(0.21)
euro area shock	0.04	0.30	0.36	-0.01	0.11	0.12
	(0.18)	(0.19)	(0.18)	(0.21)	(0.17)	(0.20)
country shock	0.00	0.11	-0.31	0.16	0.09	-0.23
	(0.21)	(0.18)	(0.25)	(0.19)	(0.21)	(0.18)

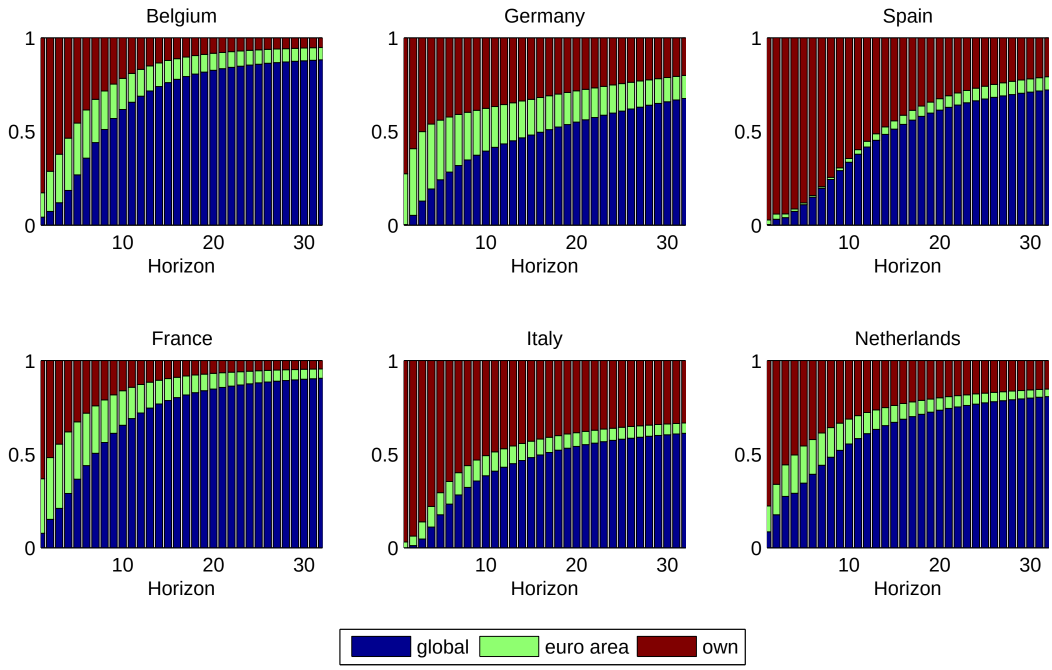
Notes: The output gap measure is the CF-filter. The last panel shows the difference between the estimates of the second and first sub-periods reported in the third and second panels, respectively. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

We show the change in the share of shocks from the first sub-period to the second sub-period in the last panel of Table 3.3. The standard errors are in most cases large enough so that most of the change is found not to be statistically significant. Only the decline in the share of global shocks in Germany's output gap variance and the increase in the share of euro area shocks in Spanish output gaps are significant.

All in all, we find a statistically significant increase in the share of neither global shocks (due to, e.g., the globalisation) nor euro area shocks (due to, e.g., the EMU process). Furthermore, there is no evidence for a statistically significant decrease in the share of country-specific shocks in output gap variance of the euro area member countries. This suggests that output gaps are not being driven more by common factors than country-specific factors in the more recent sub-period. Yet, euro area shocks are statistically significant in the output gap fluctuations of all countries in the second sub-period, while they have insignificant and negligible shares in Italy and Spain in the first sub-period.

Forecast error variance decomposition

Recall from the first chapter that the implications of the output gap variance decomposition may deviate from the implications of the FEVD due to filtering. Therefore, we also present the FEVD results in the following. The FEVD estimates for the business cycle horizon, based on all sample periods, are displayed in Figures 3.2(a) to 3.2(c) as well as for a forecast horizon of 12 quarters in Table 3.4. The first difference to the previous output gap variance decomposition estimates is the strikingly higher share of global shocks over the business cycle horizon from 6 to 32 quarters. This share increases for all member countries with increasing forecast horizon. Second, the FEVD shares of euro area shocks are never found to be significant at the 5-percent significance level, while they were often found to be significant by the output gap variance decomposition. Finally, country-specific shocks are more important in the output fluctuations of Spain and Italy, especially at short forecast horizons, than in the other member countries. However, country-specific shock shares in the forecast error



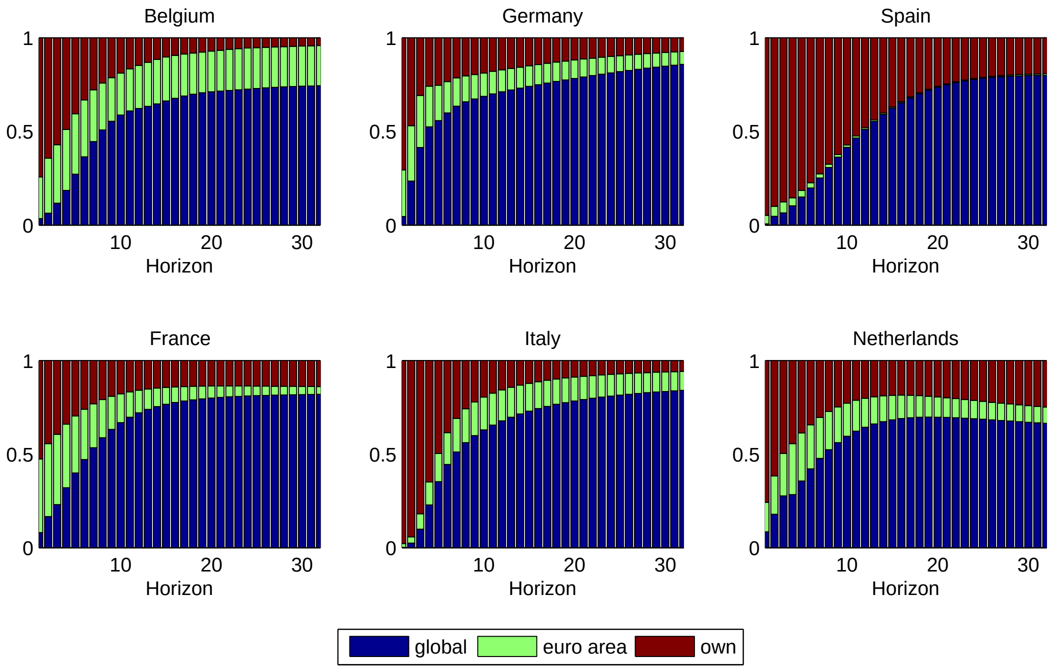
(a) Sample: 1970Q1–2007Q4

Figure 3.2: FEVD of output

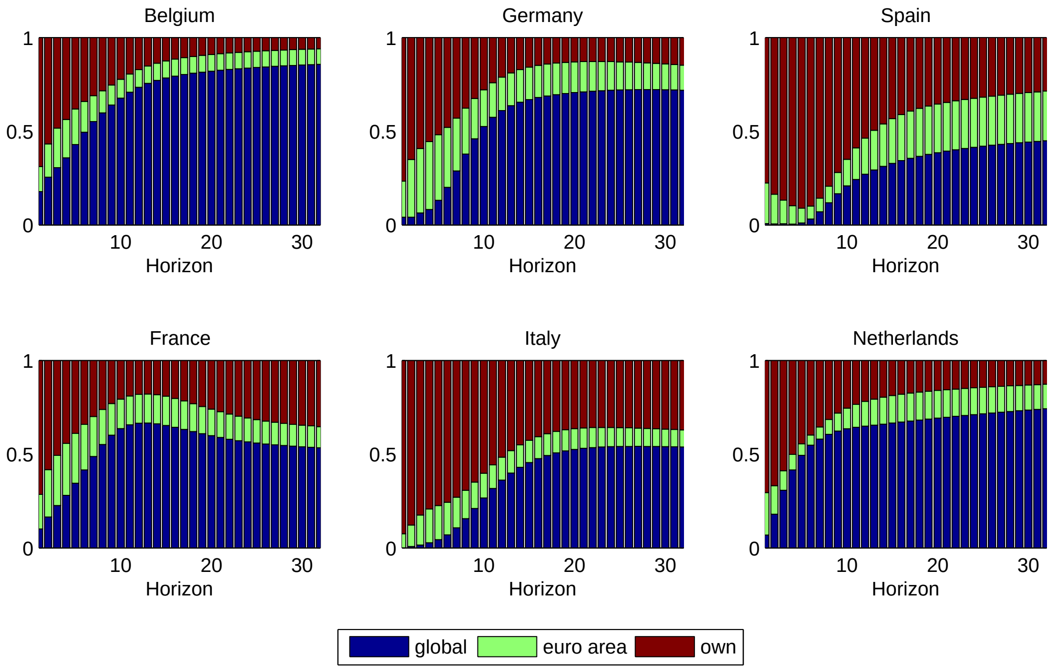
variance decrease in all countries with increasing forecast horizon.

3.2.4 Heterogeneity

The subject of this sub-section is the driving forces of heterogeneity in the euro area. High shares of common (global and/or euro area) shocks in the output gap volatility of member countries contribute to stronger business cycle co-movement only if these shocks lead to homogeneous dynamics across the member countries. In order to account for the relative importance of differing shock propagation mechanisms and of exposure to asymmetric shocks in the existing business cycle heterogeneity within the euro area, two tools are employed. First, counterfactual correlations are computed in order to see whether common shocks alone lead to high correlations of entire euro area cycles with individual member countries' cycles. Counterfactual correlation analysis gives us hints on the homogeneity of the relationship of each member country with the entire euro area. Second, we apply the aforementioned



(b) Sample: 1970Q1–1990Q2



(c) Sample:1990Q3–2007Q4

Figure 3.2: FEVD of output (cont.)

Table 3.4: FEVD of euro area countries' output

	bel	deu	esp	fra	ita	nld
Sample: 1970Q1–2007Q4						
global shock	0.69	0.43	0.42	0.72	0.43	0.61
	(0.12)	(0.16)	(0.15)	(0.12)	(0.16)	(0.14)
euro area shock	0.14	0.21	0.03	0.15	0.10	0.11
	(0.08)	(0.12)	(0.05)	(0.09)	(0.08)	(0.10)
country shock	0.17	0.36	0.55	0.13	0.47	0.28
	(0.08)	(0.12)	(0.15)	(0.07)	(0.14)	(0.10)
Sample: 1970Q1–1990Q2						
global shock	0.62	0.71	0.51	0.72	0.68	0.64
	(0.17)	(0.19)	(0.21)	(0.17)	(0.16)	(0.15)
euro area shock	0.23	0.12	0.01	0.12	0.17	0.15
	(0.14)	(0.13)	(0.07)	(0.12)	(0.13)	(0.11)
country shock	0.15	0.17	0.48	0.16	0.16	0.20
	(0.11)	(0.14)	(0.20)	(0.12)	(0.10)	(0.11)
Sample: 1990Q3–2007Q4						
global shock	0.73	0.61	0.27	0.67	0.36	0.65
	(0.14)	(0.16)	(0.17)	(0.14)	(0.16)	(0.15)
euro area shock	0.09	0.18	0.19	0.15	0.12	0.13
	(0.08)	(0.11)	(0.12)	(0.10)	(0.10)	(0.10)
country shock	0.17	0.21	0.54	0.18	0.52	0.22
	(0.12)	(0.12)	(0.18)	(0.11)	(0.16)	(0.12)
Change in the share of shocks over time						
global shock	0.11	-0.10	-0.24	-0.05	-0.32	0.01
	(0.23)	(0.25)	(0.28)	(0.22)	(0.23)	(0.22)
euro area shock	-0.14	0.06	0.18	0.03	-0.04	-0.02
	(0.17)	(0.17)	(0.15)	(0.15)	(0.16)	(0.14)
country shock	0.02	0.04	0.06	0.02	0.36	0.02
	(0.16)	(0.18)	(0.27)	(0.16)	(0.18)	(0.16)

Notes: Forecast error variance shares are reported for a forecast horizon of 12 quarters. The last panel shows the difference between the estimates of the second and first sub-periods reported in the third and second panels, respectively. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

variance decomposition to output gap differentials for estimating the driving forces of them.

Counterfactual correlations

We estimate six different trivariate models. All these models imply that the output gaps of the US, the euro area and a member country comprise three counterfactual series, i.e., series that would have been observed had only one of the three structural shocks in the model taken place. The counterfactual correlations are correlations that are computed between such series with respect to each one of the shocks. Formally,

$$corr\left(\tilde{y}_{m,t},\tilde{y}_{n,t}|k\right)=\frac{cov\left(\tilde{y}_{m,t},\tilde{y}_{n,t}|k\right)}{\sqrt{var\left(\tilde{y}_{m,t}|k\right)var\left(\tilde{y}_{n,t}|k\right)}},\tag{3.10}$$

where $corr\left(\tilde{y}_{m,t},\tilde{y}_{n,t}|k\right)$ stands for the correlation between the output gaps of countries m and n when only the shock k takes place and the other shocks are set to zero, $cov\left(\tilde{y}_{m,t},\tilde{y}_{n,t}|k\right)$ stands for the corresponding covariance, and $var\left(\tilde{y}_{m,t}|k\right)$ and $var\left(\tilde{y}_{n,t}|k\right)$ are the variances of the output gaps of countries m and n conditional on the shock k. Since we are interested in the relationship between a member country and the entire euro area in our analysis, we compute counterfactual correlations only between member countries' and the euro area's output gaps with respect to each shock. Note that with the process in (3.7) governing the motion of output gaps, the covariance of both series is given by

$$cov\left(\tilde{y}_{EA,t},\tilde{y}_{i,t}|k\right)=\left(\sum_{m=-\kappa}^{\kappa}\Psi_{EU,k,m}\Psi_{i,k,m}\right)\sigma_k^2.\tag{3.11}$$

The corresponding variances can be inserted into (3.10) by modifying the formula in (3.8) accordingly. The term "counterfactual correlation" refers to the fact that those correlations correspond to one aspect of reality only. A high (low) counterfactual correlation between the sub-components of the euro area's and a member country's output gaps with respect to a certain shock implies similar (diverse) shock propagation with respect to that shock over the business cycle.

Table 3.5 shows the true and counterfactual correlations based on the trivariate models of the euro area countries in the full sample period as well as the two sub-periods. In all panels, the first row contains the true correlations between the output gap of a member country and the euro area output gap in the corresponding period.[1] The second, third and fourth rows show the counterfactual correlations with respect to global, euro area and country-specific shocks, respectively. For instance, we would have observed a correlation of 0.40 between the output gaps of Spain and the euro area if only global shocks had taken place in the period 1970Q1–1990Q2.

In some cases, the true correlation is lower than all reported counterfactual correlations in both sub-periods. This result is due to the fact that counterfactual correlations are computed under the assumption that a member country and the euro area are both subject to only one and the same shock (global, euro area or country-specific of the particular country), while the true correlations are generated when the series are subject to all shocks, which leads to a more mixed picture, with the dynamics corresponding to different shocks obviously counteracting each other in some cases.

The counterfactual correlations with respect to common shocks, i.e., global and euro area shocks, are generally quite high in both sub-periods for the member countries. Only the counterfactual correlations of Spain with respect to global shocks are somewhat lower than other countries' corresponding correlations in the full sample period and the first sub-period. It is interesting to note that the counterfactual correlations with respect to country-specific shocks are in general also quite high.[2] Nevertheless, we obtain that each country-specific shock has a distinct effect on the euro area output. Figure 3.3 shows that the response of the euro area output to different country-specific shocks varies with respect to the country that the shock is stemming from. This finding is indeed in accordance with our previous finding, reported in Table 3.2, that the estimated country-specific shocks are in general roughly

[1]Note that the reported true correlations in Table 3.5 follow from the estimated business cycle generating process based on an (almost) ideal band-pass filter and the trivariate SVAR model given by (3.5). These "true" correlations are slightly different from the ones reported in Chapter 2, which follow from applying the *asymmetric* Christiano-Fitzgerald filter to the observed data.

[2]This is, however, quite a different result from what Giannone and Reichlin (2006) obtain. They report very low counterfactual correlations with respect to country-specific shocks. Yet, this comes from their choice of the business cycle measure—the output growth rate—while we use the CF-filter to measure the cycle.

Table 3.5: True and counterfactual correlations of output gaps with the euro area

	Sample: 1970Q1–2007Q4					
	bel	deu	esp	fra	ita	nld
true	0.82	0.84	0.60	0.87	0.85	0.77
	(0.06)	(0.06)	(0.13)	(0.05)	(0.04)	(0.07)
only global shock	0.98	0.93	0.59	1.00	0.98	0.92
	(0.05)	(0.07)	(0.27)	(0.03)	(0.04)	(0.08)
only euro area shock	0.94	0.98	0.87	0.98	0.92	0.99
	(0.05)	(0.03)	(0.22)	(0.02)	(0.07)	(0.03)
only country shock	0.98	0.88	0.98	0.92	0.94	0.70
	(0.13)	(0.25)	(0.20)	(0.27)	(0.05)	(0.41)

	Sample: 1970Q1–1990Q2					
	bel	deu	esp	fra	ita	nld
true	0.80	0.84	0.47	0.88	0.84	0.83
	(0.07)	(0.08)	(0.21)	(0.06)	(0.07)	(0.08)
only global shock	0.91	0.90	0.40	0.99	0.96	0.94
	(0.10)	(0.07)	(0.35)	(0.05)	(0.07)	(0.11)
only euro area shock	0.81	0.95	0.92	0.94	0.81	1.00
	(0.08)	(0.09)	(0.30)	(0.05)	(0.14)	(0.05)
only country shock	0.99	0.68	0.92	0.60	0.90	0.86
	(0.14)	(0.34)	(0.44)	(0.27)	(0.10)	(0.31)

	Sample: 1990Q3–2007Q4					
	bel	deu	esp	fra	ita	nld
true	0.87	0.93	0.88	0.91	0.90	0.78
	(0.06)	(0.06)	(0.08)	(0.07)	(0.05)	(0.12)
only global shock	0.87	1.00	0.94	0.97	0.95	0.90
	(0.11)	(0.05)	(0.23)	(0.07)	(0.10)	(0.11)
only euro area shock	0.98	1.00	0.99	0.98	0.97	0.90
	(0.06)	(0.05)	(0.08)	(0.06)	(0.08)	(0.11)
only country shock	0.91	0.82	0.77	0.95	0.91	0.10
	(0.08)	(0.15)	(0.13)	(0.16)	(0.06)	(0.28)

Notes: The output gap measure is the CF-filter. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

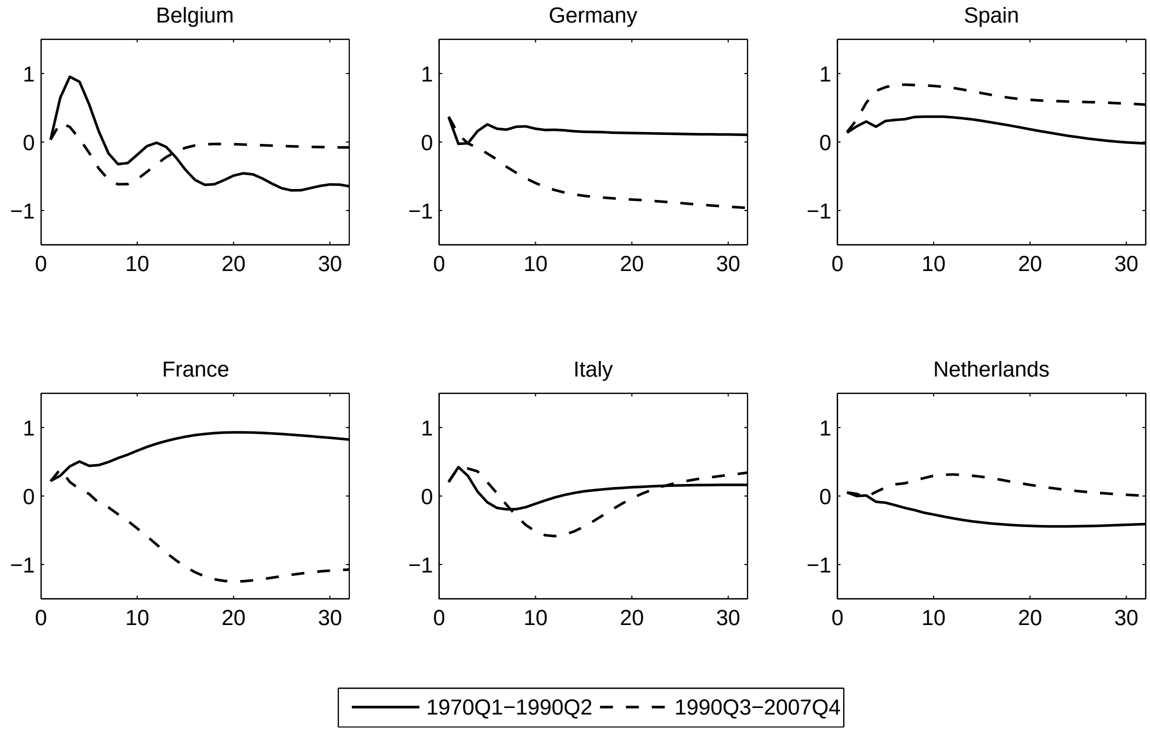


Figure 3.3: Response of euro area output to country-specific shocks

orthogonal to each other and suggests that asymmetric shocks are behind the heterogeneity of output gaps.

As a final check of heterogeneity in terms of co-movement, we compute the correlations among the historical, i.e. estimated in-sample, component of each member country's output gap. We use the estimated coefficients and residuals of the model in (3.5) to this end. We first compute the historical sub-component of each variable with respect to each shock and then filter each estimated sub-component with the asymmetric CF-filter. The bilateral correlations of member countries' historical output gap sub-components corresponding to global and euro area shocks are in many cases strikingly high, while similar bilateral correlations corresponding to country-specific shocks are rarely statistically significant (see Table 3.6). This finding is supportive of our previous conclusion. Hence, in the light of all hitherto discussed information, our exercise brings us to a similar conclusion as in Giannone and Reichlin

(2006) that "asymmetries are explained by idiosyncratic shocks rather than heterogeneous responses to common shocks" in the euro area.

Driving forces of output (gap) differentials

Next, we carry out variance decompositions of output gap *differentials* in order to detect the driving forces of their dynamics. We are interested in finding out whether our previous finding on heterogeneity is also supported by this type of analysis. Recall from the discussion in Chapter 2 that there is no a priori reason for the driving force of output gap differentials to be the same as the driving force of output gaps.

According to Table 3.7, which shows the shares of shocks in the output gap differential variance of the euro area countries, the driving force of this variance is the own shock for every member country in all sample periods considered. The impact of global and euro area shocks is relatively small. Country-specific shocks have in most cases shares above 0.60. Their share is below 0.50 only in Germany in the first sub-period and in the Netherlands in the second sub-period. While differences exist between the first and second sub-period estimates of shares, these are often not statistically significant.

Global shocks deliver a small but significant contribution to the output gap differential variance of Spain in the full-sample estimation. Euro area shocks have minor but statistically significant shares in the output gap differential variance of Belgium, Spain, France and Italy for the same period. Turning to the first sub-period estimates, global shocks contribute significantly and non-negligibly to the differentials of Belgium, Germany and Spain, whereas euro area shocks are important for the differentials of Belgium and France. In the second sub-period, only the shares of country-specific shocks are statistically significant, while global and euro area shocks do not have a significant contribution to the variance of output gap differentials (abstracting from the role played by euro area shocks for the differential of the Netherlands).

Finally, we turn our attention to the FEVD of differentials between the *levels* of the

Table 3.6: Correlations of output gap sub-components

Correlations with respect to global shock

	Sample: 1970Q1–1990Q2					Sample: 1990Q3–2007Q4				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	0.66					0.93				
	(0.05)					(0.04)				
esp	0.49	-0.13				0.73	0.85			
	(0.05)	(0.12)				(0.18)	(0.11)			
fra	0.84	0.84	0.29			0.96	0.91	0.73		
	(0.07)	(0.05)	(0.10)			(0.04)	(0.05)	(0.21)		
ita	0.91	0.54	0.62	0.76		0.85	0.95	0.90	0.88	
	(0.05)	(0.05)	(0.04)	(0.09)		(0.08)	(0.03)	(0.07)	(0.05)	
nld	0.80	0.82	0.25	0.89	0.77	0.96	0.92	0.72	0.97	0.87
	(0.12)	(0.04)	(0.03)	(0.07)	(0.09)	(0.03)	(0.04)	(0.20)	(0.03)	(0.04)

Correlations with respect to euro area shock

	Sample: 1970Q1–1990Q2					Sample: 1990Q3–2007Q4				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	0.61					0.74				
	(0.18)					(0.15)				
esp	0.76	0.79				0.51	0.70			
	(0.13)	(0.08)				(0.20)	(0.10)			
fra	0.37	0.60	0.64			0.79	0.91	0.83		
	(0.24)	(0.11)	(0.16)			(0.13)	(0.05)	(0.05)		
ita	0.49	0.17	0.40	0.18		0.70	0.68	0.21	0.64	
	(0.16)	(0.12)	(0.17)	(0.27)		(0.11)	(0.14)	(0.26)	(0.15)	
nld	0.72	0.90	0.85	0.73	0.41	0.76	0.86	0.78	0.87	0.51
	(0.15)	(0.03)	(0.12)	(0.08)	(0.11)	(0.12)	(0.09)	(0.07)	(0.04)	(0.26)

Correlations with respect to country-specific shock

	Sample: 1970Q1–1990Q2					Sample: 1990Q3–2007Q4				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	-0.16					-0.13				
	(0.18)					(0.20)				
esp	-0.16	-0.31				0.19	-0.35			
	(0.26)	(0.20)				(0.17)	(0.24)			
fra	-0.32	-0.47	0.23			0.22	-0.31	0.57		
	(0.24)	(0.15)	(0.33)			(0.18)	(0.31)	(0.11)		
ita	0.38	-0.04	-0.23	0.04		0.38	0.18	-0.47	0.07	
	(0.13)	(0.16)	(0.18)	(0.23)		(0.19)	(0.35)	(0.31)	(0.27)	
nld	0.16	0.15	-0.25	-0.36	0.16	-0.16	-0.12	0.30	-0.22	-0.57
	(0.18)	(0.29)	(0.34)	(0.19)	(0.18)	(0.17)	(0.31)	(0.31)	(0.24)	(0.24)

Notes: The output gap measure is the asymmetric CF-filter. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

Table 3.7: Shares of shocks in output gap differential variance of euro area countries

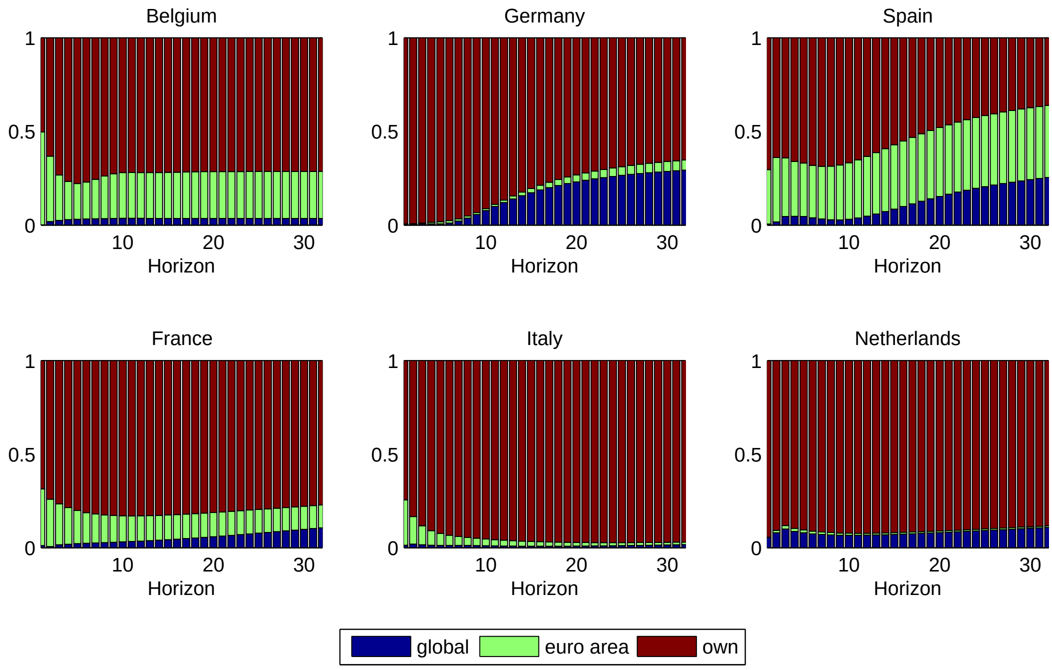
	Sample: 1970Q1–2007Q4					
	bel	deu	esp	fra	ita	nld
global shock	0.03	0.13	0.27	0.03	0.06	0.11
	(0.06)	(0.09)	(0.11)	(0.06)	(0.07)	(0.06)
euro area shock	0.15	0.07	0.15	0.18	0.09	0.02
	(0.05)	(0.06)	(0.08)	(0.08)	(0.04)	(0.05)
country shock	0.82	0.80	0.58	0.79	0.85	0.87
	(0.07)	(0.10)	(0.11)	(0.09)	(0.08)	(0.08)

	Sample: 1970Q1–1990Q2					
	bel	deu	esp	fra	ita	nld
global shock	0.20	0.39	0.39	0.15	0.10	0.12
	(0.11)	(0.14)	(0.16)	(0.13)	(0.10)	(0.10)
euro area shock	0.22	0.18	0.06	0.23	0.14	0.03
	(0.10)	(0.12)	(0.08)	(0.11)	(0.10)	(0.07)
country shock	0.58	0.44	0.56	0.62	0.76	0.85
	(0.13)	(0.13)	(0.16)	(0.15)	(0.12)	(0.11)

	Sample: 1990Q3–2007Q4					
	bel	deu	esp	fra	ita	nld
global shock	0.20	0.01	0.17	0.07	0.08	0.22
	(0.13)	(0.09)	(0.12)	(0.11)	(0.12)	(0.13)
euro area shock	0.11	0.02	0.19	0.24	0.08	0.30
	(0.10)	(0.10)	(0.13)	(0.14)	(0.08)	(0.16)
country shock	0.69	0.97	0.64	0.69	0.83	0.47
	(0.16)	(0.13)	(0.14)	(0.16)	(0.14)	(0.15)

	Change in the share of shocks over time					
	bel	deu	esp	fra	ita	nld
global shock	0.00	-0.38	-0.22	-0.08	-0.01	0.10
	(0.18)	(0.17)	(0.20)	(0.17)	(0.16)	(0.17)
euro area shock	-0.11	-0.15	0.13	0.01	-0.06	0.28
	(0.14)	(0.16)	(0.16)	(0.18)	(0.13)	(0.17)
country shock	0.11	0.53	0.08	0.07	0.07	-0.38
	(0.21)	(0.19)	(0.22)	(0.22)	(0.18)	(0.19)

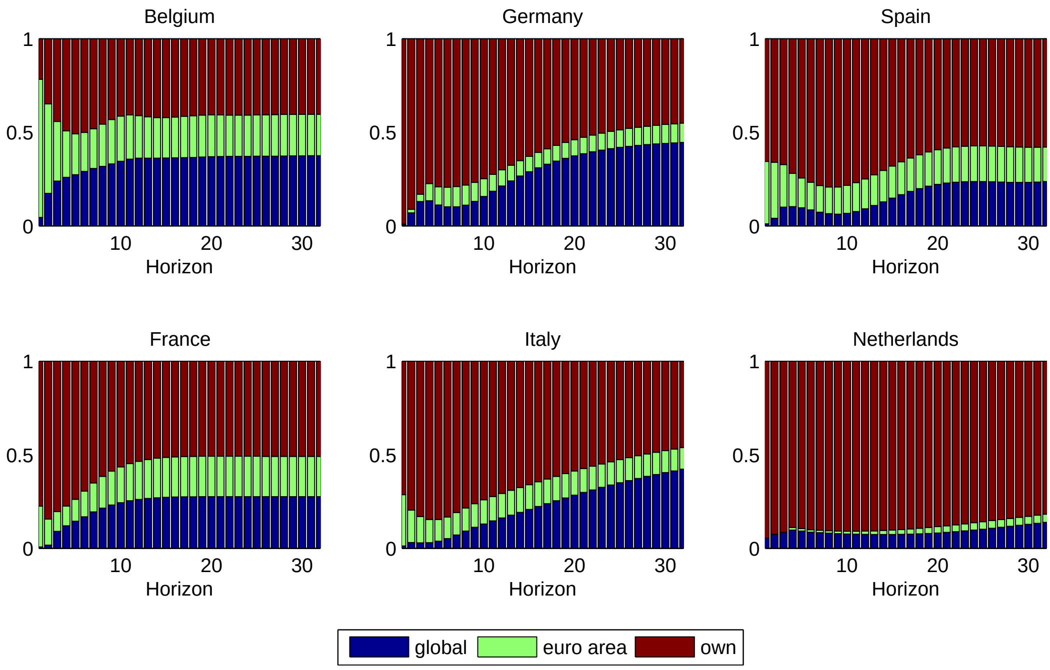
Notes: The output gap measure is the CF-filter. The last panel shows the difference between the estimates of the second and first sub-periods reported in the third and second panels, respectively. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.



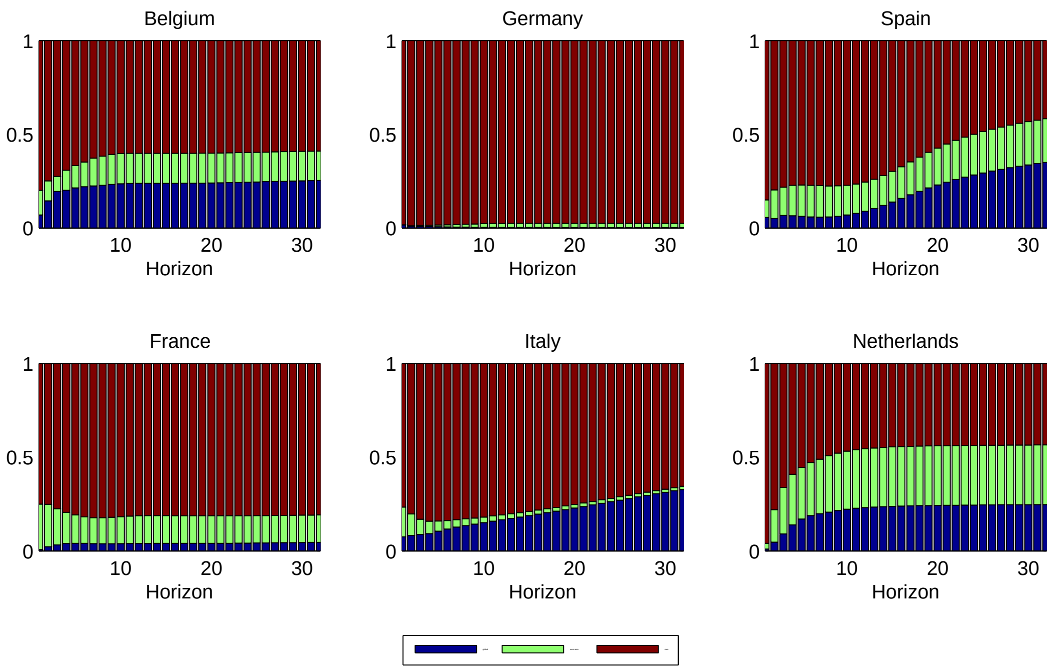
(a) Sample: 1970Q1–2007Q4

Figure 3.4: FEVD of output differential

euro area output and the output of the member countries. The FEVD results, displayed in Figure 3.4, point to country-specific shocks as the force driving the dynamics of output level differentials to a large extent at the business cycle horizon. This is particularly evident in the estimates in Figure 3.4(a) based on the full sample period, with the exception of the share of euro area shocks in the differential corresponding Spain. Global shocks are of some (statistically significant) importance for the differentials of Belgium, Germany, France and Italy in the first sub-period, while their shares are insignificant in the second sub-period. Euro area shocks have a significant share in the output differential forecast error variance of Belgium and France in the first sub-period and France and the Netherlands in the second sub-period.



(b) Sample: 1970Q1–1990Q2



(c) Sample:1990Q3–2007Q4

Figure 3.4: FEVD of output differential (cont.)

3.2.5 The Great Moderation

The descriptive statistics reported in the previous chapter point to changes in business cycle dynamics of the euro area since the 1970s. Output gap volatility and output gap differential volatility both became lower after the 1990s. In this section, we report on the statistical significance of this moderation based on our estimated SVAR models. The moderation may theoretically result from two fundamental sources: (i) changes in the size of shocks or (ii) changes in shock transmission. In the following, we first document changes in the size of shocks and shock transmission. Then, we conduct a different type of decomposition analysis than before in order to detect the channels that led to the moderation of both output gap volatility and output gap differential volatility.

Size of shocks

A widely used approach in the SVAR literature is to set the standard deviation of structural shocks to one. We have also imposed this normalisation in the estimation of our B-models. However, we cannot compute the impact of the aforementioned first channel on the moderation of output fluctuations when the standard deviations of shocks are set to one. In order to tackle this problem, we rewrite our estimated B-model, given by

$$Y_t = ad_t + A_1 Y_{t-1} + \cdots A_p Y_{t-p} + B\varepsilon_t, \tag{3.12}$$

as an AB-model,

$$\tilde{A} Y_t = \tilde{a} d_t + \tilde{A}_1 Y_{t-1} + \cdots \tilde{A}_p Y_{t-p} + \tilde{B}\varepsilon_t, \tag{3.13}$$

by multiplying both sides of (3.12) by $\tilde{A}$, where $\tilde{A}$ is a matrix with ones on its diagonal, $\tilde{B}$ is a diagonal matrix, $B := \tilde{A}^{-1}\tilde{B}$, and $A_i = \tilde{A}^{-1}\tilde{A}_i$ for $i = 1, \ldots, p$. Note that (3.12) and (3.13) are equivalent, and the hitherto variance decomposition and counterfactual correlation computations are not affected by this transformation. That $\tilde{A}$ has only ones on its diagonal amounts to normalising the contemporaneous relationships among the endogenous variables of the VAR. The non-zero (unrestricted) diagonal elements of $\tilde{B}$ stand for the standard deviations of the structural shocks.

The first panel of Table 3.8 shows the estimated standard deviations of global, euro area and country-specific shocks in each country-specific model over the full sample period, while the second and third panels show the standard deviation estimates from the sub-periods. The last panel shows the change in the standard deviation of shocks, i.e., each standard deviation in the third panel subtracted by the corresponding standard deviation in the second panel. Thus, a negative figure indicates that the standard deviation of the corresponding shock has decreased in the second sub-period relative to the first sub-period. Note that the ideal situation would be that the entries corresponding to global and euro area shocks in the first and second rows of each panel are exactly the same for each country's estimated model. This is, however, not possible with the simple methodology we apply. Yet, the reported values are generally roughly close to each other. An important exception is the estimate of the euro area shock standard deviation coming from Germany's model: these estimates differ from the estimates of the other country-specific models for all sample periods considered. Looking at the last panel, two important changes regarding the size of shocks can be read out. First, the standard deviation of both global and euro area shocks decreased in the second sub-period relative to the first sub-period. The relative decline is higher in the case of global shocks, that is, their standard deviation decreased more strongly than the standard deviation of euro area shocks. Second, the size of country-specific shocks decreased as well in all countries except Belgium. The decline in France is also relatively weak in comparison to other member countries in our sample. Note that all reported changes in the last panel are statistically significant.

Shock transmission

The conventional tool employed by macroeconomists for examining the shock transmission is the impulse response function. Figures 3.5(a)-3.5(c) show the response of output in the

Table 3.8: Standard deviation of shocks

	Sample: 1970Q1–2007Q4					
	bel	deu	esp	fra	ita	nld
global shock	7.63	7.51	7.68	7.49	7.47	7.54
	(0.34)	(0.35)	(0.37)	(0.35)	(0.33)	(0.34)
euro area shock	4.03	2.60	4.00	3.72	3.54	3.97
	(0.18)	(0.12)	(0.19)	(0.16)	(0.16)	(0.18)
country shock	2.97	4.60	5.58	3.06	5.53	8.60
	(0.14)	(0.26)	(0.26)	(0.14)	(0.28)	(0.39)

	Sample: 1970Q1–1990Q2					
	bel	deu	esp	fra	ita	nld
global shock	9.15	9.07	9.53	8.94	9.07	9.13
	(0.66)	(0.67)	(0.71)	(0.62)	(0.63)	(0.66)
euro area shock	4.50	3.02	4.56	4.07	3.93	4.55
	(0.34)	(0.21)	(0.31)	(0.29)	(0.27)	(0.32)
country shock	1.93	4.73	5.45	3.15	6.10	10.26
	(0.14)	(0.41)	(0.40)	(0.23)	(0.46)	(0.79)

	Sample: 1990Q3–2007Q4					
	bel	deu	esp	fra	ita	nld
global shock	4.10	3.97	3.61	3.80	4.00	3.93
	(0.32)	(0.32)	(0.27)	(0.30)	(0.31)	(0.31)
euro area shock	2.36	1.63	2.31	2.26	2.18	2.49
	(0.19)	(0.13)	(0.18)	(0.18)	(0.17)	(0.19)
country shock	2.83	3.18	2.83	2.34	3.34	3.37
	(0.22)	(0.32)	(0.23)	(0.20)	(0.31)	(0.27)

	Change in standard deviation					
	bel	deu	esp	fra	ita	nld
global shock	-5.05	-5.10	-5.92	-5.14	-5.07	-5.20
	(0.75)	(0.75)	(0.77)	(0.69)	(0.70)	(0.75)
euro area shock	-2.14	-1.40	-2.25	-1.81	-1.74	-2.06
	(0.38)	(0.25)	(0.38)	(0.35)	(0.32)	(0.38)
country shock	0.90	-1.55	-2.62	-0.81	-2.77	-6.89
	(0.26)	(0.52)	(0.46)	(0.30)	(0.56)	(0.83)

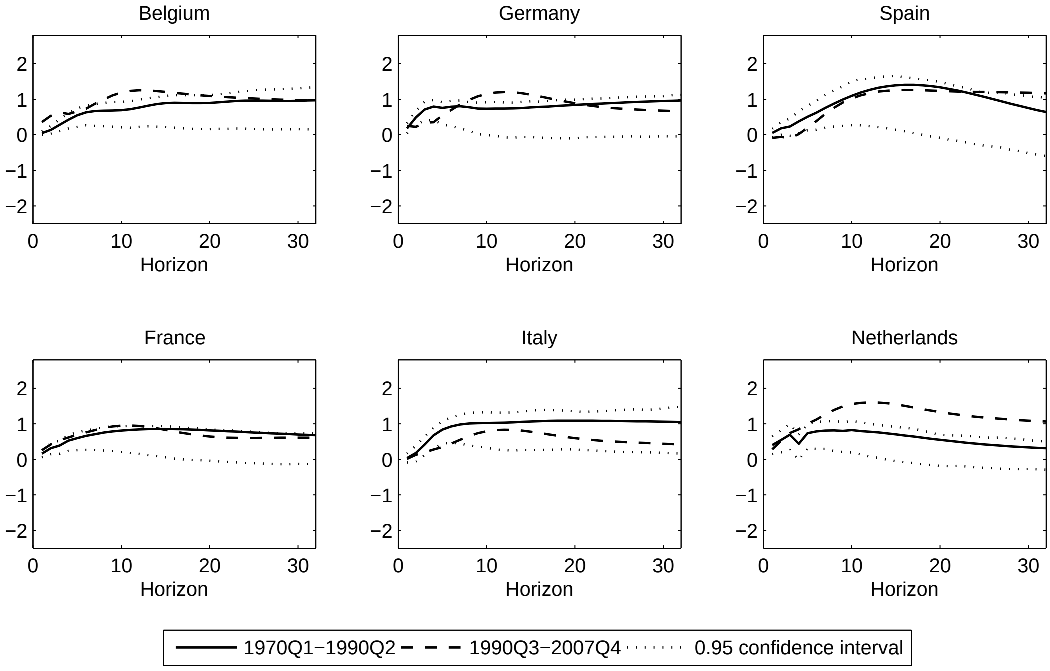
Notes: The last panel shows the difference between the estimates of the second and first sub-periods reported in the third and second panels, respectively. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

euro area countries to a one-unit global, euro area and country-specific shock for the first (solid) and the second (dashed) sub-periods, respectively. Thus, we can assess whether euro area economies underwent structural changes over time. For example, if the response to a certain shock in the second sub-period is lower than in the first sub-period in absolute value, this implies, everything else equal, that the share of that shock in the variance of output fluctuations has decreased due to the change in the propagation of the shock. Moreover, we can also see whether the change is only quantitative, i.e., in the magnitude of the impulse response, or also qualitative, i.e., in the shape of the impulse response.

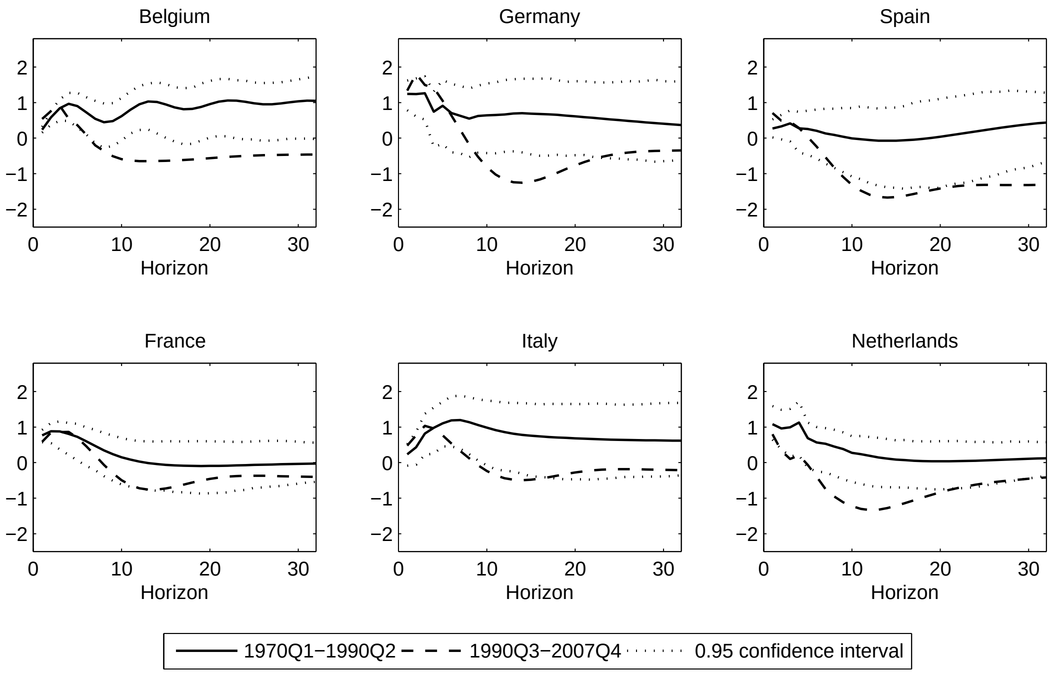
In all graphs of Figure 3.5, 0.95 confidence intervals (the area between the dotted lines) corresponding to the first-sub-period estimates are also added to the graphs, in order to enable the reader to see whether the change in shock transmission from the first sub-period to the second sub-period was statistically significant. It is observed that in some but not all cases the impulse response function of the second sub-period is outside the 0.95 confidence band. This suggests that important changes occurred in the output dynamics of the euro area countries over time. However, it is generally hard to draw conclusions from Figures 3.5(a)-3.5(c) that apply to all countries similarly. Every country seems to rather have its own peculiar story. In the following, we use a tool for assessing the impact of changes in the magnitude of shocks as well as in their transmission, which encompasses both effects in a unifying framework.

Moderation of output fluctuations

Moderation of output gaps Quoting Stock and Watson (2005), "the variance of [output forecast errors] in a given country can change because the magnitude of the shocks impinging on that economy have changed or because the effects of those shocks have changed." The above findings show that both effects are relevant for the euro area economies: on the one hand, the volatility of global, euro area and country-specific shocks and, on the other hand, the response of the economies to those shocks underwent changes. In order to compute the



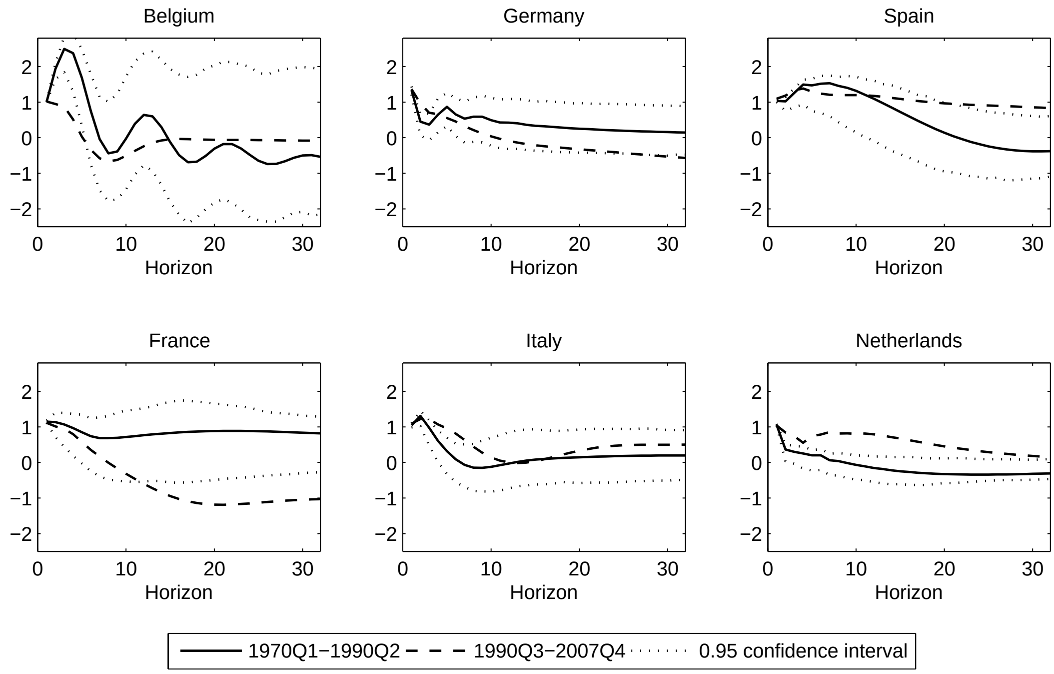
(a) Response to global shock



(b) Response to euro area shock

Note: 0.95 confidence intervals correspond to the first sub-period estimates.

Figure 3.5: Impulse response of output in the euro area



(c) Response to own shock

Figure 3.5: Impulse response of output in the euro area (cont.)

weight of both channels in the Great Moderation observed in each euro area country, we employ the decomposition suggested by Stock and Watson (2005). We write the variance of the output gap of a country at period p, with $p = 1, 2$ corresponding to the first (1970Q1–1990Q2) and second (1990Q3–2007Q4) sub-periods, as

$$V_p = V_{p1} + V_{p2} + V_{p3}, \tag{3.14}$$

where V_{pk} is the variance of output gap at period p with respect to the shock k, i.e., the variance that would have been observed if only the shock k took place. (3.14) is clearly analogous to (3.8). Note that the variance V_{pk} is given by $a_{pk}\sigma^2_{pk}$, $a_{pk} := \sum_{m=-\kappa}^{\kappa} \Psi^2_{p,jk,m}$ in terms of (3.8) being a quadratic term and σ^2_{pk} the variance of the shock k in period p. We are interested in explaining the change (decline) in the variance of output gap in each euro area country. The linear structure allows us to write the change in the contribution of the shock k as

$$V_{2k} - V_{1k} = \left(\frac{a_{1k} + a_{2k}}{2}\right)\left(\sigma^2_{2k} - \sigma^2_{1k}\right) + \left(\frac{\sigma^2_{1k} + \sigma^2_{2k}}{2}\right)(a_{2k} - a_{1k})\,. \tag{3.15}$$

The first term on the right-hand side of (3.15) measures the contribution of the change in the standard deviation of shock k, while the second term measures the contribution of the change in the propagation of the same shock.

The first box in the upper panel of Table 3.9 shows the absolute change in output gap variance of the euro area countries from the first to the second sub-period, derived from the estimated output gap generating process given in (3.7) for each country. The decline in output gap volatility in terms of point estimates is evident in every euro area country. However, this decline is not found be statistically significant in any of the member countries.

The left and right boxes of the lower panel in Table 3.9 show the contributions of changes in shock variance as well as shock propagation to the output gap volatility decline, respectively. A negative (positive) value in these two boxes indicates that the corresponding factor led to a decline (increase) in the corresponding output gap volatility. We have reported in Table 3.8 that the magnitude of global and euro area shocks have declined in the second sub-period. This is reflected in the first two columns (that correspond to global and euro area shocks) of the left box in the lower panel of Table 3.9 as a positive contribution to the decline in output gap volatility. In Belgium, changes in the size of own shocks contributed negatively to the Great Moderation, but the total contribution of the change in shock variance is positive. Interesting is that the contribution of change in the size of individual shocks is statistically insignificant in almost all cases, whereas the total contribution of change in the size of all shocks is significant in all member countries except Belgium. The latter result suggests that we would have observed a statistically significant decline in the output gap variance of all member countries except Belgium, if only the size of shocks had changed and no changes in the shock transmission had occurred.

Positive estimates are in many cases registered for the contribution of the change in shock propagation to the change in output gap volatility. Note, however, that all estimates in the right box of the lower panel of Table 3.9 are statistically insignificant. This implies that this channel—change in shock transmission—could not be attributed a role in the decline of

Table 3.9: Decomposition of change in output gap variance into change in size of shocks and change in propagation

	Variances			Total contribution from shocks		
	1970–1990	1991–2007	Change	World	Euro Area	Own
bel	1.03	0.58	-0.45	-0.13	-0.08	-0.24
	(0.35)	(0.23)	(0.43)	(0.19)	(0.19)	(0.27)
deu	0.93	0.68	-0.25	-0.44	0.15	0.03
	(0.33)	(0.31)	(0.47)	(0.33)	(0.20)	(0.15)
esp	1.52	0.54	-0.97	-0.31	0.14	-0.80
	(0.76)	(0.28)	(0.80)	(0.50)	(0.21)	(0.47)
fra	0.74	0.51	-0.23	-0.16	-0.10	0.03
	(0.30)	(0.25)	(0.38)	(0.22)	(0.22)	(0.16)
ita	2.06	0.70	-1.36	-0.57	-0.10	-0.69
	(0.69)	(0.36)	(0.79)	(0.39)	(0.25)	(0.54)
nld	1.57	0.51	-1.06	-0.24	-0.26	-0.56
	(0.67)	(0.27)	(0.71)	(0.44)	(0.30)	(0.30)

	Contribution of change in shock variance				Contribution of change in shock propagation			
	World	Euro Area	Own	Total	World	Euro Area	Own	Total
bel	-0.31	-0.29	0.41	-0.19	0.18	0.21	-0.65	-0.26
	(0.25)	(0.17)	(0.20)	(0.37)	(0.32)	(0.28)	(0.38)	(0.63)
deu	-0.54	-0.47	-0.17	-1.18	0.10	0.63	0.20	0.93
	(0.38)	(0.23)	(0.13)	(0.53)	(0.54)	(0.39)	(0.23)	(0.84)
esp	-0.58	-0.36	-0.61	-1.55	0.27	0.49	-0.19	0.58
	(0.49)	(0.25)	(0.26)	(0.72)	(0.57)	(0.40)	(0.35)	(0.96)
fra	-0.35	-0.35	-0.12	-0.81	0.19	0.24	0.15	0.58
	(0.23)	(0.19)	(0.09)	(0.36)	(0.31)	(0.33)	(0.19)	(0.59)
ita	-0.42	-0.28	-0.93	-1.64	-0.14	0.18	0.25	0.28
	(0.35)	(0.22)	(0.39)	(0.65)	(0.47)	(0.36)	(0.57)	(0.99)
nld	-0.64	-0.41	-0.68	-1.73	0.39	0.15	0.12	0.66
	(0.39)	(0.26)	(0.43)	(0.79)	(0.51)	(0.39)	(0.49)	(1.01)

Notes: Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

output gap volatility.

Moderation of output forecast errors Table 3.10, which is analogous to Table 3.9, shows the change in the variance of 12-quarters-ahead forecast errors over the two sub-periods. These are computed using a formula analogous to the one in (3.15). In contrast to the previous estimations corresponding to output gaps, the decline in the 12-quarters-ahead forecast error variance is strongly significant for all member countries (see the upper left box of Table 3.10). The main contribution to this volatility decline comes from the decline in the size of the shocks. In the case of four countries (Belgium, Germany, France and the Netherlands), the total contribution of the decline in the size of the shocks even exceeds the change in the variance of the 12-quarters-ahead forecast errors. Hence, the contribution of change in shock propagation to the forecast error variance moderation is negative in these countries. In Spain and Italy, the contribution of the same channel is positive but well below the contribution of the other channel—change in the size of the shocks.

When we turn our attention to the total contribution from shocks, i.e., the sum of their contribution via both channels, reported in the upper right box of Table 3.10, we see that global shocks are the main driving force behind the moderation of the forecast errors in terms of point estimates. However, it should be noted that their contribution is significantly different from the contribution of euro area and country-specific shocks in the case of France and Italy only. The total contribution to the output forecast error variance moderation of euro area shocks is significant in Belgium and Italy only, while the total contribution of country-specific shocks is significant in Spain, France and the Netherlands.

Moderation of output (gap) differentials

Tables 3.11 and 3.12 are analogous to Tables 3.9 and 3.10, respectively. They show the decomposition of the change in output gap differential variance and in output differential forecast error variance into change in the size of shocks and change in shock propagation.

Table 3.10: Decomposition of change in output forecast error variance into change in size of shocks and change in propagation

	Variances			Total contribution from shocks		
	1970–1990	1991–2007	Change	World	Euro Area	Own
bel	5.31	2.20	-3.11	-1.69	-1.01	-0.41
	(1.50)	(0.57)	(0.81)	(0.68)	(0.38)	(0.25)
deu	6.97	2.11	-4.86	-3.67	-0.44	-0.75
	(1.92)	(0.58)	(1.22)	(1.09)	(0.40)	(0.42)
esp	13.16	2.70	-10.46	-6.00	0.40	-4.86
	(3.87)	(0.76)	(1.69)	(1.18)	(0.28)	(1.18)
fra	5.63	1.51	-4.11	-3.05	-0.45	-0.62
	(1.62)	(0.41)	(0.85)	(0.70)	(0.32)	(0.30)
ita	10.18	1.63	-8.55	-6.31	-1.48	-0.76
	(2.69)	(0.41)	(1.40)	(1.19)	(0.59)	(0.45)
nld	7.96	4.06	-3.90	-2.49	-0.70	-0.72
	(2.19)	(1.04)	(1.41)	(1.21)	(0.55)	(0.35)

	Contribution of change in shock variance				Contribution of change in shock propagation			
	World	Euro Area	Own	Total	World	Euro Area	Own	Total
bel	-4.54	-0.72	0.55	-4.71	2.85	-0.30	-0.96	1.60
	(0.57)	(0.19)	(0.18)	(0.64)	(0.72)	(0.29)	(0.32)	(0.81)
deu	-4.73	-0.75	-0.60	-6.07	1.06	0.31	-0.15	1.22
	(0.72)	(0.24)	(0.20)	(0.78)	(0.93)	(0.36)	(0.34)	(1.03)
esp	-5.07	-0.79	-4.27	-10.13	-0.93	1.20	-0.60	-0.33
	(0.70)	(0.15)	(0.70)	(0.97)	(0.90)	(0.24)	(0.84)	(1.29)
fra	-3.93	-0.50	-0.31	-4.74	0.89	0.05	-0.31	0.63
	(0.53)	(0.17)	(0.11)	(0.56)	(0.66)	(0.27)	(0.23)	(0.77)
ita	-4.00	-0.80	-1.55	-6.35	-2.31	-0.68	0.79	-2.19
	(0.62)	(0.28)	(0.39)	(0.78)	(0.83)	(0.42)	(0.50)	(1.07)
nld	-7.91	-1.06	-4.37	-13.34	5.42	0.36	3.66	9.44
	(0.95)	(0.26)	(0.72)	(1.32)	(1.22)	(0.40)	(0.80)	(1.66)

Notes: Change in the variance of 12-quarters-ahead forecast error is reported. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

The change in the variance of output gap differentials is not significant for any of the member countries, as has been the case for the change in the variance of output gaps. Similar also to the output gap findings, we would have observed a statistically significant change in the variance of output gap differentials if merely the sizes of the shocks had changed.

A statistically significant moderation is found in the 12-quarters-ahead forecast error variance of output (level) differentials for Belgium, Spain, France and the Netherlands. The main contribution to this moderation comes from the shock propagation channel for Belgium, whereas the moderation is due to the change in the sizes of the shocks in France and the Netherlands. In Spain, the shares of both channels are close to each other. In Germany and Italy, the positive contribution of the shock-size channel is way above the total change, while the shock propagation channel contributes negatively to the decline so that no statistically significant change is found in the output differential forecast error variance of these two countries.

3.2.6 Sensitivity of the results

We checked the sensitivity of our findings with respect to a number of factors. Our conclusions are generally robust with respect to lower or higher lag orders and other measures of the business cycle such as the BK-filter or HP-filter. There is, however, some sensitivity with respect to the period at which the sample is split. As there may be arguments to split the sample, for example, in the mid-1980s, since the Great Moderation is often dated back to that time in many studies, there are also arguments to choose a later date, for example 1993Q4, after which the Maastricht Treaty came into effect. We try to find a more comprehensive solution to this problem by running regressions over rolling estimation windows, results of which are presented in the next section.

Table 3.11: Decomposition of change in output gap differential variance into change in size of shocks and change in propagation

	Variances			Total contribution from shocks		
	1970–1990	1991–2007	Change	World	Euro Area	Own
bel	0.37	0.14	-0.23	-0.05	-0.07	-0.12
	(0.13)	(0.05)	(0.14)	(0.05)	(0.05)	(0.09)
deu	0.28	0.10	-0.19	-0.11	-0.05	-0.03
	(0.13)	(0.04)	(0.13)	(0.08)	(0.05)	(0.05)
esp	1.24	0.13	-1.11	-0.46	-0.04	-0.61
	(0.66)	(0.05)	(0.66)	(0.38)	(0.10)	(0.42)
fra	0.20	0.09	-0.11	-0.02	-0.02	-0.06
	(0.07)	(0.04)	(0.08)	(0.04)	(0.04)	(0.05)
ita	0.69	0.13	-0.55	-0.05	-0.09	-0.41
	(0.24)	(0.06)	(0.25)	(0.09)	(0.08)	(0.19)
nld	0.49	0.21	-0.28	-0.01	0.05	-0.32
	(0.13)	(0.10)	(0.16)	(0.07)	(0.06)	(0.11)

	Contribution of change in shock variance				Contribution of change in shock propagation			
	World	Euro Area	Own	Total	World	Euro Area	Own	Total
bel	-0.09	-0.05	0.15	0.01	0.04	-0.02	-0.26	-0.24
	(0.06)	(0.03)	(0.07)	(0.09)	(0.08)	(0.05)	(0.14)	(0.18)
deu	-0.05	-0.02	-0.09	-0.16	-0.06	-0.03	0.06	-0.03
	(0.04)	(0.03)	(0.04)	(0.07)	(0.06)	(0.05)	(0.06)	(0.11)
esp	-0.27	-0.06	-0.37	-0.70	-0.19	0.02	-0.24	-0.41
	(0.19)	(0.06)	(0.17)	(0.30)	(0.22)	(0.09)	(0.26)	(0.41)
fra	-0.03	-0.04	-0.05	-0.12	0.00	0.02	-0.01	0.01
	(0.03)	(0.03)	(0.02)	(0.05)	(0.04)	(0.05)	(0.05)	(0.09)
ita	-0.05	-0.05	-0.31	-0.41	-0.00	-0.04	-0.10	-0.14
	(0.07)	(0.04)	(0.11)	(0.15)	(0.09)	(0.06)	(0.15)	(0.22)
nld	-0.13	-0.08	-0.59	-0.80	0.11	0.13	0.27	0.52
	(0.13)	(0.09)	(0.21)	(0.31)	(0.17)	(0.13)	(0.23)	(0.39)

Notes: Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

Table 3.12: Decomposition of change in output differential forecast error variance into change in size of shocks and change in propagation

	Variances			Total contribution from shocks		
	1970–1990	1991–2007	Change	World	Euro Area	Own
bel	0.87	0.28	-0.59	-0.25	-0.15	-0.19
	(0.22)	(0.07)	(0.18)	(0.12)	(0.06)	(0.09)
deu	0.88	0.66	-0.23	-0.19	-0.06	0.02
	(0.22)	(0.17)	(0.19)	(0.05)	(0.08)	(0.16)
esp	4.99	0.41	-4.58	-0.42	-0.73	-3.43
	(1.41)	(0.10)	(0.87)	(0.26)	(0.36)	(0.79)
fra	0.46	0.20	-0.26	-0.11	-0.06	-0.08
	(0.11)	(0.06)	(0.11)	(0.06)	(0.04)	(0.07)
ita	1.32	0.90	-0.43	-0.07	-0.15	-0.21
	(0.31)	(0.25)	(0.32)	(0.13)	(0.08)	(0.27)
nld	2.09	1.26	-0.84	0.14	0.36	-1.33
	(0.40)	(0.31)	(0.37)	(0.17)	(0.13)	(0.30)

	Contribution of change in shock variance				Contribution of change in shock propagation			
	World	Euro Area	Own	Total	World	Euro Area	Own	Total
bel	-0.26	-0.13	0.25	-0.14	0.01	-0.02	-0.44	-0.45
	(0.09)	(0.04)	(0.07)	(0.13)	(0.13)	(0.07)	(0.13)	(0.21)
deu	-0.08	-0.04	-0.56	-0.68	-0.11	-0.02	0.58	0.45
	(0.07)	(0.05)	(0.11)	(0.15)	(0.09)	(0.08)	(0.17)	(0.22)
esp	-0.31	-0.39	-1.79	-2.48	-0.11	-0.34	-1.64	-2.10
	(0.16)	(0.15)	(0.35)	(0.40)	(0.19)	(0.23)	(0.48)	(0.55)
fra	-0.07	-0.07	-0.12	-0.26	-0.05	0.00	0.04	-0.00
	(0.04)	(0.03)	(0.04)	(0.06)	(0.05)	(0.04)	(0.07)	(0.10)
ita	-0.39	-0.09	-1.18	-1.66	0.33	-0.06	0.97	1.23
	(0.18)	(0.05)	(0.24)	(0.31)	(0.26)	(0.07)	(0.31)	(0.43)
nld	-0.70	-0.48	-3.21	-4.39	0.84	0.83	1.88	3.56
	(0.26)	(0.16)	(0.49)	(0.64)	(0.37)	(0.26)	(0.50)	(0.76)

Notes: Change in the variance of 12-quarters-ahead forecast error is reported. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

3.3 Results from rolling regressions

The hitherto presented results were based on the assumption of a discrete break in the data in 1990Q2. Changing the break date in the data leads to changes in some of the results, but our previous conclusions generally hold. However, as mentioned in Chapter 2, each euro area member country possesses its own peculiarities. In order to capture these peculiarities, we estimate in this section, following Stock and Watson (2005) and Blanchard and Gali (2008) among others, SVARs of the kind described by (3.5) for each member country in rolling windows of 15 years (60 quarters). Hence, the estimation windows cover the periods 1970Q1–1984Q4, 1970Q2–1985Q1, etc., and the last estimation window covers the period 1993Q1–2007Q4. In the forthcoming graphs displaying the results from the rolling window estimations, each statistic is reported at the quarter that is at the center of the corresponding estimation window.

Size of shocks

Figure 4.6 illustrates the standard deviations of global, euro area and country-specific shocks. It can be seen that the standard deviation of global shocks decreases steadily until roughly the middle of the sample period and stays more or less constant around the same level afterwards. Thus, the rolling regression estimations show that the moderation of the global shocks indeed takes place in the first half of the sample period, and the variance is steady in the second half of the sample period. Therefore, we find in our estimations reported in Table 3.8 based on a single break that the variance of global shocks has decreased in the second sub-period. It is harder to recognise from the graphs, but the standard deviation of euro area shocks is constant roughly in the first half of the sample period, while it decreases steadily in the second half. In line with the findings reported in Table 3.8, the standard deviation of the own shocks of Belgium becomes generally higher, while it becomes lower in the second half of the sample period in all other countries.

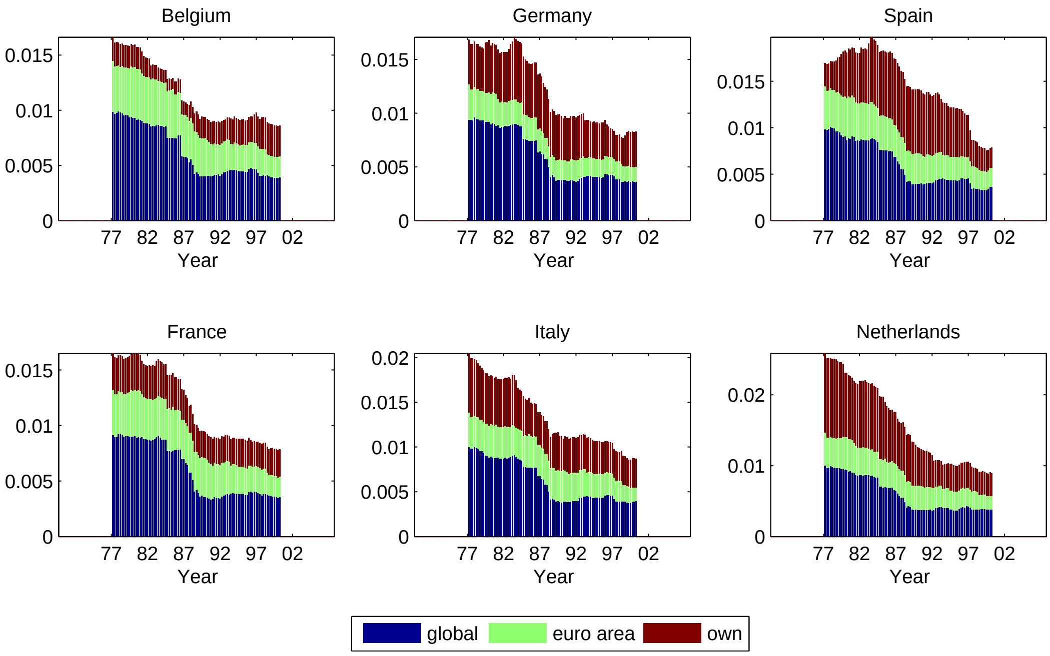
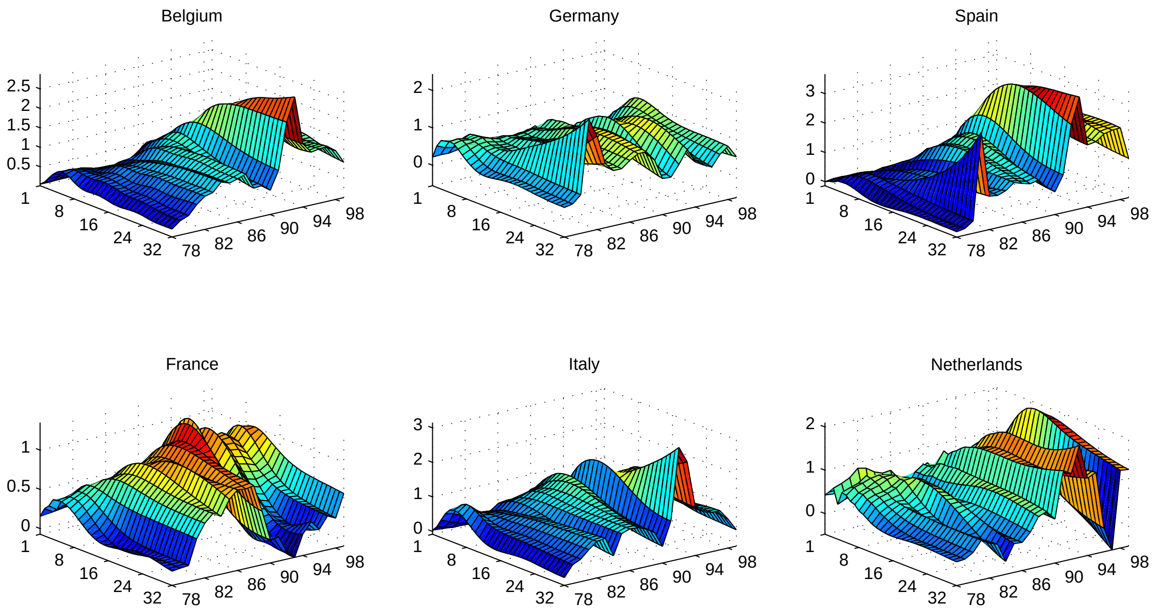


Figure 3.6: Standard deviation of shocks over 15-year rolling windows

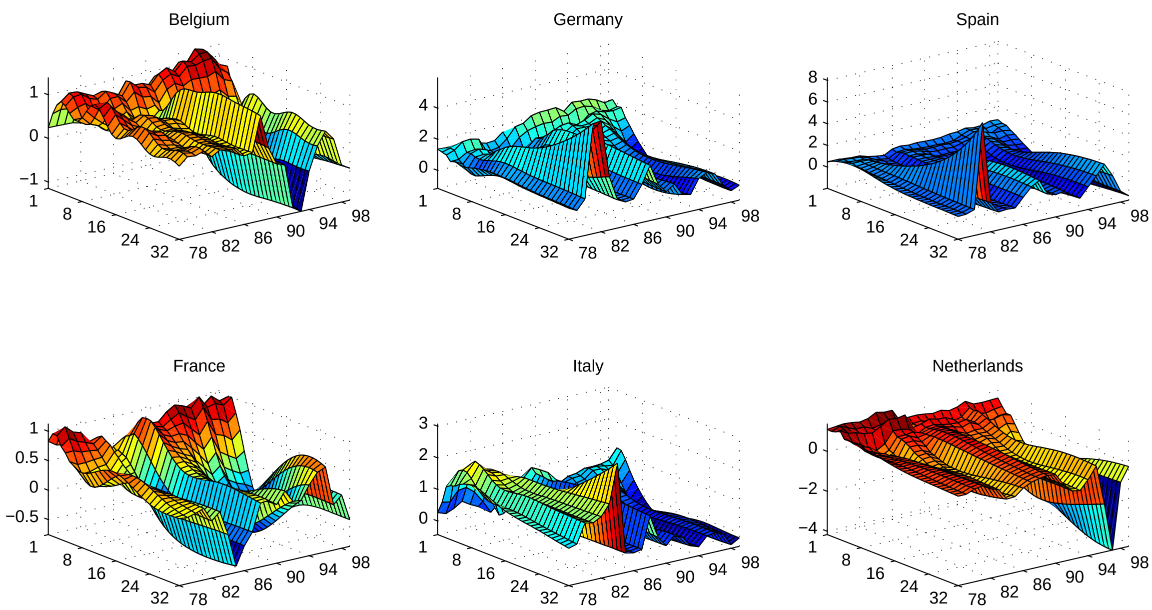
Shock transmission

As before, we plot impulse response functions in order to capture changes in shock propagation over time. Figures 3.7(a)–3.7(c) illustrate three-dimensional shaded surface plots of the impulse response functions of the euro area countries with respect to global, euro area and country-specific shocks over rolling regression estimations. In order to facilitate better visual perception, we display the impulse response of the first quarter for each calendar year. The first impulse response in the graphs of all three figures is, for example, the impulse response from the rolling regression corresponding to the estimation window 1970Q1–1984Q4. The second impulse response is the estimate from the window 1971Q1–1985Q4, etc.

It is clear from all figures that the member countries underwent important changes throughout the sample period. For instance, output response to global shocks is weak in France at the beginning of the sample period, but it becomes stronger over time reaching a peak in the rolling regression the center of which is about 1990 and tapering off after that

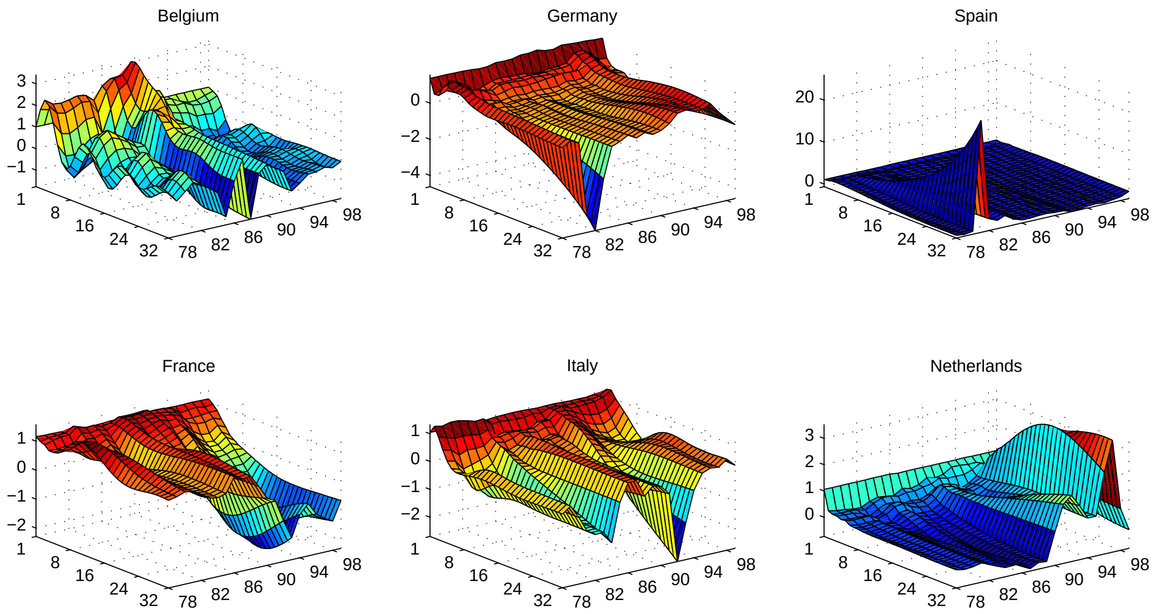


(a) Response to world shock over 15-year rolling windows



(b) Response to euro area shock over 15-year rolling windows

Figure 3.7: Impulse response of output in the euro area



(c) Response to own shock over 15-year rolling windows

Figure 3.7: Impulse response of output in the euro area (cont.)

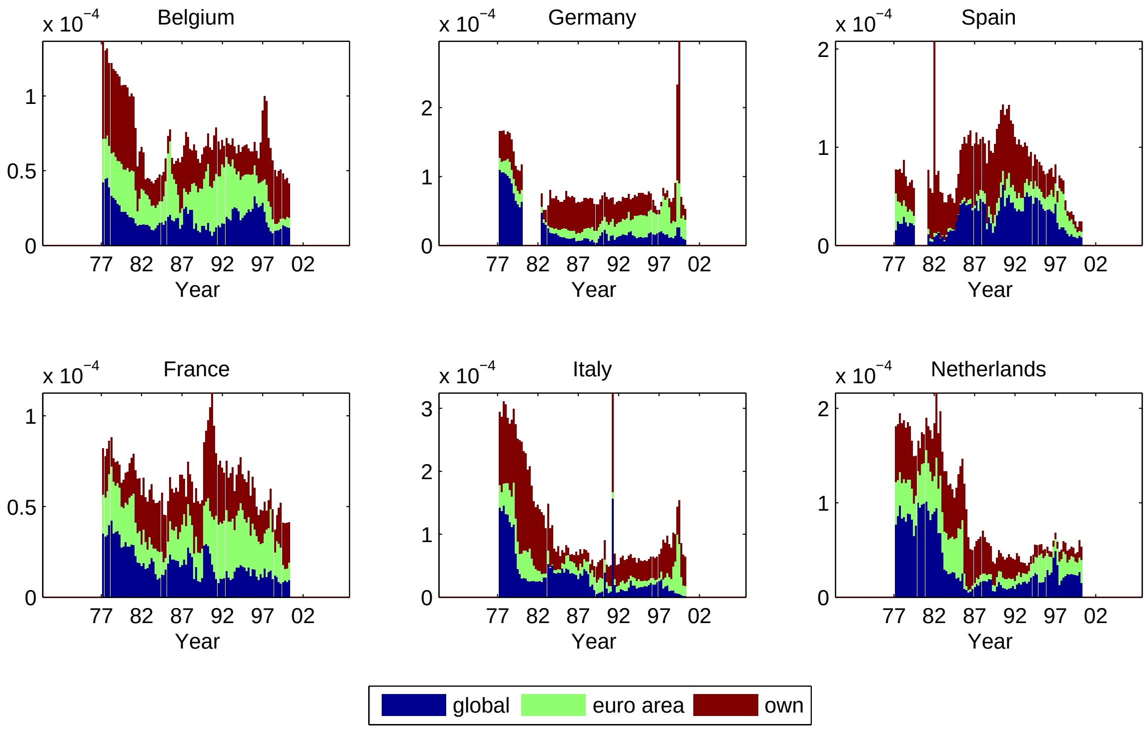
period. However, it is not possible to find general patterns applying to all or a sub-group of member countries. The responses to euro area shocks are behaving more erratic than the responses to global shocks, which suggests that member countries' output dynamics are more sensitive to small changes in the data set in this regard. It can hence be concluded that there is a high uncertainty in the estimation of euro area shocks and their dynamic multipliers. Finally, notice the strong response of output to country-specific shocks in Germany and Spain around 1981–1982. This behavior is observed also in the forthcoming variance decomposition results.

Variance of output gaps

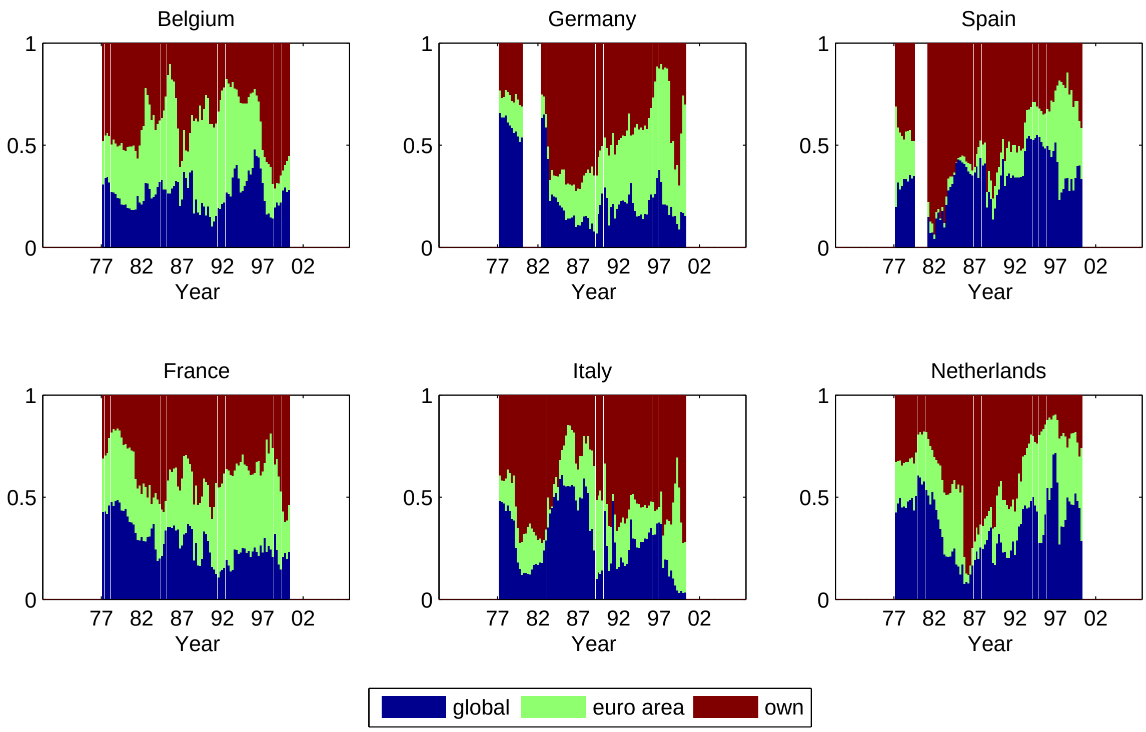
It is beyond the scope of this study to interpret the changes in the impulse response functions over each rolling regression, for each country and with respect to each structural shock. It is clear that each euro area country has its own peculiar history of changing dynamics over time. We leave further interpretations to the interested reader and turn our attention to the changing variance of output gaps in the euro area countries. Figure 3.8(a) shows the total variance of output gaps in the member countries as well as a decomposition of the total variance with respect to global, euro area and country-specific shocks in bar graphs. Note that we truncated the rolling window estimates corresponding roughly to 1980–1982 for Germany and Spain, due to implausibly high estimated variances for these rolling windows. In Germany, the output gap variance is lower in the 1970s than in the 1980s, while a gradual decline is observed after the peak in the rolling window around 1982. The output gap variance decreases steadily in Spain starting with the rolling window around 1980, reaching historically low levels most recently.

We have documented before that the variances of output gaps are higher in the first half of the sample period than in the second half. The rolling regression estimations illustrated in Figure 3.8(a) generally confirm this conclusion. However, it is not possible to recognise a country, where the variance of the output gap is roughly constant in the first half of the sample period and decreases to a lower constant level in the second half of the sample period. For example, Belgium, Germany, Italy and the Netherlands see important declines in their output gap variances at the beginning of the sample period, which then stay roughly around constant levels, abstracting from some erratic behavior in Belgium in rolling windows around 1997, in Italy around 1992 and in Italy and Germany around 1999. A moderation in the output gap variance of France is less visible: the recent rolling window estimates of output gap variance are not lower than the ones from the rolling windows around the mid-1980s. The output gap variance rises steadily in Spain until reaching a peak in the rolling window around 1992 and tapers off after that period until recently.

Figure 3.8(b) displays relative output gap variance decompositions over rolling regressions, i.e., the percentage shares of shocks in the variances reported in Figure 3.8(a). The dynamics in this figure are not exactly in accordance with the estimated shares from the sub-periods in Table 3.3. While the latter estimations give a share of 0.55 to country-specific shocks in Belgium in both sub-periods, there are many rolling windows where the share of



(a) Variance of output gap over 15-year rolling windows



(b) Variance decomposition of output gap over 15-year rolling windows

Figure 3.8: Variance decomposition of output gap

country-specific shocks in output gap variance is below 0.35. Moreover, euro area shocks are in some estimation windows attributed higher shares—about 0.40—than the previous sub-period estimates of about 0.25. The high share of global shocks in the early estimation windows and the strongly increasing share of euro area shocks in more recent rolling windows in Germany were suggested by Table 3.3 as by Figure 3.8(a). While the decreasing share of country-specific shocks in the output gap variance of Spain in the rolling windows centered in the second half of the whole sample are in line with Table 3.3, the statistically significant and strong increase in the share of euro area shocks from 0.06 in the first sub-period to 0.41 in the second sub-period is not reflected in the rolling window estimations. The sub-period estimates in Table 3.3 suggest a significant share for global and euro area shocks in the first sub-period and for euro area shocks only in the second sub-period in the output gap variance of France, which is roughly supported by Figure 3.8(b). That country-specific shocks dominate the Italian output gap fluctuations in both sub-periods, while global shocks are also significant in the first sub-period in Table 3.3 is also a result that is roughly in line with the rolling window estimates. Finally, the sub-period estimates of shock shares in the output gap variance of the Netherlands, the significance of all shocks in the first sub-period and the significance of only global and euro area shocks in the second sub-period, coincide with the rolling window estimates as well.

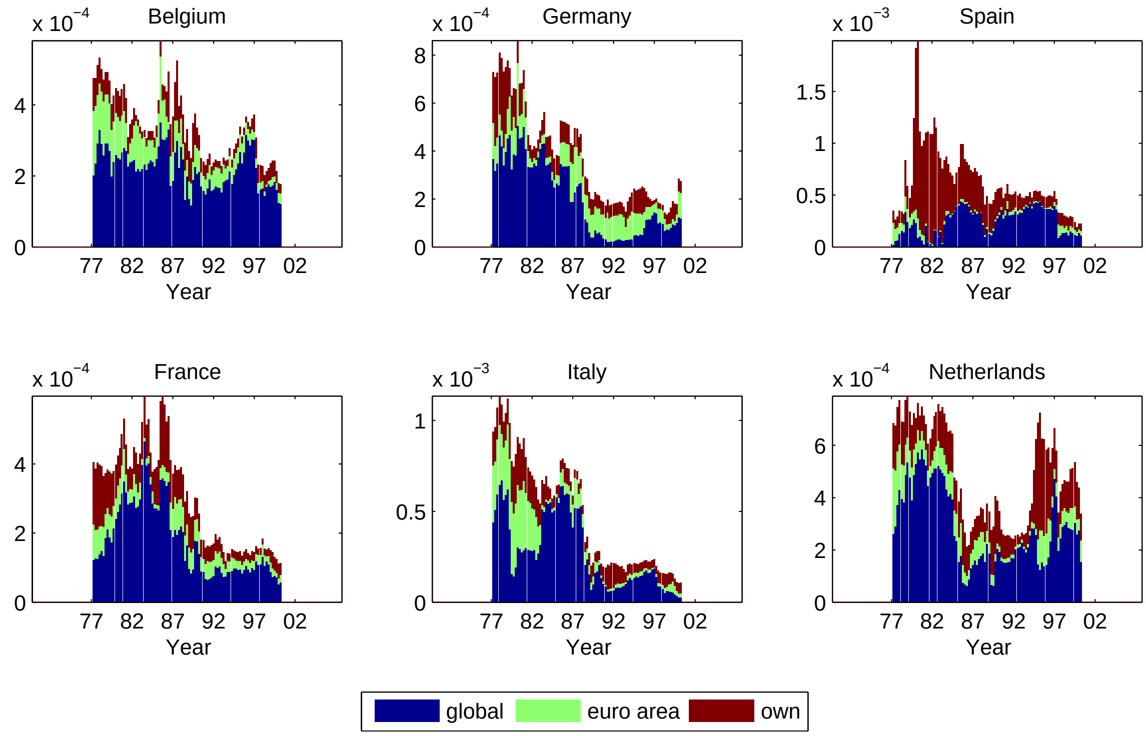
Forecast error variance of output

Figure 3.9(a) shows the evolution of 12-quarters-ahead forecast error variance of output in the member countries. The moderation in this variance is stronger in Germany, Spain, France and Italy than in Belgium. A moderation in the Netherlands is even less evident. The 12-quarters-ahead forecast error variance of output suddenly drops to much lower values in the rolling windows centered between the mid-1980s and the mid-1990s, whereas it rises again in more recent windows for that country. Note also that the evolution pattern of the output gap variance in Figure 3.8(a) is quite distinct from the pattern of the forecast error variance in Figure 3.9(a).

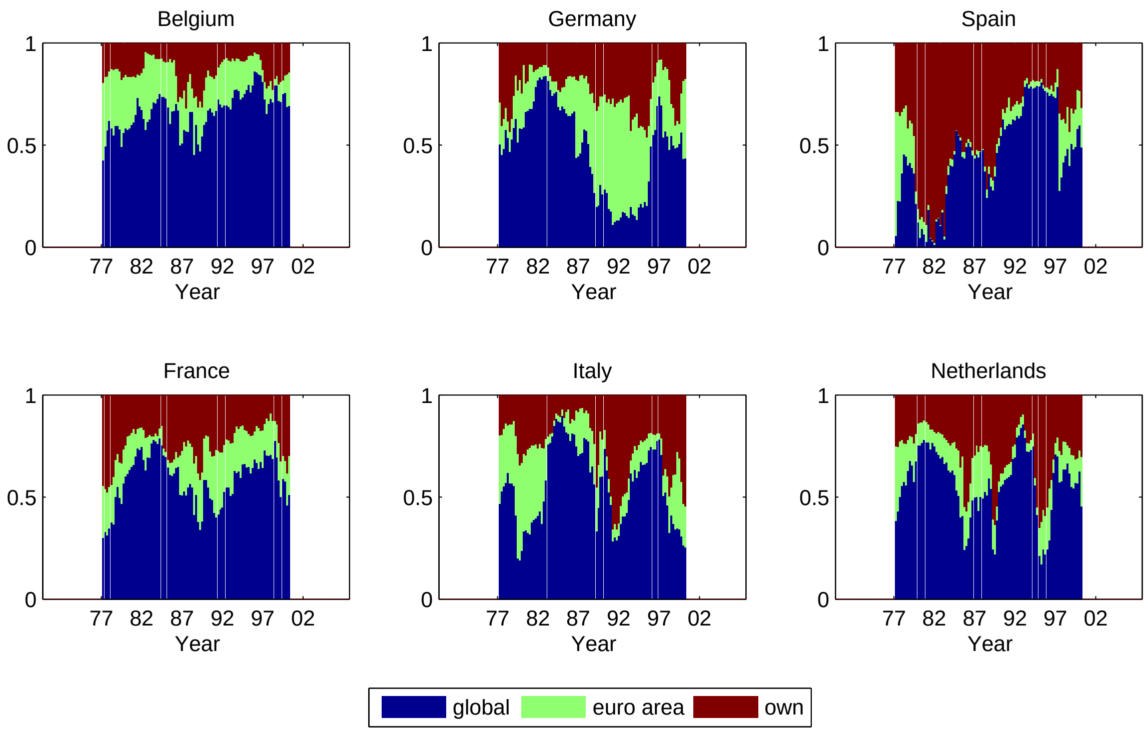
The shares of shocks in the 12-quarters-ahead forecast error variance, displayed in Figure 3.9(b), are in line with the previous sub-period results given in Figure 3.2. Global shocks are the dominant driving force of output forecast error variance in the member countries in many periods. The most important exception is Spain until the 1990s, where country-specific shocks dominate the output forecast error volatility. Euro area shocks are of some significant importance only in Germany in the rolling windows centered roughly between 1987 and 1997 and in Italy in some early rolling windows.

Driving forces of output (gap) differentials

Figures 3.10 and 3.11 are analogous to Figures 4.8 and 4.9, respectively. The former figure shows the variance of output gap differentials and its decomposition, while the latter shows the variance of 12-quarters-ahead output differential forecast errors. For both of these heterogeneity measures, it can be claimed that their variance is generally lower recently than in the first half of the full sample period, although the evolution patterns of the measure differ to a large extent across the countries. The other commonality is that country-specific shocks are the main driving force of output gap differentials as well as 12-quarters-ahead output differential forecast errors in many rolling windows, although there are some episodes where global or euro area shocks have a relatively large share. As noted before, our general finding suggests that heterogeneity in the euro area in terms of output gaps can be to a large extent traced back to asymmetric shocks.

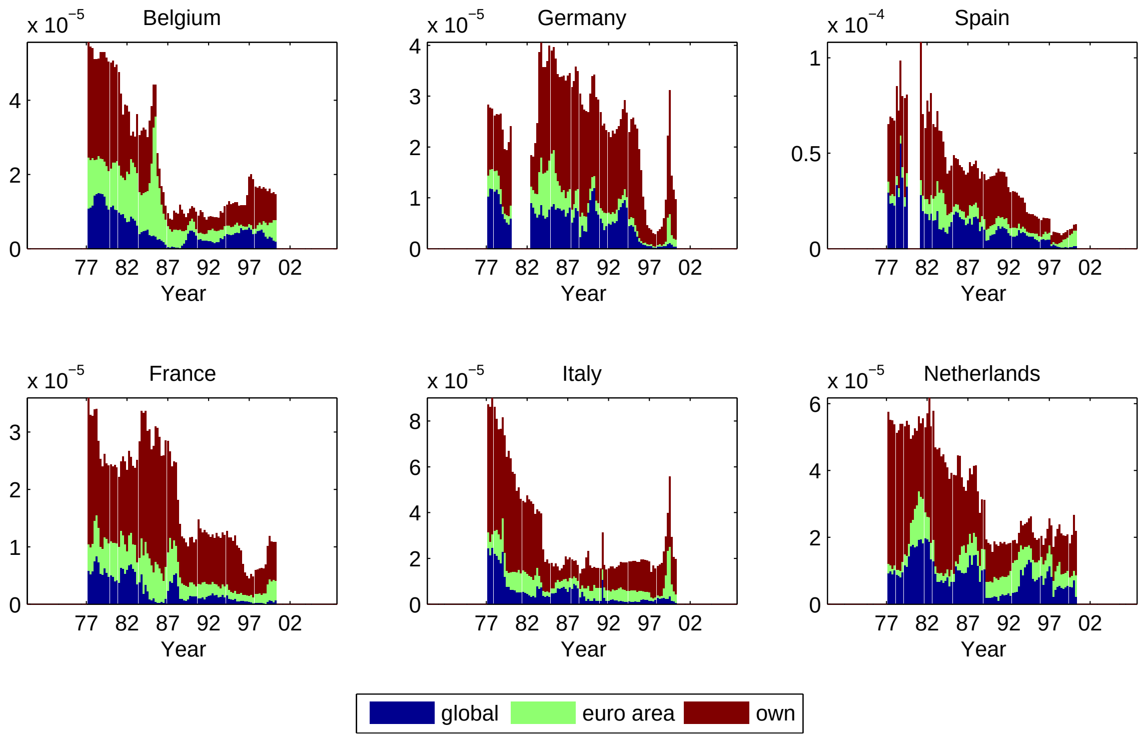


(a) Variance of output 12-quarters-ahead forecast errors over 15-year rolling windows

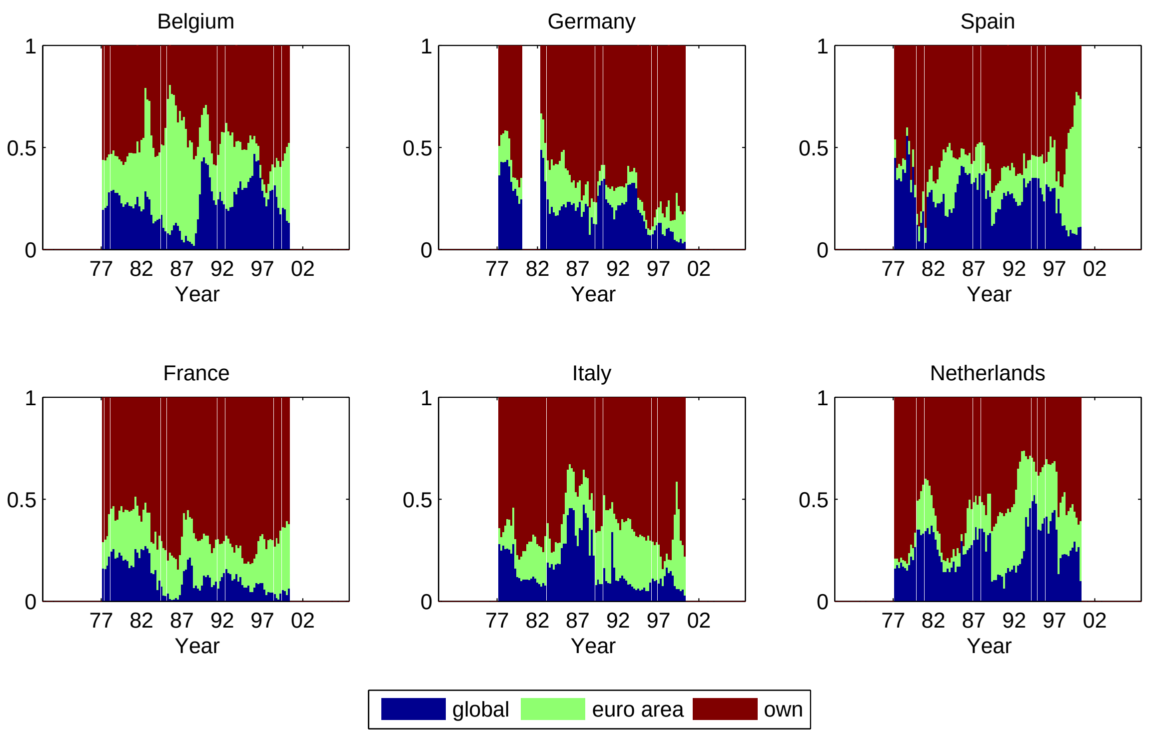


(b) Variance decomposition of output forecast errors over 15-year rolling windows

Figure 3.9: Variance decomposition of output forecast errors

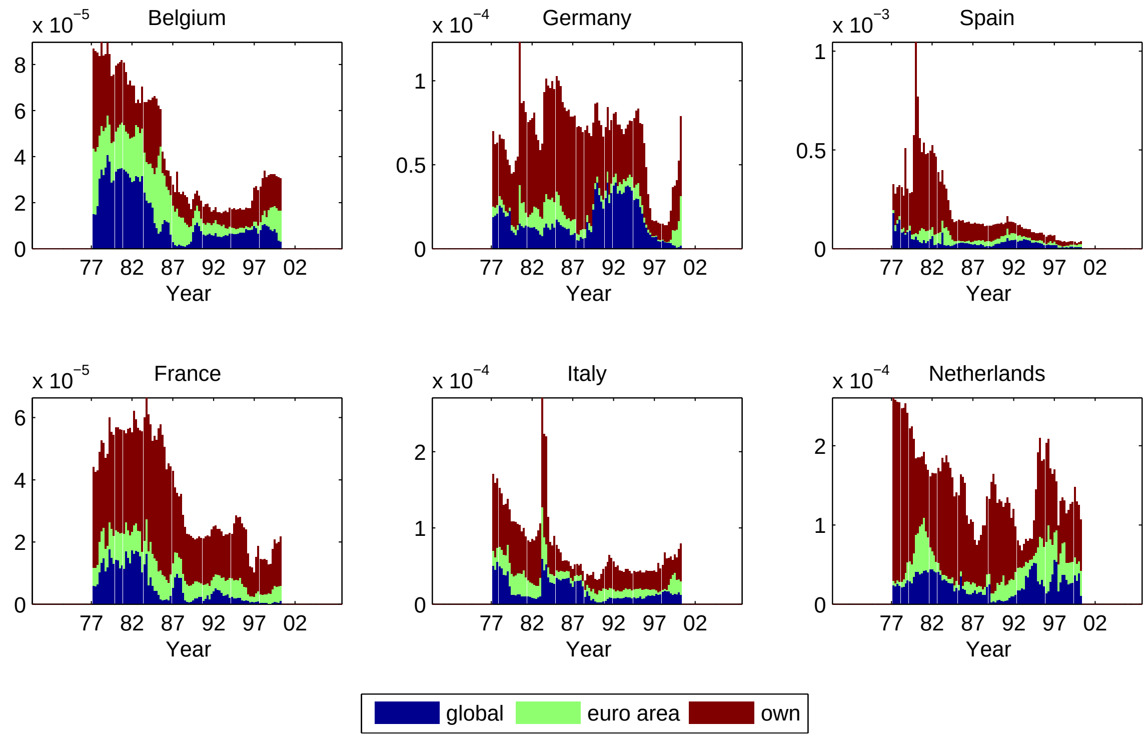


(a) Variance of output gap differential over 15-year rolling windows

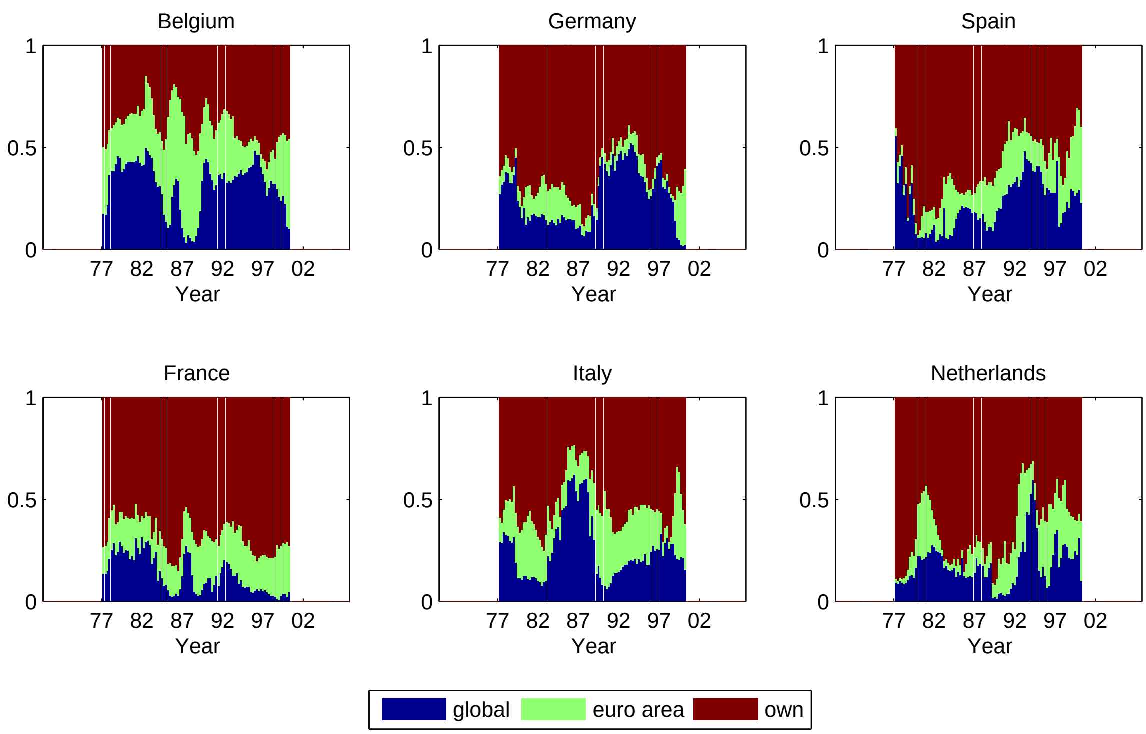


(b) Variance decomposition of output gap differential over 15-year rolling windows

Figure 3.10: Variance decomposition of output gap differential



(a) Variance of 12-quarters-ahead output differential forecast errors over 15-year rolling windows



(b) Variance decomposition of output differential forecast errors over 15-year rolling windows

Figure 3.11: Variance decomposition of output differential forecast errors

3.4 Summary and remarks

In this chapter, we investigated the properties of business cycle dynamics in the euro area with the aid of structural VAR models. After establishing the statistical properties of the cyclical fluctuations in the previous chapter, we addressed the three questions posed at the beginning of the chapter by estimating our SVAR models initially using the full sample. However, we have also carried out our estimations in sub-samples as well as rolling windows in order to capture changes that occurred in the business cycle dynamics over time.

The first question we dealt with was the driving forces of output fluctuations. In order to detect the extent to which euro area countries' business cycles are driven by common (global and euro area) factors, we computed decompositions of the output gap variance—the measure of the output gap being the symmetric CF-filter—as well as decompositions of the output forecast error variance at the business cycle horizon for each member country. We found changes in the share of shocks in the output gap variance from the first sub-period (1970Q1–1990Q2) to the second sub-period (1990Q3–2007Q4), while these changes were rarely statistically significant. For output gap variance, we found significant shares of global shocks (except in Spain) and euro area shocks (except in Spain and Italy) in the first sub-period. However, global shocks had a significant share only in the Netherlands in the second sub-period, whereas euro area shocks were significant in all countries except Italy. The country-specific shocks were found to be an important driving force of output gap fluctuations in all sample periods considered, with the exception of the Netherlands in the second sub-period.

The forecast error dynamics were found to be different from the output gap dynamics. Our estimations suggested that global shocks were often the main driving force of output forecast error variance at the business cycle horizon of up to 32 quarters; they were almost always playing a statistically significant role even if the point estimate of their share was not very high in some cases. While country-specific shocks played the dominant role in some cases (such as Spain in the second sub-period), euro area shocks were not found to be a statistically significant driving force of output forecast errors in any of the samples.

The second question we posed at the beginning of this chapter—the extent and sources of cyclical heterogeneity in the euro area—has been addressed by computing counterfactual correlations, variance decompositions of output gap differentials as well as FEVD of output (level) differentials at the business cycle horizon. Although there were occasional exceptions in some of the discrete sample as well as rolling window estimations, the general finding was supportive of the previous literature in that asymmetric shocks are the main driving force behind the existing heterogeneity of macroeconomic fluctuations in the euro area. The other channel—heterogeneous response to common shocks—was often not found to play a significant role.

Finally, with respect to the third question we posed at the beginning, we reported significant changes in the size of shocks as well as shock transmission from the first sub-period to the second. However, the point estimates of the change in output gap and output gap differential variance was always negative, but never statistically significant, while we found a statistically significant decline in the variance of output as well as output differential forecast errors. Yet, the common finding for both gaps and both forecast errors was that the first channel considered—change in the size of shocks—had a significant contribution to a decline in cyclical volatility, while the other channel—change in shock transmission—contributing either less or insignificantly. There were even cases where the latter channel was found to have contributed negatively to the moderation.

Giannone and Reichlin (2006) state in the introduction to their paper that their "ambition is not structural [...] and this evidence is meant to provide food for thought for a deeper analysis." This chapter, relying on a modified version of their empirical model, should also be seen in the same manner. An important shortcoming of the empirical approach of this chapter is that spillovers are not modelled among the member countries. While this may be convenient if spillovers play (virtually) no role in business cycle fluctuations in reality, and international business cycle dynamics are (virtually) totally due to common shocks, our empirical approach may lead to wrong conclusions if there are no common shocks, and only country-specific shocks are transmitted through a channel such as trade. The next chapter addresses this critical issue.

Another critical issue is the somehow arbitrarily chosen break date. In the next chapter, we estimate a time-varying coefficient version of the SVAR of this chapter in order to present another perspective with respect to this problem. Breaks in the data are included naturally, when SVAR coefficient matrices as well as covariance matrix of structural shocks are allowed to vary in each period included in the sample.

Chapter 4

Business cycle dynamics in the euro area: two alternative approaches*

The previous chapter dealt with various issues concerning the business cycle dynamics in the euro area. The analysis depended on a conventional SVAR approach, with the help of which global, euro area and country-specific shocks and their transmission mechanisms were identified. Although the results helped answering the questions posed at the end of Chapter 2, there were several issues left deserving more scrutiny. First, six different trivariate models were estimated comprising the output of the US, the euro area and the output of one of the six member countries included in the data set. This implied six different estimations of global and euro area shocks, which were assumed to be common to all member countries. Although the estimated global and euro area shocks from each trivariate model were highly correlated among each other, and the standard deviations of both sorts of shocks were generally similar, the match of these shocks across different trivariate models was not perfect. It is instructive to repeat the estimations in an empirical framework that does not suffer from this type of critique. Second, the trivariate models did not comprehend the bilateral relationships among further economies included in the sample. It is theoretically possible that some economies

*Most of the estimations and calculations in this chapter are carried out using MATLAB codes written by the author. JMulTi is used for the specification of the FSVAR model. The GAUSS codes of Stock and Watson (2005) have been translated into MATLAB for the estimation of the FSVAR model. The MATLAB codes of Gali and Gambetti (2009) have been modified for the estimation of the reduced form time-varying coefficient SVARs. The MATLAB code included in the Spatial Econometrics Toolbox of James P. LeSage is used for the estimation of the structural parameters in the time-varying coefficients VARs.

have important spillover effects on others that cannot be captured by the simple empirical approach employed in the previous chapter. Third, the euro area of the first 12 member countries did not exist before 1999.[1] Output data extrapolated by the OECD via specific methods for EU12 is harder to measure for quarters before 1999, where the exchange rates were not fixed across the member countries. An additional problem in this context could be that quarterly GDP data for countries not included in the data set in the previous chapter's estimations are not reliable, and that the EU12 GDP data, which has to be partly based on such unreliable data, may possess some deficiencies.

In order to address these issues, we estimate a factor-structural VAR (FSVAR) model in this chapter. While we use the same data set as in the previous chapter, only one model is estimated for investigating properties of the business cycle dynamics in the euro area. The model comprises the output of the US, as well as the output of the previously considered six member countries of the euro area, and discards the output of the entire euro area. It contains global and euro area factors as well as country-specific shocks as potential driving forces of countries' output dynamics. Note that all aforementioned critiques are addressed with such type of model. Countries are exposed to the "same" global and euro area shocks, while country-specific shocks can be spilled over across the countries included in the model. Finally, the model does not comprise the euro area output, and the euro area factor is extracted only with respect to the six member countries contained in the sample.

The rolling-window estimations of Chapter 3 gave us a sense about the sensitivity of the results with respect to the specific break date—1990Q2—at which the sample was split into two parts. In this chapter, we estimate, in addition to the FSVAR model, a time-varying coefficient (TVC) version of the trivariate SVARs of the previous chapter in order to provide another perspective with respect to this issue. Since breaks in the data are naturally included in a TVC framework, the choice of the break date is not an issue for TVC-SVAR models, whereas the previous criticism on fixed-coefficient SVARs of Chapter 3 also applies to them.

[1] To be precise, the exchange rates were fixed for among the first 11 members after 1999; Greece joined them in 2001.

The questions that we address in this chapter are the same as in the previous one: (i) To what extent are the business cycles of the euro area countries driven by common (global and euro area) factors? (ii) What are the extent and sources of heterogeneity in the euro area in terms of business cycles? (iii) If the moderation of business cycles and business cycle differentials were statistically significant, which mechanisms led to it in the euro area? Note that the heterogeneity analysis of the previous chapter was partly based on the output gap differential between the output gap of each country and the output gap of the entire euro area. Since the euro area output is not included in the FSVAR model of this chapter, we check the properties of all possible bilateral differentials of member countries' business cycles when examining the dynamics of heterogeneity with that model.

This chapter is structured as follows. The next section presents the FSVAR model and discusses its specification for our data set. Results for sample periods 1970Q1–1990Q2 and 1990Q3–2007Q4 are provided subsequently. As in the previous chapter, we also discuss properties of rolling windows estimates in the FSVAR context. Next, trivariate SVAR models of the type used in Chapter 3 with time-varying coefficients (TVC-SVARs) are discussed. The findings from this alternative framework are then compared to the findings of the SVAR and FSVAR approaches. The chapter closes with a summary of the findings on the euro area business cycle dynamics.

4.1 The factor-structural VAR model

The empirical approach underlying the estimations of this chapter is borrowed from Stock and Watson (2005). The point of departure is a seven-variable reduced-form VAR that contains the log output of the seven countries included in the analysis. The only deterministic term is assumed to be a constant in each equation. The moving-average representation of the model, which was given by (1.2) in Chapter 1,

$$y_t = \mu + \sum_{j=0}^{\infty} \phi_j u_{t-j}, \tag{4.1}$$

is reproduced here for the sake of convenience. We order the variables in (4.1) as

$$y_t = \left[\begin{array}{ccccccc} y_t^{US} & y_t^{bel} & y_t^{deu} & y_t^{esp} & y_t^{fra} & y_t^{ita} & y_t^{nld} \end{array} \right]',$$

i.e., as the log output of the US, Belgium, Germany, Spain, France, Italy and the Netherlands, respectively.

The identification of international and country-specific shocks follows from a different procedure than in the case of a conventional SVAR model. Namely, it is assumed that the error terms u_t in (4.1) possess a factor structure given by

$$u_t = \Gamma f_t + \xi_t, \tag{4.2}$$

where f_t stands for a $k \times 1$ vector of common factors at period t, Γ is a $7 \times k$ matrix of loadings, and ξ_t is a 7×1 vector of country-specific (idiosyncratic) shocks. The common factors and country-specific shocks are assumed to be independent from each other as well as among each other such that $E(\xi_t' f_t) = 0$, and their covariance matrices,

$$E(f_t f_t') = \begin{bmatrix} \sigma_{f_1} & & 0 \\ & \ddots & \\ 0 & & \sigma_{f_k} \end{bmatrix} \text{ and } E(\xi_t \xi_t') = \begin{bmatrix} \sigma_{\xi_1} & & 0 \\ & \ddots & \\ 0 & & \sigma_{\xi_7} \end{bmatrix},$$

are diagonal. Notice that ϕ_0 in (4.1) is a 7×7 identity matrix in this framework. This implies that the impact effect of international shocks, represented here by the common factors in f_t, is solely determined by the loadings in Γ, while no spillover of country-specific shocks is allowed to other countries at the impact period. However, country-specific shocks are spilled over to other countries in the model after the impact period, since ϕ_j are neither 7×7 zero matrices nor diagonal matrices for $j > 0$.[2]

An issue of concern when estimating the VAR underlying (4.1) is the number of lags to be included in the estimation. The convention is that each equation has $7p$ regressors,

[2]Note that we have also considered to augment our FSVAR model with the euro area output. However, including the euro area output in this model framework would have the implausible implication that there are euro-area-specific shocks with a non-zero impact effect on the entire euro area, but no impact effect on the individual member countries. Moreover, a likelihood ratio test did also not support a common factor structure for that eight-variable model.

which would obviously imply a very high number of regressors even for a small p given the length of the small samples at hand. We follow Stock and Watson (2005) and estimate a VAR(p_1, p_2) with GLS techniques, where p_1 is the number of lags of own output and p_2 is the number of lags of the other countries' outputs in each country's equation in the VAR. This approach reduces the number of regressors to be estimated drastically. In our sample, while the AIC chooses a VAR$(4, 1)$, the BIC favors one of either VAR$(4, 1)$, VAR$(3, 1)$ or VAR$(2, 1)$. Therefore, we report results from a VAR$(4, 1)$ estimation.

Another important issue of concern is the number of factors to be included in (4.2). Since the factor-structural VAR (FSVAR) in (4.2) is overidentified if $k > 0$, likelihood ratio tests can be carried out to determine the appropriate number of factors to be included in the model. Applying the overidentification tests, we obtain that $k = 1$ is rejected neither for the full sample nor the first sub-sample, while it is rejected for the second sub-period. $k = 2$ is also rejected for the second sub-period when both factors are left unrestricted, whereas it cannot be rejected when the second factor is not allowed to have an impact effect on the US output, i.e, $\Gamma(1, 2) = 0$. Note that the first and second factors can respectively be labelled as the global and euro area factors in such a framework, which is in line with the previous chapter, so that euro area shocks are spilled over to the US with a time lag of one quarter, while global shocks affect all countries in the model at the impact period.

4.1.1 Results from discrete samples

Our analysis is structured as in the previous chapter. We start with the presentation of results from the full sample and the sub-samples and investigate the driving forces of fluctuations, the dynamics of heterogeneity, and the existence and significance of moderation in output gaps and output gap differentials. Then, we report our findings from rolling regression estimations.

Driving forces of business cycles

Variance decomposition of output gaps The FSVAR model contains six spillover shocks in addition to global, euro area and own shocks of the member countries. We report the shares of these shocks in the output gap variance of the euro area countries in Table 4.1. These shares are computed using the formula in (3.9) adapted to our model framework. The last panel shows the change in the share of shocks from the first to the second sub-period.

In the first row of all panels in Table 4.1, the total share of global and US spillover shocks in the output gap variance of the member countries is given. According to full-sample estimates, these shocks have a significant share in France and Spain only (in the latter country at 10-percent significance level). Turning to the sub-period estimates, the FSVAR model attributes a significant share to global plus US shocks in all member countries in the first sub-period. However, these shares decrease to low and statistically insignificant levels in the second sub-period. The decline is particularly strong and significant in Germany, France and Italy.

The second and third rows of the panels in Table 4.1 correspond to the shares of euro area shocks and spillover shocks from other member countries, respectively. It can be seen that the sharp decline in the share of global plus US shocks in the second sub-period is often compensated by increases in the share of common euro area and euro area spillover shocks. The only exception to this rule is Italy, where the strong decline in the global plus US shocks share is counterbalanced by the increase in the share of own country-specific shocks. The share of common euro area shocks in the output gap variance increases significantly (at least at the 10-percent significance level) in all member countries in the second sub-period according to the last panel in Table 4.1. Significant increases also occur in the share of euro area spillover shocks for Belgium and France. Although common euro area and euro area spillover shocks often have small and insignificant shares in the variance of the member countries' output gaps in the full-sample and first sub-period estimates, they account for a

Table 4.1: Shares of shocks in output gap variance of euro area countries

	Sample: 1970Q1–2007Q4					
	bel	deu	esp	fra	ita	nld
global + us	0.16	0.14	0.24	0.27	0.12	0.13
	(0.10)	(0.15)	(0.14)	(0.14)	(0.12)	(0.11)
euro area shock	0.16	0.28	0.05	0.26	0.16	0.18
	(0.11)	(0.10)	(0.07)	(0.12)	(0.09)	(0.11)
eu spillover	0.04	0.02	0.13	0.08	0.12	0.09
	(0.07)	(0.11)	(0.09)	(0.09)	(0.11)	(0.08)
country shock	0.64	0.56	0.59	0.39	0.61	0.60
	(0.14)	(0.06)	(0.14)	(0.13)	(0.10)	(0.12)

	Sample: 1970Q1–1990Q2					
	bel	deu	esp	fra	ita	nld
global + us	0.26	0.66	0.35	0.49	0.47	0.41
	(0.10)	(0.15)	(0.14)	(0.14)	(0.12)	(0.11)
euro area shock	0.01	0.08	0.08	0.02	0.18	0.00
	(0.11)	(0.10)	(0.07)	(0.12)	(0.09)	(0.11)
eu spillover	0.06	0.25	0.18	0.11	0.23	0.09
	(0.07)	(0.11)	(0.09)	(0.09)	(0.11)	(0.08)
country shock	0.66	0.00	0.39	0.38	0.12	0.50
	(0.14)	(0.06)	(0.14)	(0.13)	(0.10)	(0.12)

	Sample: 1990Q3–2007Q4					
	bel	deu	esp	fra	ita	nld
global + us	0.06	0.08	0.06	0.03	0.06	0.18
	(0.10)	(0.15)	(0.14)	(0.14)	(0.12)	(0.11)
euro area shock	0.30	0.40	0.31	0.28	0.15	0.28
	(0.11)	(0.10)	(0.07)	(0.12)	(0.09)	(0.11)
eu spillover	0.47	0.15	0.31	0.42	0.15	0.22
	(0.07)	(0.11)	(0.09)	(0.09)	(0.11)	(0.08)
country shock	0.16	0.37	0.32	0.27	0.64	0.32
	(0.14)	(0.06)	(0.14)	(0.13)	(0.10)	(0.12)

	Change in the share of shocks over time					
	bel	deu	esp	fra	ita	nld
global + us	-0.20	-0.58	-0.29	-0.46	-0.41	-0.23
	(0.17)	(0.20)	(0.17)	(0.18)	(0.16)	(0.16)
euro area shock	0.29	0.32	0.23	0.26	-0.03	0.28
	(0.15)	(0.18)	(0.14)	(0.16)	(0.13)	(0.15)
eu spillover	0.41	-0.10	0.14	0.31	-0.08	0.13
	(0.14)	(0.17)	(0.15)	(0.16)	(0.14)	(0.15)
country shock	-0.50	0.36	-0.08	-0.11	0.52	-0.18
	(0.16)	(0.14)	(0.18)	(0.16)	(0.18)	(0.17)

Notes: The output gap measure is the CF-filter. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

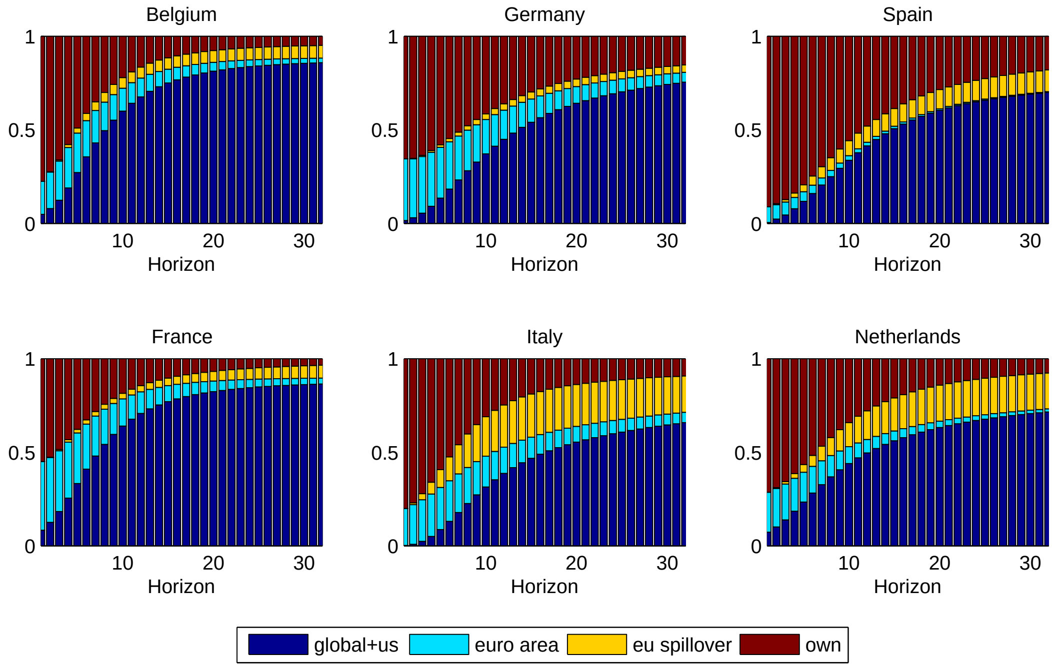
significant portion of output gap volatility in the second sub-period. Except for Italy, the total share of these shocks is at least 0.50 or higher.

A commonality of the FSVAR findings of this chapter and the SVAR findings of the previous one is that country-specific shocks have the highest share in the output gap variance according to the full-sample estimates. This result is more pronounced in the FSVAR case, where point estimates of the shares of country-specific shocks exceed 0.50 for all member countries except France. However, it should also be noted that important differences are observed in the shares of country-specific shocks across the different samples considered.

To summarise, we find that the implied shares of shocks differ to an important degree across countries with respect to the underlying empirical model. The SVAR model of the previous chapter and the FSVAR model of this one both corroborate that the shares of euro area shocks become statistically significant in all member countries in the second sub-period with the exception of Italy. However, it should also be added that the quantitative estimates of both models differ to a non-negligible extent. Moreover, the FSVAR model attributes, with the exceptions of Germany and Italy, significant shares to the spillover shocks from other member countries in the second sub-period, whereas these types of shocks were absent in the previous SVAR model.

Forecast error variance decomposition Another common property of the SVAR and FSVAR models can be found in the implications of FEVD with respect to full-sample and first sub-period estimates. As shown in Figures 4.1(a) and 4.1(b), the FSVAR model attributes—just as the SVAR model does—an important share to global (plus US) shocks over the business cycle horizon. For these two periods, the shares of country-specific shocks are often higher at shorter forecast horizons, but decrease steadily as the forecast horizon rises. On the other hand, common euro area or euro area spillover shocks have only negligible shares.

The second sub-period FEVD estimates differ strongly from the other two sample estimates. Shares of common euro area shocks are still often insignificant, but higher in terms



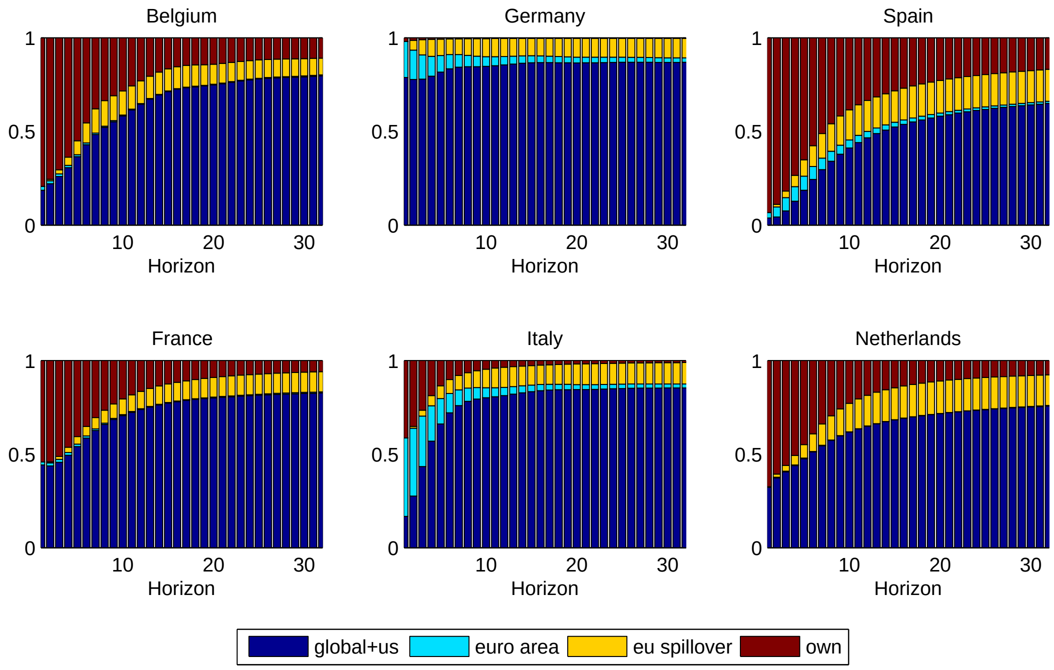
(a) Sample: 1970Q1–2007Q4

Figure 4.1: FEVD of output

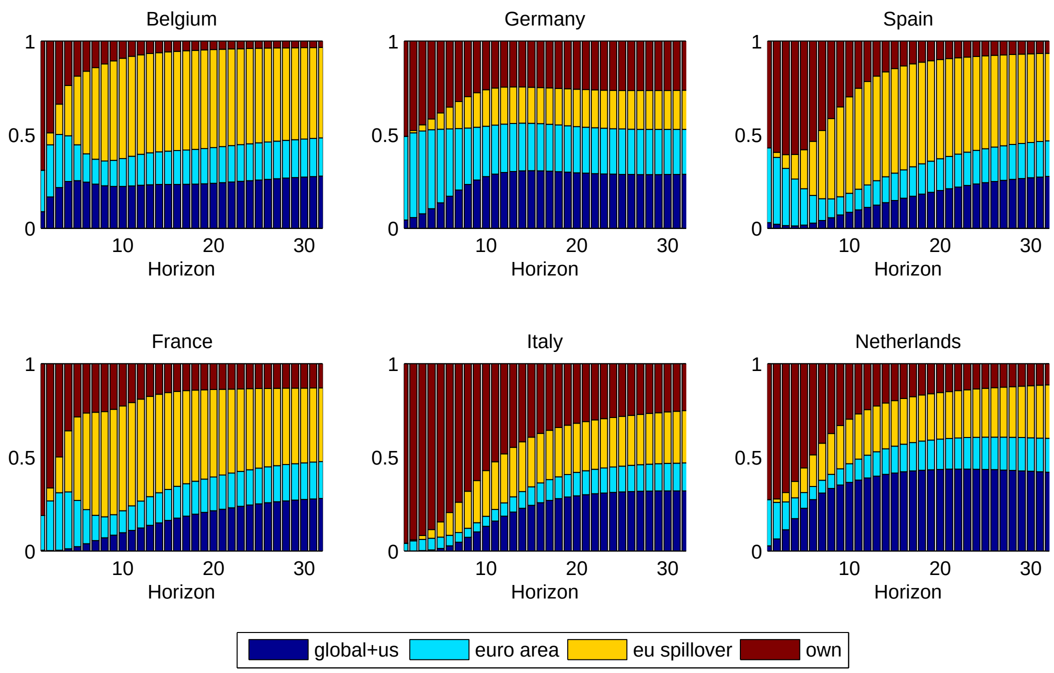
of point estimates than in the other samples. More importantly, euro area spillover shocks are particularly important for the output fluctuations of particularly Belgium, Spain and France in the second sub-period. In total, the output fluctuations of the member countries seem to be much more exposed to euro area dynamics, be it through common shocks or spillovers of country-specific shocks within the euro area, in the second sub-period. Note that this finding is in accordance with the output gap variance decomposition findings. Finally, country-specific shocks seem to matter rather at shorter forecast horizons than at longer horizons.

Heterogeneity

We investigate the sources of heterogeneity with the two types of tools known from the previous chapter: counterfactual correlations and variance decompositions.



(b) Sample: 1970Q1–1990Q2



(c) Sample:1990Q3–2007Q4

Figure 4.1: FEVD of output (cont.)

Counterfactual correlations While in the previous chapter the subject of interest was the correlation between the entire euro area and each individual member country, in this one we examine the correlation between all possible country pairs due to the lack of the euro area output in the model. The results are given in Table 4.2 for the full sample period only, since most of the counterfactual correlations are estimated very imprecisely in the sub-periods due to the high number of parameters to be estimated with short samples. The upper left panel of the table shows the true correlations conditional on the estimated FSVAR model, while the second, third and fourth panels show the counterfactual correlations conditional on global, euro area and country-specific shocks, respectively. Note that even full-sample estimates are subject to high standard errors. However, it is possible to observe the same structure as before: country-specific shocks lead to statistically insignificant bilateral correlations of member countries' output gaps, whereas the correlations conditional on common, i.e., global and euro area shocks, are high and significant.

Variance decompositions In Table 4.3, we report the results from the decomposition of bilateral output gap differentials. In line with the above findings, we find support for the view that country-specific (asymmetric) shocks are predominantly behind the observed heterogeneity of output gaps. The last column of both boxes corresponding to the two sub-periods in Table 4.3 gives the share of own shocks, i.e., the sum of shares of both relevant countries' shocks for each differential. Especially in the second sub-period, with the exception of the output gap differential between Belgium and Spain, we observe statistically significant shares of own shocks above 0.50. There are less cases in the first sub-period where the point estimates of own shock shares are above 0.50, yet own shocks are often the main driving force of output gap differentials. Common euro area shocks almost never play a significant role in the output gap differential variances, except the strange result corresponding to the German/Italian output gap differential, in the variance of which common euro area shocks have a share of 0.51. Global shocks have almost always insignificant shares in the second

Table 4.2: True and counterfactual correlations of output gaps in the euro area

	True correlations					Only global shock				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	0.36					0.99				
	(0.09)					(0.19)				
esp	0.35	0.19				0.76	0.80			
	(0.10)	(0.14)				(0.33)	(0.36)			
fra	0.49	0.39	0.35			0.98	0.99	0.72		
	(0.09)	(0.11)	(0.12)			(0.07)	(0.18)	(0.35)		
ita	0.30	0.40	0.17	0.40		0.92	0.96	0.91	0.91	
	(0.11)	(0.10)	(0.15)	(0.13)		(0.25)	(0.25)	(0.34)	(0.27)	
nld	0.35	0.33	0.21	0.37	0.26	0.89	0.88	0.49	0.93	0.71
	(0.08)	(0.11)	(0.11)	(0.10)	(0.11)	(0.15)	(0.27)	(0.36)	(0.12)	(0.33)

	Only euro area shock					Only country-specific shocks				
	bel	deu	esp	fra	ita	bel	deu	esp	fra	ita
deu	0.90					0.05				
	(0.25)					(0.13)				
esp	0.91	0.89				0.19	-0.07			
	(0.34)	(0.39)				(0.12)	(0.17)			
fra	0.94	0.98	0.94			0.19	-0.09	0.13		
	(0.25)	(0.22)	(0.39)			(0.13)	(0.18)	(0.16)		
ita	0.95	0.94	0.98	0.98		0.04	0.13	-0.08	0.08	
	(0.25)	(0.13)	(0.45)	(0.22)		(0.14)	(0.14)	(0.16)	(0.17)	
nld	0.81	0.98	0.79	0.93	0.85	0.13	0.01	0.09	0.01	0.05
	(0.33)	(0.30)	(0.37)	(0.37)	(0.31)	(0.12)	(0.14)	(0.13)	(0.15)	(0.13)

Notes: The output gap measure is the CF-filter. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

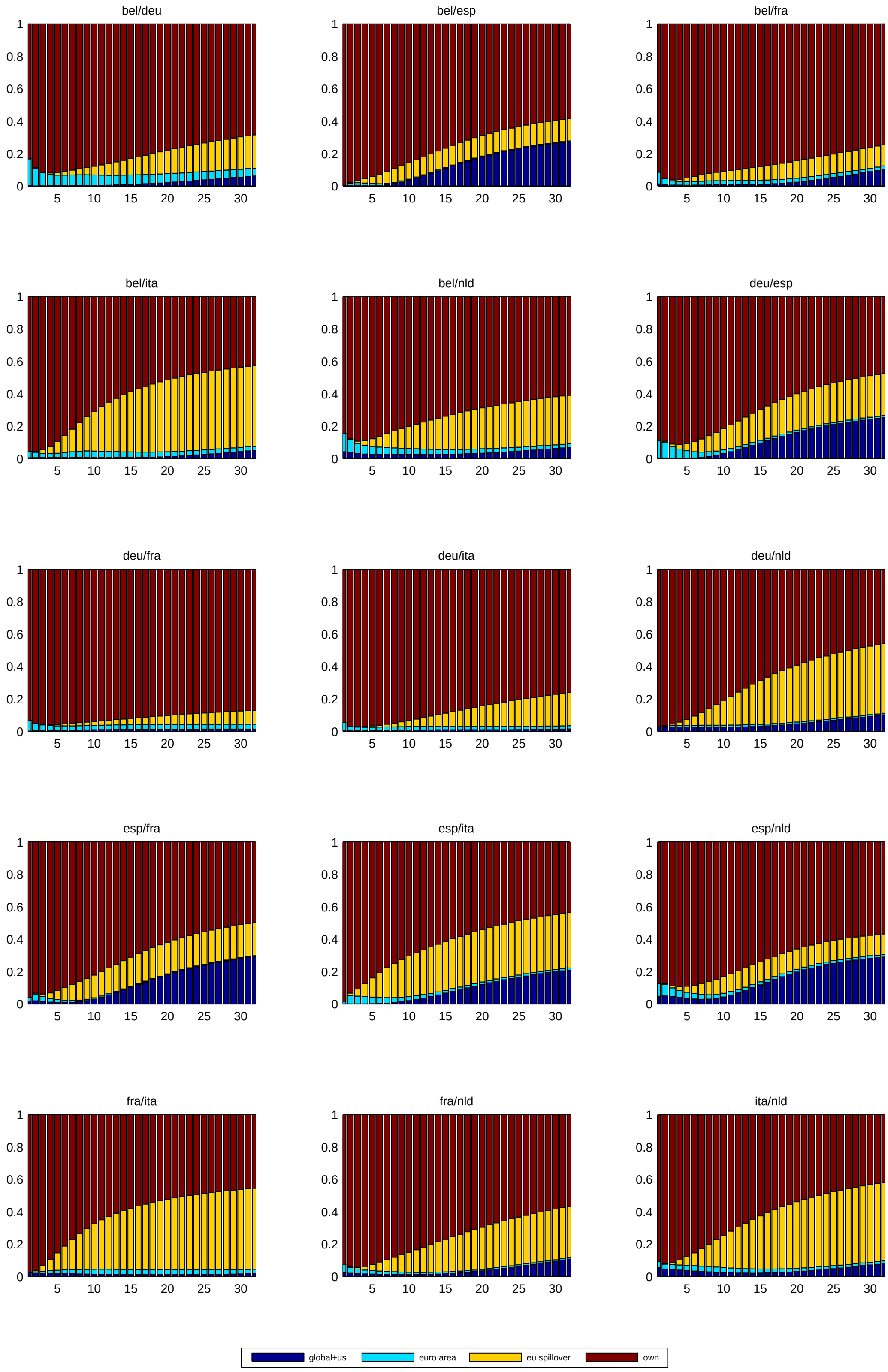
sub-period, with the exception of the Belgian/Spanish output gap differentials, whereas they often have small but statistically significant shares in the first sub-period. Note that the full-sample estimates, which we do not report here, overwhelmingly show large shares for own shocks in the variances of bilateral output gap differentials.

The forecast error variance decomposition of output differentials at the business cycle horizon is complementary to the foregoing results. Own shocks, i.e., shocks of the two countries that are the subject of an output differential, as well as other country-specific shocks drive the fluctuations of output differentials over the full sample according to Figure 4.2(a). The same applies also to the second sub-period (see Figure 4.2(c)). However, shares of spillover shocks are estimated to be higher when the second sub-sample underlies the estimations than when the entire sample is used. Global shocks are of some importance for the variance of bilateral output differentials according to FEVD as well, as suggested by the previous output gap differential analysis.

Table 4.3: Shares of shocks in output gap differential variance of euro area countries

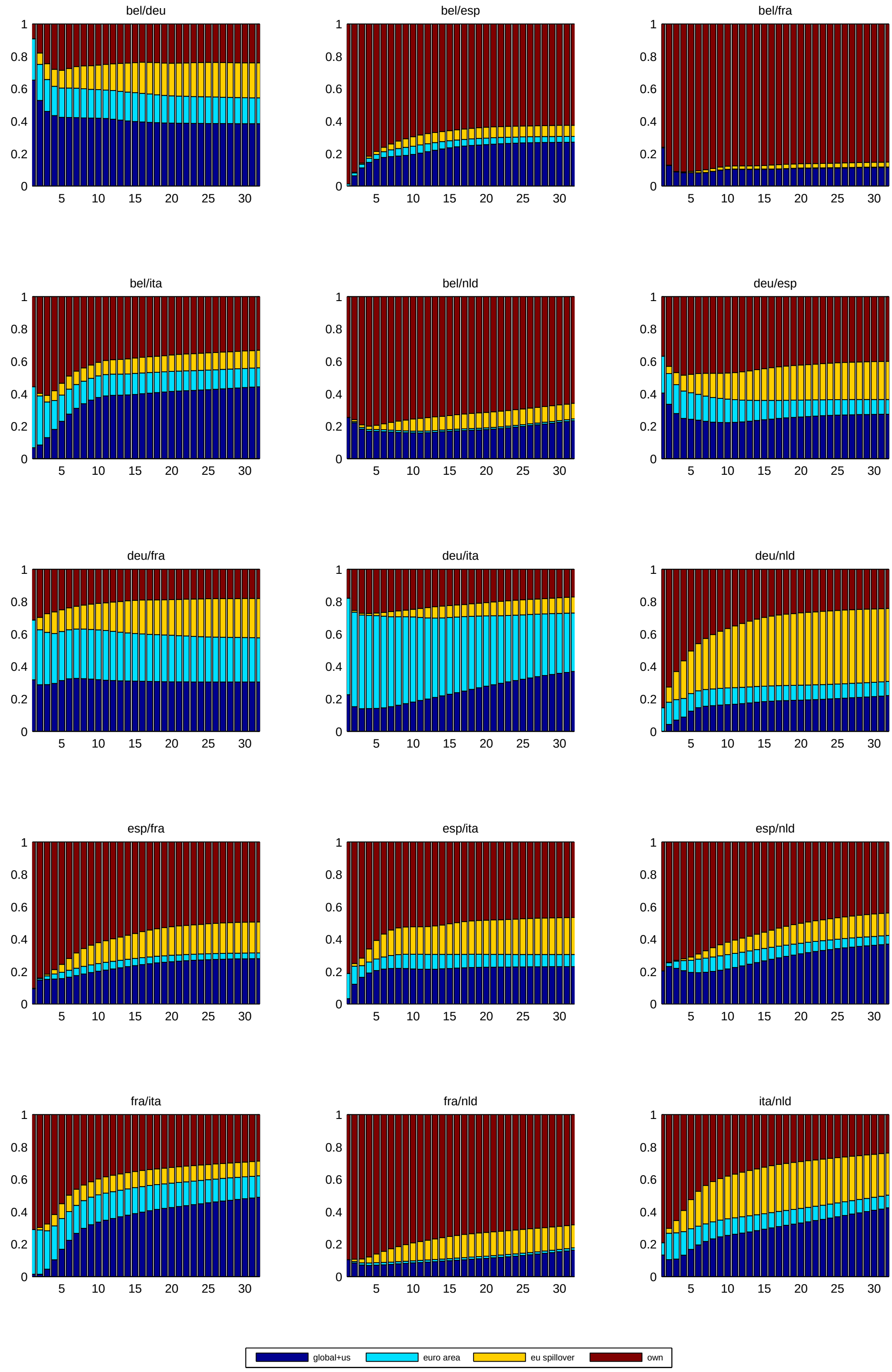
	Sample: 1970Q1–1990Q2				Sample: 1990Q3–2007Q4			
	global+us	eu	spillover	own	global+us	eu	spillover	own
bel/deu	0.36	0.11	0.08	0.44	0.06	0.09	0.35	0.51
	(0.11)	(0.08)	(0.06)	(0.13)	(0.10)	(0.07)	(0.12)	(0.12)
bel/esp	0.20	0.04	0.05	0.71	0.27	0.06	0.29	0.38
	(0.09)	(0.09)	(0.07)	(0.13)	(0.11)	(0.06)	(0.11)	(0.13)
bel/fra	0.11	0.00	0.01	0.87	0.18	0.06	0.25	0.50
	(0.08)	(0.11)	(0.05)	(0.13)	(0.11)	(0.06)	(0.11)	(0.13)
bel/ita	0.19	0.16	0.06	0.60	0.10	0.05	0.24	0.62
	(0.10)	(0.09)	(0.06)	(0.14)	(0.10)	(0.07)	(0.11)	(0.12)
bel/nld	0.18	0.01	0.03	0.77	0.11	0.03	0.33	0.53
	(0.08)	(0.10)	(0.05)	(0.12)	(0.09)	(0.07)	(0.12)	(0.11)
deu/esp	0.33	0.15	0.13	0.39	0.17	0.02	0.18	0.63
	(0.12)	(0.11)	(0.09)	(0.13)	(0.15)	(0.09)	(0.12)	(0.17)
deu/fra	0.29	0.25	0.19	0.28	0.13	0.08	0.28	0.51
	(0.13)	(0.11)	(0.10)	(0.12)	(0.12)	(0.09)	(0.13)	(0.15)
deu/ita	0.15	0.51	0.08	0.26	0.07	0.07	0.08	0.78
	(0.14)	(0.19)	(0.10)	(0.20)	(0.11)	(0.09)	(0.09)	(0.15)
deu/nld	0.20	0.07	0.29	0.44	0.04	0.11	0.23	0.62
	(0.09)	(0.08)	(0.09)	(0.13)	(0.09)	(0.11)	(0.13)	(0.14)
esp/fra	0.22	0.06	0.12	0.61	0.05	0.09	0.16	0.70
	(0.11)	(0.09)	(0.09)	(0.14)	(0.11)	(0.10)	(0.10)	(0.18)
esp/ita	0.23	0.16	0.16	0.45	0.01	0.04	0.11	0.84
	(0.10)	(0.09)	(0.09)	(0.12)	(0.11)	(0.09)	(0.10)	(0.15)
esp/nld	0.25	0.10	0.07	0.58	0.15	0.07	0.15	0.63
	(0.11)	(0.10)	(0.07)	(0.12)	(0.12)	(0.10)	(0.13)	(0.15)
fra/ita	0.17	0.22	0.15	0.45	0.02	0.01	0.17	0.80
	(0.11)	(0.11)	(0.11)	(0.16)	(0.10)	(0.07)	(0.10)	(0.14)
fra/nld	0.11	0.02	0.06	0.80	0.16	0.08	0.25	0.51
	(0.10)	(0.11)	(0.07)	(0.17)	(0.11)	(0.08)	(0.13)	(0.13)
ita/nld	0.23	0.18	0.21	0.38	0.07	0.07	0.05	0.81
	(0.10)	(0.12)	(0.10)	(0.12)	(0.11)	(0.07)	(0.09)	(0.15)

Notes: The output gap measure is the CF-filter. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.



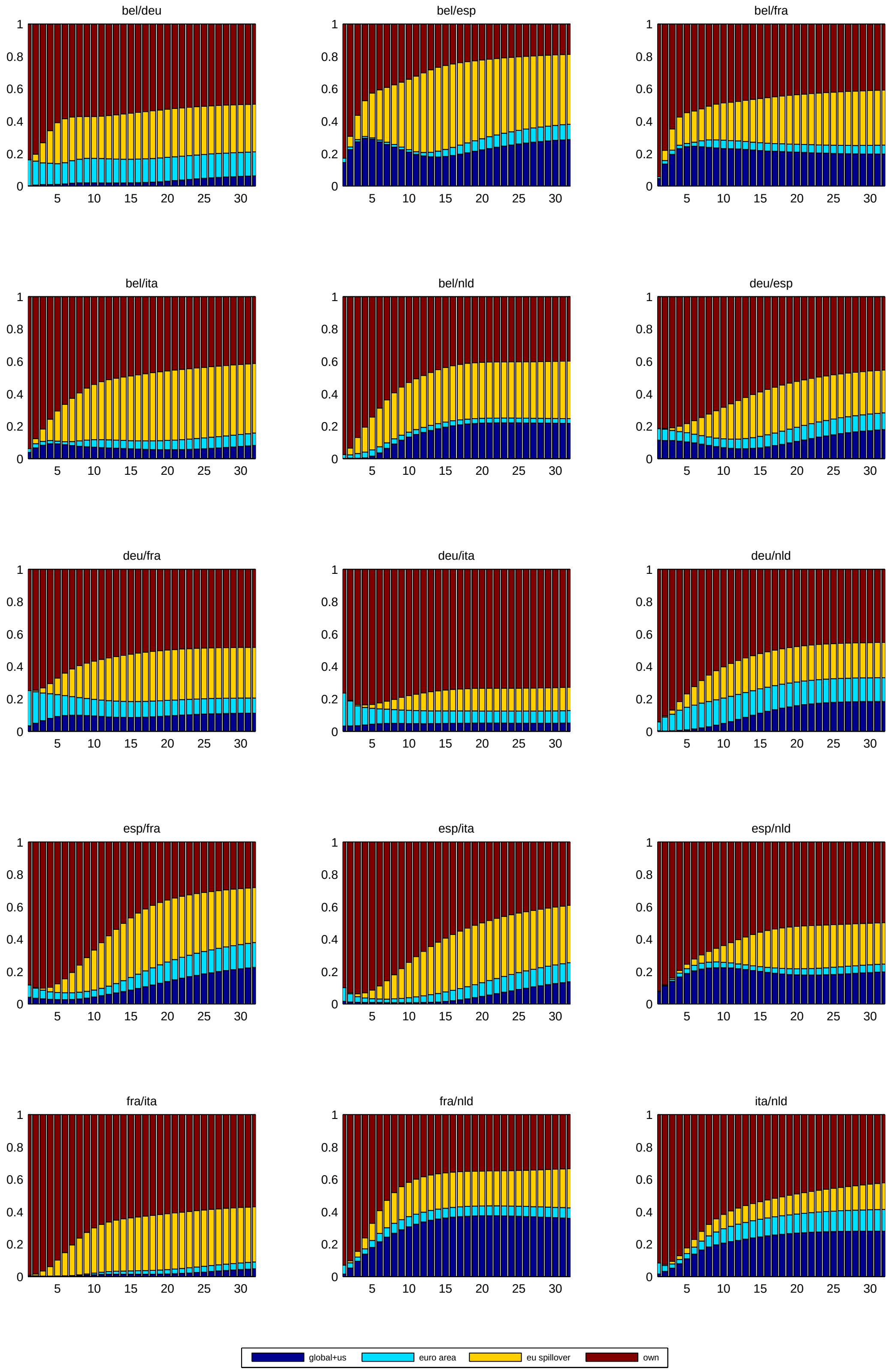
(a) Sample: 1970Q1–2007Q4

Figure 4.2: FEVD of output differentials



(b) Sample: 1970Q1–1990Q2

Figure 4.2: FEVD of output differentials (cont.)



(c) Sample:1990Q3–2007Q4

Figure 4.2: FEVD of output differentials (cont.)

Table 4.4: Standard deviation of shocks

	global	eu	us	bel	deu	esp	fra	ita	nld
1970Q1–2007Q4	0.82	0.80	0.20	0.30	0.65	0.55	0.32	0.54	0.89
	(0.10)	(0.11)	(0.19)	(0.02)	(0.11)	(0.05)	(0.03)	(0.06)	(0.07)
1970Q1–1990Q2	1.15	0.56	0.86	0.20	0.12	0.57	0.37	0.40	1.02
	(0.16)	(0.16)	(0.15)	(0.03)	(0.18)	(0.06)	(0.07)	(0.17)	(0.18)
1990Q3–2007Q4	0.40	0.51	0.09	0.26	0.37	0.26	0.24	0.37	0.38
	(0.05)	(0.06)	(0.10)	(0.05)	(0.07)	(0.08)	(0.03)	(0.04)	(0.05)
change	-0.75	-0.05	-0.77	0.06	0.26	-0.31	-0.14	-0.03	-0.64
	(0.17)	(0.17)	(0.18)	(0.05)	(0.19)	(0.10)	(0.07)	(0.17)	(0.19)

Notes: The fourth row shows the difference between the third and second rows. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

The Great Moderation

Size of shocks and shock transmission In Chapter 3, based on SVAR estimations, we saw that the size of shocks as well as the shock transmission underwent significant changes over time. Table 4.4 reports the standard deviation of estimated structural shocks of the FSVAR model. It is not surprising, given the different structures of the FSVAR model and the previous SVAR models, that the estimated sizes of shocks from both models as well as relative changes in the sizes of shocks from the first sub-period to the second differ. Looking at the full-sample and second sub-period estimates, we see that the size of the country-specific US shock is the lowest among the different sources of shocks considered and is highly imprecisely estimated. The decline in the size of the country-specific US shock seems implausibly high. Robustness checks show that this result is sensitive to the choice of the sample break date and does not occur in slightly different sub-sample periods. However, since our other conclusions are not affected by the choice of the break date, we stick to our benchmark break date of 1990Q2.

The SVAR models predicted a decline in the size of all shocks except the country-specific shock of Belgium. Moreover, the changes in the sizes of all shocks were statistically significant according to those estimates. The picture following from the FSVAR estimation is different. The standard deviation of Germany's country-specific shock, in addition to Belgium's country-specific shock, increases according to the FSVAR estimation. However, none of these increases are significant. Significant declines occur in the standard deviation of the global shock as well as the country-specific shocks of the US, Spain, France and the Netherlands, whereas the changes in the size of the common euro area shock and the country-specific shock of Italy are insignificant.

Changes also occur in the shock transmission from the first sub-period to the second according to the FSVAR model. As before with the SVAR estimations, every country has its own peculiar history of these changes, and it is hard to see patterns applying to most countries. Therefore, we skip reporting these impulse response graphs and turn our attention directly to the decomposition of changes in the output gaps and output forecast errors along the lines of Chapter 3.

Moderation of output fluctuations The decomposition of the change in output gap variance due to changes in the size of shocks and changes in shock transmission is reported in Table 4.5. Similar to the SVAR findings, the change in output gap variance, given in the upper left box, is negative in all member countries in terms of point estimates, but this change is not significant in any of the cases considered. The same is found also with respect to the contribution of change in the shock propagation (in the lower right box), the only exception to this rule being Belgium, and with respect to the total contribution from different shocks (in the upper right box), the contribution of own shocks in Belgium being an exception again. We have seen in Table 3.9 that the contribution of change in shock variance to output gap moderation was in total significant in all member countries except Belgium according to the SVAR model estimates. However, that finding cannot be verified by the FSVAR model, from which a significant contribution of this channel can be registered only for the Netherlands.

When we turn our attention to the change in the volatility of output forecast errors at the business cycle horizon, however, we obtain significant results for all member countries. This is reported in the upper left box of Table 4.6. In line with the previous SVAR estimates, FSVAR findings also suggest that the first channel—changes in the size of the shocks—is the main driving force behind the moderation of output fluctuations. Yet, differences exist across both models in terms of the contributions of individual shocks to the moderation. The SVAR estimates implied that changes in the sizes of *all* types of shocks contributed significantly to the moderation of output forecast errors, whereas the main contribution comes from the decline in the sizes of global and spillover shocks in most cases according to the FSVAR estimates (see the lower left box of Table 4.6). Similarly, both models generally attribute negative contributions of the second channel—changes in the transmission of shocks—to the moderation of output fluctuations. Yet, estimates of these contributions are rarely significant in the FSVAR case, whereas some significant results were obtained by the SVAR estimations, as a comparison of Tables 4.6 and 3.10 shows.

Table 4.5: Decomposition of change in output gap variance into change in size of shocks and change in propagation

	Variances			Total contribution from shocks			
	1970–1990	1991–2007	Change	global	eu	own	spillover
bel	1.79	0.72	-1.07	-0.17	0.20	-1.07	-0.03
	(0.90)	(0.29)	(0.94)	(0.22)	(0.24)	(0.37)	(0.61)
deu	0.97	0.88	-0.09	-0.30	0.28	0.32	-0.38
	(0.30)	(0.44)	(0.52)	(0.18)	(0.19)	(0.31)	(0.17)
esp	1.58	0.83	-0.75	0.02	0.13	-0.36	-0.54
	(0.72)	(0.44)	(0.82)	(0.17)	(0.21)	(0.55)	(0.35)
fra	0.65	0.58	-0.07	-0.13	0.15	-0.09	0.01
	(0.26)	(0.27)	(0.37)	(0.10)	(0.13)	(0.23)	(0.14)
ita	1.58	0.73	-0.85	-0.33	-0.18	0.27	-0.62
	(0.52)	(0.32)	(0.60)	(0.18)	(0.19)	(0.43)	(0.23)
nld	1.26	0.66	-0.60	-0.16	0.18	-0.42	-0.20
	(0.38)	(0.34)	(0.47)	(0.15)	(0.17)	(0.31)	(0.22)

	Contribution of change in shock variance					Contribution of change in shock propagation				
	global	eu	own	spillover	total	global	eu	own	spillover	total
bel	-0.23	-0.02	0.42	-0.71	-0.54	0.06	0.22	-1.49	0.68	-0.53
	(0.25)	(0.19)	(0.39)	(0.36)	(0.65)	(0.30)	(0.33)	(0.54)	(0.77)	(1.21)
deu	-0.41	-0.04	0.17	-0.40	-0.68	0.10	0.32	0.15	0.02	0.60
	(0.36)	(0.22)	(0.45)	(0.15)	(0.73)	(0.42)	(0.32)	(0.62)	(0.20)	(1.11)
esp	-0.17	-0.04	-0.76	-0.50	-1.46	0.19	0.16	0.40	-0.04	0.71
	(0.33)	(0.22)	(0.51)	(0.37)	(0.93)	(0.42)	(0.32)	(0.77)	(0.44)	(1.35)
fra	-0.11	-0.02	-0.19	-0.50	-0.82	-0.02	0.17	0.10	0.50	0.75
	(0.18)	(0.15)	(0.35)	(0.11)	(0.50)	(0.21)	(0.21)	(0.48)	(0.14)	(0.73)
ita	-0.31	-0.03	-0.05	-0.49	-0.89	-0.01	-0.14	0.32	-0.13	0.04
	(0.22)	(0.16)	(0.41)	(0.25)	(0.59)	(0.24)	(0.24)	(0.64)	(0.23)	(0.91)
nld	-0.51	-0.02	-0.91	-0.62	-2.07	0.35	0.20	0.50	0.42	1.47
	(0.29)	(0.18)	(0.37)	(0.41)	(0.81)	(0.35)	(0.18)	(0.54)	(0.40)	(1.08)

Notes: Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

Table 4.6: Decomposition of change in output forecast error variance into change in size of shocks and change in propagation

	Variances			Total contribution from shocks			
	1970–1990	1991–2007	Change	global	eu	own	spillover
bel	5.99	2.17	-3.82	-0.92	0.34	-1.21	-2.02
	(0.78)	(0.31)	(1.79)	(0.70)	(0.33)	(1.26)	(0.50)
deu	7.88	2.00	-5.88	-2.72	0.16	0.46	-3.78
	(1.16)	(0.44)	(2.33)	(1.21)	(0.43)	(1.58)	(0.32)
esp	15.27	3.47	-11.80	-0.00	-0.10	-4.36	-7.33
	(1.82)	(0.41)	(4.38)	(1.24)	(0.81)	(3.21)	(1.24)
fra	5.78	1.71	-4.07	-1.57	0.22	-0.63	-2.10
	(0.79)	(0.18)	(1.77)	(0.80)	(0.34)	(1.23)	(0.45)
ita	9.97	1.82	-8.15	-3.08	-0.31	0.52	-5.28
	(1.24)	(0.34)	(2.75)	(1.38)	(0.40)	(1.96)	(0.38)
nld	6.99	3.63	-3.36	-0.20	0.43	-0.41	-3.19
	(0.74)	(0.53)	(1.85)	(0.83)	(0.42)	(1.38)	(0.44)

	Contribution of change in shock variance					Contribution of change in shock propagation				
	global	eu	own	spillover	total	global	eu	own	spillover	total
bel	-2.18	-0.04	0.49	-4.90	-6.63	1.26	0.37	-1.70	2.87	2.81
	(0.59)	(0.29)	(1.14)	(0.32)	(1.47)	(0.73)	(0.43)	(1.49)	(0.61)	(2.13)
deu	-3.43	-0.08	0.37	-3.82	-6.96	0.71	0.24	0.09	0.04	1.09
	(1.04)	(0.31)	(1.30)	(0.33)	(1.96)	(1.22)	(0.42)	(1.71)	(0.22)	(2.71)
esp	-1.33	-0.08	-3.49	-6.56	-11.47	1.33	-0.01	-0.87	-0.77	-0.33
	(0.93)	(0.45)	(1.87)	(0.82)	(2.49)	(1.25)	(0.79)	(2.99)	(0.90)	(3.96)
fra	-1.42	-0.03	-0.53	-3.46	-5.43	-0.15	0.25	-0.10	1.36	1.36
	(0.49)	(0.24)	(0.78)	(0.23)	(1.09)	(0.64)	(0.37)	(1.15)	(0.33)	(1.61)
ita	-2.62	-0.05	-0.10	-4.18	-6.95	-0.46	-0.26	0.62	-1.10	-1.20
	(0.84)	(0.23)	(1.12)	(0.42)	(1.62)	(1.05)	(0.38)	(1.68)	(0.33)	(2.48)
nld	-5.39	-0.05	-3.30	-5.99	-14.72	5.19	0.48	2.89	2.80	11.36
	(1.53)	(0.41)	(1.66)	(0.98)	(2.83)	(1.88)	(0.51)	(2.08)	(1.00)	(3.64)

Notes: Change in the variance of 12-quarters-ahead forecast error is reported. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

Moderation of output (gap) differentials The change in the variances of bilateral output gap differentials is not found to be significant in any of the cases considered. The same applies also to the decomposition of changes in output gap differential variances: the results corresponding to both channels are very often statistically insignificant. Therefore, we do not document here these statistics and report only statistics corresponding to the change in bilateral output differential forecast error variance in Table 4.7. Indeed, half of the changes in bilateral output differential forecast error variance, reported in the upper left box of Table 4.7, are also insignificant. Yet, the point estimates of most of them are negative. Changes in the size of shocks deliver an important contribution to the moderation of output differential forecast errors. The contribution of this channel is statistically significant in 11 of the 15 cases. The contribution of the other channel—changes in shock propagation—to the moderation of output differential forecast errors is very often statistically insignificant. Hence, the first channel generally seems to be behind the moderation of these forecast errors according to the FSVAR estimates. This is in accordance with the previous findings based on the country-specific SVAR models of Chapter 3.

Table 4.7: Decomposition of change in output differential forecast error variance

	Variances			Total contribution from shocks			
	1970–1990	1991–2007	Change	global	eu	own	spillover
bel/deu	2.74	1.49	-1.25	-0.68	-0.26	0.17	-0.47
	(0.54)	(0.34)	(0.87)	(0.28)	(0.29)	(0.43)	(0.45)
bel/esp	8.13	0.96	-7.16	-0.41	-0.38	-5.21	-1.17
	(1.52)	(0.15)	(2.38)	(0.57)	(0.52)	(1.14)	(1.40)
bel/fra	1.86	0.60	-1.26	-0.00	0.03	-1.34	0.06
	(0.51)	(0.14)	(0.66)	(0.13)	(0.17)	(0.21)	(0.52)
bel/ita	2.68	1.70	-0.98	-0.42	-0.27	-0.17	-0.12
	(0.48)	(0.34)	(0.80)	(0.24)	(0.25)	(0.41)	(0.45)
bel/nld	3.84	1.79	-2.05	-0.22	0.01	-2.00	0.16
	(0.81)	(0.34)	(1.19)	(0.35)	(0.35)	(0.50)	(0.77)
deu/esp	11.71	3.14	-8.57	-1.70	-1.39	-3.43	-2.06
	(1.91)	(0.73)	(3.34)	(0.98)	(0.99)	(1.85)	(1.42)
deu/fra	1.68	1.90	0.21	-0.15	-0.32	0.70	-0.01
	(0.32)	(0.48)	(0.77)	(0.25)	(0.25)	(0.44)	(0.40)
deu/ita	2.29	2.46	0.16	-0.18	-0.95	1.33	-0.04
	(0.46)	(0.67)	(1.01)	(0.36)	(0.52)	(0.41)	(0.68)
deu/nld	3.62	2.70	-0.92	-0.29	0.05	0.31	-0.99
	(0.61)	(0.56)	(1.24)	(0.39)	(0.38)	(0.71)	(0.52)
esp/fra	8.28	0.60	-7.68	-0.72	-0.36	-4.60	-1.99
	(1.37)	(0.10)	(2.37)	(0.57)	(0.58)	(1.28)	(1.09)
esp/ita	10.07	2.39	-7.69	-1.91	-0.83	-3.65	-1.30
	(1.67)	(0.40)	(2.83)	(0.88)	(0.76)	(1.45)	(1.22)
esp/nld	6.58	2.17	-4.41	-0.31	-0.49	-2.60	-1.01
	(1.02)	(0.46)	(1.65)	(0.47)	(0.49)	(0.86)	(0.91)
fra/ita	1.96	1.40	-0.57	-0.32	-0.30	0.19	-0.14
	(0.32)	(0.27)	(0.58)	(0.21)	(0.23)	(0.34)	(0.33)
fra/nld	3.15	1.74	-1.41	0.31	0.06	-1.77	-0.02
	(0.56)	(0.36)	(0.95)	(0.35)	(0.34)	(0.52)	(0.55)
ita/nld	4.51	1.88	-2.63	-0.61	-0.27	-0.52	-1.23
	(0.73)	(0.41)	(1.08)	(0.51)	(0.37)	(0.61)	(0.46)

Notes: Change in the variance of 12-quarters-ahead forecast error is reported. Approximate standard errors, shown in parentheses, are computed by Monte Carlo simulation. See Table 2.1 for abbreviations.

Table 4.7: Decomposition of change in output differential forecast error variance (cont.)

	Contribution of change in shock variance					Contribution of change in shock propagation				
	global	eu	own	spillover	total	global	eu	own	spillover	total
bel/deu	-0.39	-0.06	0.65	-1.03	-0.84	-0.29	-0.20	-0.48	0.56	-0.41
	(0.48)	(0.16)	(0.44)	(0.31)	(0.80)	(0.59)	(0.32)	(0.62)	(0.46)	(1.32)
bel/esp	-0.87	-0.04	-0.89	-1.24	-3.05	0.46	-0.34	-4.31	0.08	-4.12
	(0.37)	(0.19)	(0.62)	(0.54)	(1.07)	(0.50)	(0.41)	(0.82)	(1.27)	(1.95)
bel/fra	-0.51	-0.00	0.10	-0.62	-1.03	0.51	0.03	-1.44	0.67	-0.23
	(0.21)	(0.09)	(0.26)	(0.28)	(0.49)	(0.25)	(0.18)	(0.33)	(0.52)	(0.80)
bel/ita	-0.58	-0.04	0.17	-1.84	-2.29	0.16	-0.23	-0.35	1.73	1.31
	(0.48)	(0.19)	(0.78)	(0.37)	(1.09)	(0.58)	(0.32)	(1.01)	(0.43)	(1.53)
bel/nld	-1.23	-0.01	-2.44	-1.25	-4.93	1.01	0.02	0.44	1.41	2.88
	(0.75)	(0.22)	(0.61)	(0.92)	(1.66)	(0.87)	(0.33)	(0.86)	(1.09)	(2.26)
deu/esp	-1.50	-0.15	-2.19	-1.17	-5.01	-0.19	-1.24	-1.24	-0.89	-3.56
	(1.06)	(0.35)	(1.29)	(0.97)	(2.20)	(1.38)	(0.79)	(2.02)	(1.23)	(3.52)
deu/fra	-0.74	-0.06	0.33	-0.68	-1.16	0.59	-0.26	0.37	0.67	1.37
	(0.60)	(0.14)	(0.76)	(0.34)	(1.13)	(0.76)	(0.30)	(1.03)	(0.38)	(1.64)
deu/ita	-0.53	-0.12	0.16	-0.89	-1.37	0.35	-0.83	1.17	0.85	1.54
	(0.70)	(0.27)	(1.16)	(0.72)	(1.70)	(0.92)	(0.57)	(1.43)	(0.65)	(2.40)
deu/nld	-0.87	-0.07	-2.30	-1.32	-4.56	0.58	0.12	2.61	0.32	3.64
	(0.61)	(0.28)	(0.78)	(0.91)	(1.71)	(0.77)	(0.50)	(1.12)	(1.12)	(2.41)
esp/fra	-0.44	-0.04	-2.38	-0.51	-3.36	-0.28	-0.33	-2.23	-1.49	-4.32
	(0.29)	(0.19)	(0.49)	(0.52)	(0.88)	(0.41)	(0.44)	(1.04)	(0.66)	(1.75)
esp/ita	-0.89	-0.09	-3.39	-0.18	-4.54	-1.02	-0.74	-0.26	-1.12	-3.14
	(0.71)	(0.35)	(0.89)	(0.96)	(1.64)	(0.90)	(0.65)	(1.48)	(0.99)	(2.68)
esp/nld	-2.00	-0.05	-4.61	-0.35	-7.02	1.69	-0.44	2.01	-0.66	2.60
	(1.01)	(0.29)	(0.54)	(1.28)	(2.03)	(1.21)	(0.45)	(0.86)	(1.39)	(2.59)
fra/ita	-0.22	-0.03	-0.30	-0.64	-1.18	-0.10	-0.27	0.49	0.50	0.61
	(0.35)	(0.15)	(0.48)	(0.35)	(0.77)	(0.44)	(0.27)	(0.68)	(0.30)	(1.10)
fra/nld	-2.13	-0.01	-2.49	-1.53	-6.17	2.45	0.08	0.72	1.51	4.76
	(0.71)	(0.19)	(0.64)	(0.74)	(1.52)	(0.89)	(0.32)	(0.97)	(0.72)	(2.05)
ita/nld	-1.84	-0.06	-1.76	-1.55	-5.20	1.24	-0.21	1.24	0.31	2.58
	(0.56)	(0.25)	(0.68)	(0.60)	(1.28)	(0.70)	(0.37)	(0.94)	(0.60)	(1.76)

4.1.2 Results from rolling regressions

Size of shocks

As a robustness check of the previous results from the two sub-samples and in order to capture the variations in business cycle dynamics over time, we also generated results from rolling regressions as in the previous chapter. We illustrate the standard deviation of structural shocks in Figure 4.3. A recent decline in the size of country-specific shocks is less evident than in the SVAR case, while the sizes of the global and common euro area shocks decrease (roughly) gradually from the beginning of the sample onwards. An important reason for our former assessment is that the patterns of evolution we observe in Figure 4.3 are much more erratic than what we observed before in Figure 4.6 based on the SVAR model. The FSVAR rolling window estimates are obviously much more sensitive to minor changes in the data set than the SVAR estimates are. This is probably due to the fact that we are estimating more coefficients and parameters in the FSVAR model, for which an estimation window of 60 quarters is too short. The pattern of change in the size of shocks over time differs from shock to shock and a declining trend is a bit more obvious for shocks of the US, Spain, Italy and the Netherlands than the shocks of Belgium, Germany and France.

Forecast error variance decomposition of output

Erratic behaviour is also observed with respect to the propagation of shocks across countries, which we do not display here. This finding points to a high sensitivity of FSVAR estimations: adding or discarding one observation often leads to jumps in the estimates, which was much less the case for the SVAR model. In some rolling windows, estimates corresponding to output gaps are particularly sensitive, their variance being implausibly high. The technical reason for this is that we use 60 moving-average coefficients when employing the formula in (1.34) that describes the process governing the motion of filtered data. Thus, there are 121 coefficients governing the motion of each one of k (the number of shocks) sub-components of

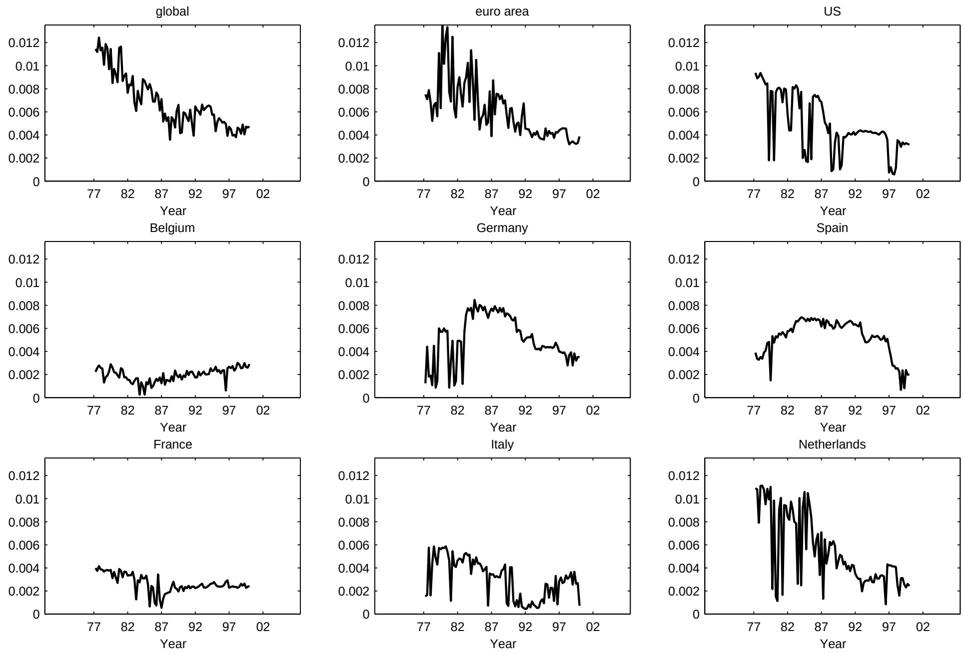


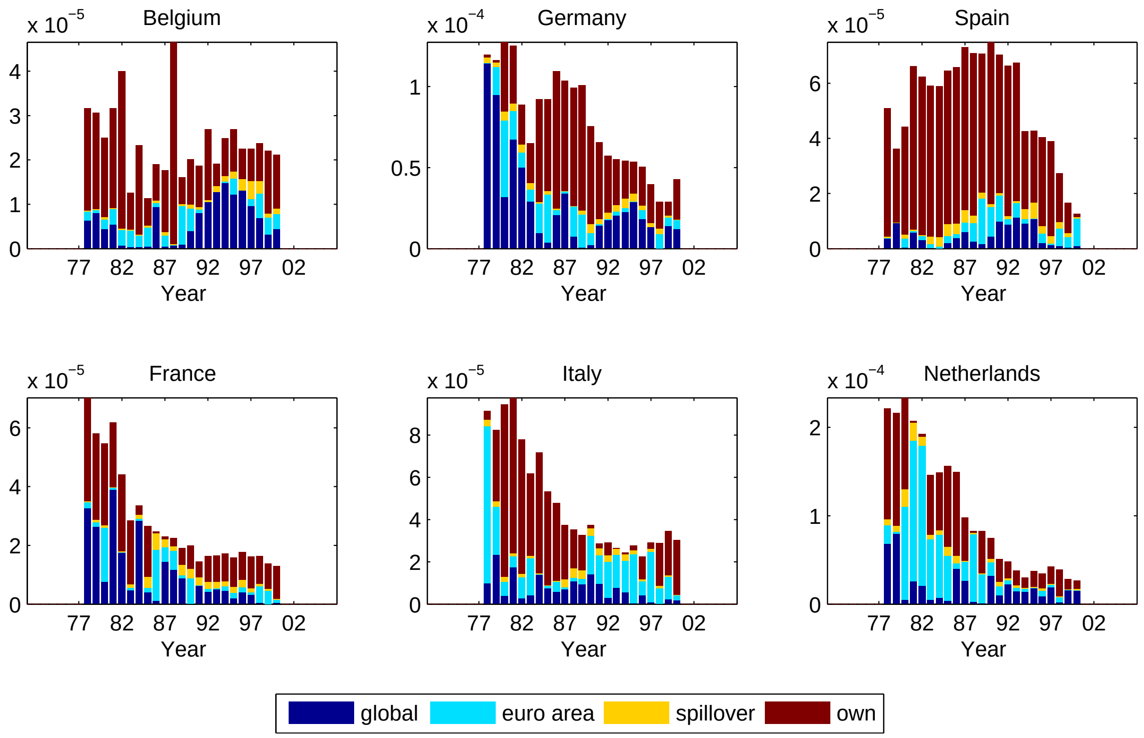
Figure 4.3: Standard deviation of shocks over 15-year rolling windows

$Y^c_{j,t}$ (the filtered variable) in that equation. Computing the variance of each sub-component of $Y^c_{j,t}$ requires summing up the squares of these 121 quadratic terms multiplied by the variance of the corresponding shock. When the coefficients have large variances due to estimation uncertainty resulting from short samples, large terms may result from the formula of the corresponding variance. The same applies to the forecast error variances at longer horizons as well, since these are the sum of many quadratic terms.

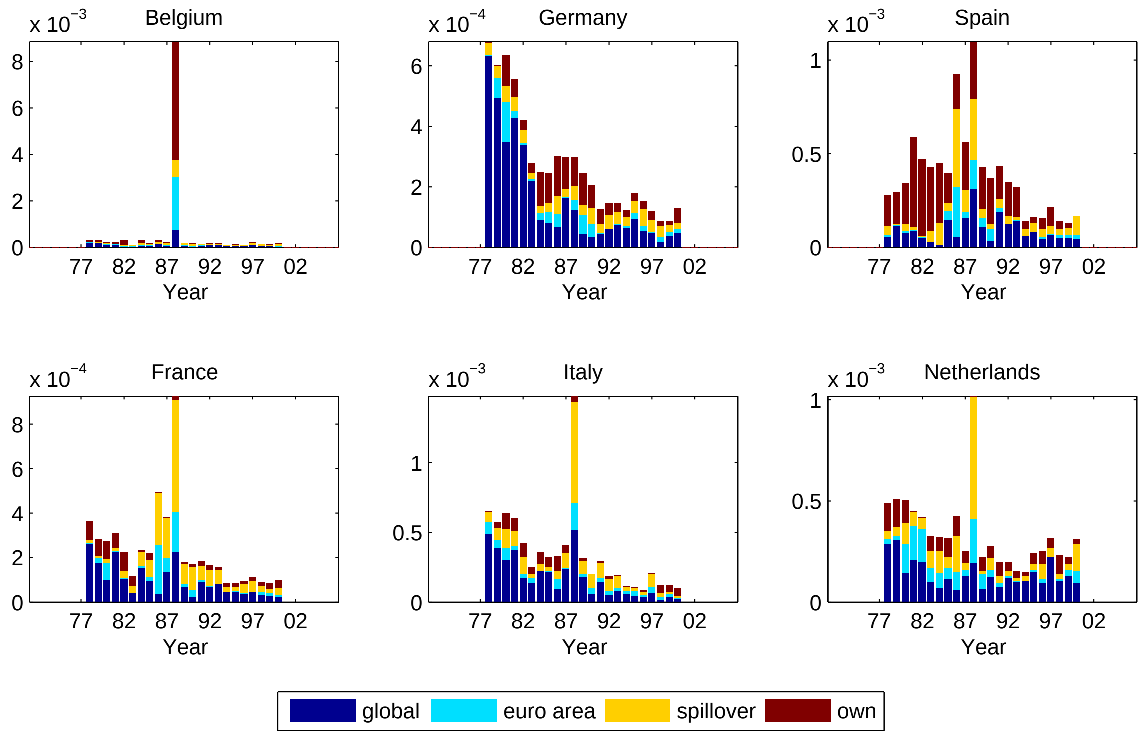
In order to give the reader an idea about the dimensions of this problem, we show the absolute forecast error variance of output of the member countries for forecast horizons of 2, 8 and 12 quarters in Figure 4.4. The reported forecast error variances come from the rolling window estimates, centers of which are the first quarters of each calendar year included in our sample. While the evolution of the forecast errors for a horizon of 2 quarters over the estimation windows shows no erratic behaviour in Figure 4.4(a), an outlier pops up corresponding to the estimation window with the center at the first quarter of 1988 in all member countries except Germany, when forecast error variances are computed for a forecast horizon of 8 quarters, as displayed in Figure 4.4(b). The outlier becomes much more distinguishable when the forecast horizon is increased to 12 quarters, see Figure 4.4(c). In Figure 4.4(d), we discard the outlier corresponding to the estimation window with the center in the first quarter of 1988 and receive a different picture for the forecast error variance evolution for a horizon of 12 quarters. It is now possible to deduce a reduction in the variance of 12-quarters-ahead output forecast errors in all member countries, although other outliers still exist for Spain, France and the Netherlands in Figure 4.4(d). Note that we are not reporting all rolling window estimation results in Figure 4.4. There are indeed other estimation windows for which we observe erratic behavior as well.

As mentioned above, the reason behind these highly sensitive results is the shortness of the rolling windows. The sensitivity becomes smaller when longer estimation windows are used, but it may exist even for rolling windows of 25 years, i.e., 100 quarters of data. Therefore, we do not report further inaccurate and sensitive findings from 15-year rolling window estimations. Note that an option could be to estimate in longer windows of, say, 25 years, but using such long rolling windows would not allow us to see changes that occurred after 1990Q2.

We conclude that the FSVAR methodology gives us interesting insights with respect to the questions we posed at the beginning of Chapter 3, particularly by letting us take account of spillovers of country-specific shocks in addition to common shocks. However, it should not be forgotten that the estimates based on the FSVAR model are associated with a higher parameter uncertainty than the SVAR model of the previous section. Yet, we think it is useful, as we did in the previous and the current chapters up to this point, to estimate both types of models to address our subjects of interest.

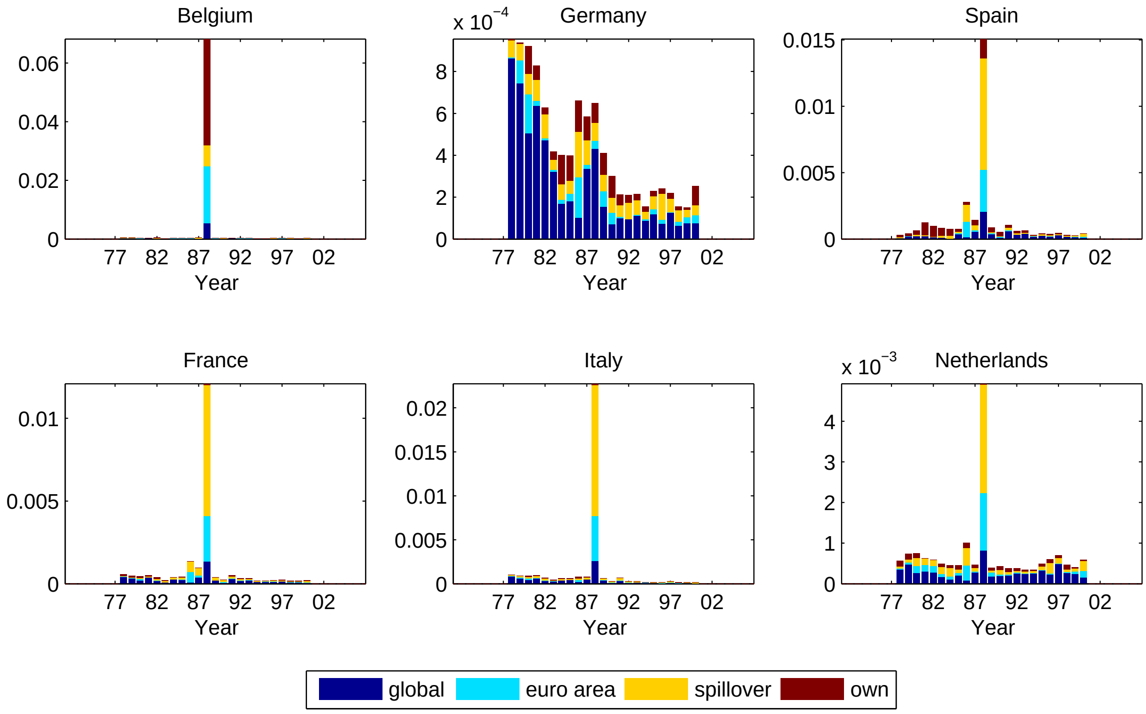


(a) Forecast error variance of output for $h = 2$

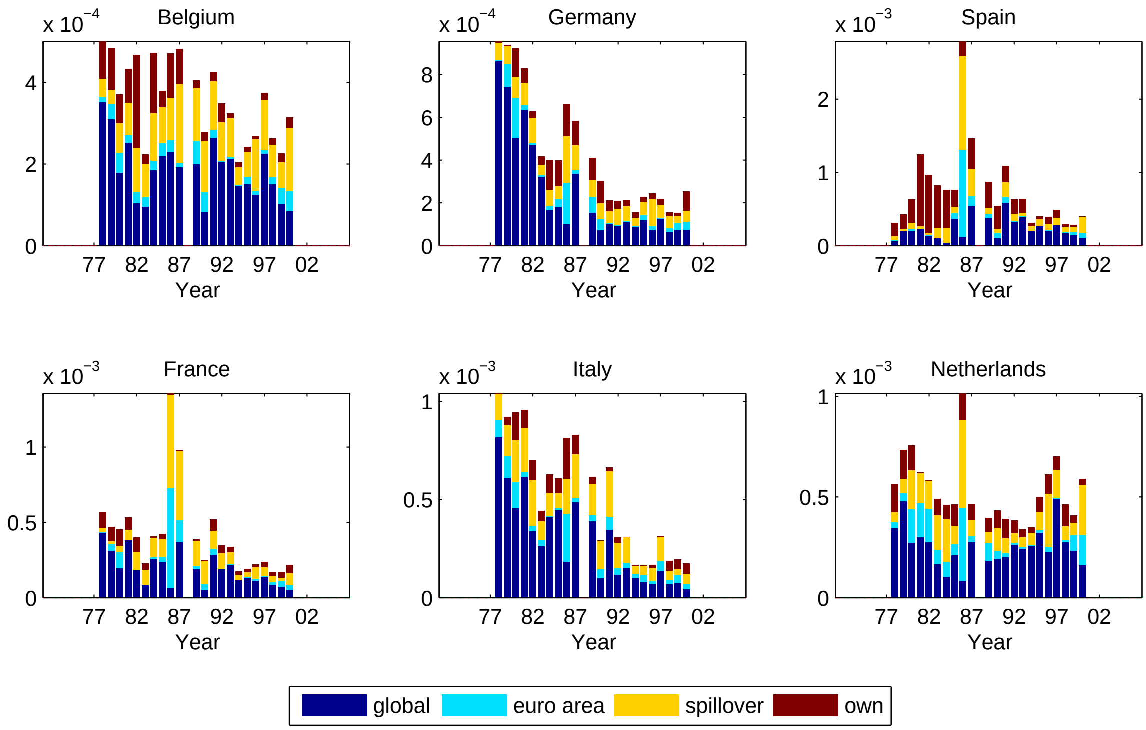


(b) Forecast error variance of output for $h = 8$

Figure 4.4: Forecast error variance of output



(c) Forecast error variance of output for $h = 12$



(d) Forecast error variance of output for $h = 12$, where the outlier is removed

Figure 4.4: Forecast error variance of output (cont.)

4.2 The time-varying coefficients SVAR model

Our sub-sample estimations in this and the previous chapters assumed a break in the data in 1990Q2, the quarter after which the first stage of the EMU process has been started. However, other plausible break dates also exist as we argued in Chapter 3. While our sub-sample conclusions generally do not change much when other plausible single break dates are employed, we also estimated both SVAR and FSVAR models over 15-year rolling windows in order to present to the reader an alternative perspective on the validity of our conclusions based on sub-sample estimates with a single break in the data in 1990Q2. In this section, we apply a more flexible approach to deal with possible breaks in the data, where the coefficients of the VAR and the parameters of the covariance matrix of shocks are assumed to be time-varying. Hence, breaks in data are naturally included in the empirical framework.

4.2.1 The model

The model we work with is borrowed from a recently developed literature in Primiceri (2005), Benati and Mumtaz (2007) and Gali and Gambetti (2009) among others. It is a (modified) time-varying coefficients (TVC) version of the trivariate model that we considered in Chapter 3.

Recall that we had estimated the SVARs of the previous chapter in levels in order to be robust with respect to unit root and cointegration issues. It is, however, not possible to estimate our TVC models in levels with our nonstationary data, since the Bayesian techniques with which we carry out our TVC estimations require the variables of the estimated model to be stationary. The Markov-Chain Monte Carlo algorithm used for the TVC-model estimation rejects each unstable draw of the VAR coefficients and repeats the corresponding draw in order to enforce the stationarity of the VAR. In case unstable draws occur very often, as happens when we estimate our VAR model in levels, the algorithm breaks down. One option to deal with this problem is to estimate the VAR in first-differences, as is done, e.g., by Stock and Watson (2005) and Perez, Osborn, and Artis (2006). Such an estimation is problematic, however, when the variables of the VAR are cointegrated, as mentioned in Chapter 3. The latter issue may be relevant in our context, since Johansen cointegration tests, the results of which were reported in Table 3.1 before, often point to a rank of one for our trivariate models. Therefore, we estimate a TVC-SVECM in this section, the reduced form of which is given by

$$\Delta Y_t = \mu_t + \alpha_t \beta' Y_{t-1} + D_{t,1}\Delta Y_{t-1} + \cdots + D_{t,p-1}\Delta Y_{t-p+1} + u_t, \tag{4.3}$$

where ΔY_t is, as before, a 3×1 vector containing the first-differenced log-output of the US, the euro area and the member country i for $i = bel, deu, esp, fra, ita, nld$ at period t, μ_t is a 3×1 vector of constant terms at period t, β' is the matrix containing the cointegrating vectors, α_t is the loading of the cointegrating vectors at period t, $D_{t,j}$ for $j = 1, \ldots, p-1$ are 3×3 coefficient matrices at period t, and u_t is a 3×1 vector of error terms with the time-varying covariance matrix Σ_{u_t}. Note that we assume the loadings of the cointegrating vectors to be time-varying in (4.3), whereas the cointegrating vectors are fixed. In our empirical approach, we first compute the error correction terms, $\beta' Y_{t-1}$, which follow stationary processes and use them as an input in the estimation of (4.3). Given the cointegration test results in Table 3.1, we assume a cointegration rank of one for each country-specific model and estimate the cointegrating vector using the dynamic OLS technique of Stock and Watson (1989). In case no-cointegration specification is suitable for a country-specific model, the loading vector α_t should contain values close to zero.

Gali and Gambetti (2009) collect the model coefficients in a vector by defining $\theta_t = vec\,(D_t)$, where $D_t = [\mu_t, \alpha_t, D_{t,1}, \ldots, D_{t,p-1}]$, and assume that θ_t follows the process

$$\theta_t = \theta_{t-1} + \omega_t, \tag{4.4}$$

with ω_t being "a Gaussian white noise process with zero mean and constant covariance Ω, and independent of u_t at all leads and lags". Σ_{u_t} is also redefined as $\Sigma_{u_t} \equiv F_t G_t F_t'$, F_t being a lower triangular matrix with ones on its main diagonal, and G_t is a diagonal matrix. The below-the-diagonal elements of F_t^{-1} are then collected in the vector γ_t, and another vector, σ_t, contains the diagonal elements of G_t. γ_t and σ_t evolve over time according to

$$\gamma_t = \gamma_{t-1} + \zeta_t \tag{4.5}$$

and

$$\log \sigma_t = \log \sigma_{t-1} + \xi_t, \tag{4.6}$$

where ζ_t and ξ_t are zero-mean Gaussian processes with constant covariance matrices. The covariance matrix of ζ_t is assumed to be block-diagonal, implying that covariances between coefficients of different equations are zero, and the covariance matrix of ξ_t is assumed to be diagonal.

We estimate the coefficients in (4.4) , (4.5) and (4.6) along the lines of Gali and Gambetti (2009) by using Bayesian techniques.[3] Then, the covariance matrix and dynamic multipliers of global, euro area and country-specific shocks are estimated for each period similar to the trivariate models of Chapter 3. Formally, the structural form of (4.3) is given by

$$\Delta Y_t = \mu_t + \alpha_t \beta' Y_{t-1} + D_{t,1} \Delta Y_{t-1} + \cdots + D_{t,p-1} \Delta Y_{t-p+1} + B_t \varepsilon_t, \tag{4.7}$$

where ε_t is the 3×1 vector containing orthogonal global, euro area and country-specific shocks at period t. B_t determines the impact effects of the shocks at period t and is modelled in the same way as Θ_0 in (3.6) of Chapter 3 so that

$$B_t = \begin{bmatrix} B_{11,t} & 0 & 0 \\ B_{21,t} & B_{22,t} & p_i B_{33,t} \\ B_{31,t} & B_{32,t} & B_{33,t} \end{bmatrix}, \tag{4.8}$$

where p_i stands for the population share of country i in the euro area. We transform the SVECM in (4.7) to the level representation for each period using the formula as described in Chapter 1 and compute the output gap sub-components using the formula in (1.34). It is then straightforward to compute variances and variance decompositions for each period as before in Chapter 3.

[3] See also the appendix in Primiceri (2005) on the estimation of such a model.

4.2.2 Results

To calibrate the prior densities of the coefficients, we estimate a VAR with fixed coefficients using the data of the first eight years in the sample. Therefore, estimates of time-varying statistics are given from 1978Q1 onwards in the following. As in the case of rolling window estimations, we first report the evolution of the size of shocks, which is followed by variance decompositions of output gaps and output gap differentials.

Size of shocks

The evolution of the standard deviation of global, euro area and country-specific shocks is displayed in Figure 4.5. Note that, as in Chapter 3, six different estimates of global and euro area shocks exist, which stem from the six different country-specific trivariate models. It can be seen in Figure 4.5 that the fit of the standard deviation estimates of global shocks is very good. The standard deviation estimates of euro area shocks of all member countries except Germany also show a good fit. The evolution of the estimates stemming from the country-specific model including the German output is quite different from the others. Note that we have established this type of a discrepancy between Germany's country-specific model and the others with the fixed-coefficient SVAR model of Chapter 3 as well (cf. Table 3.8 and Figure 4.6).

The standard deviations of country-specific shocks evolve differently across the member countries according to our TVC-SVAR estimates. The standard deviation of the own shocks of Belgium is generally found to be much higher in recent periods after increasing steadily during the 1990s. Albeit the evolution pattern of the Belgian shock differs from what we obtained before conducting rolling window estimations of the fixed-coefficient SVAR and FSVAR models (cf. Figure 4.6 and Figure 4.3), the TVC-SVAR finding is generally in accordance with what we found before for this country. The evolution of the Spanish shock's standard deviation is also roughly in line with the previous findings: we see an increase in the size of the shock towards the middle of the full sample period, which than gradually

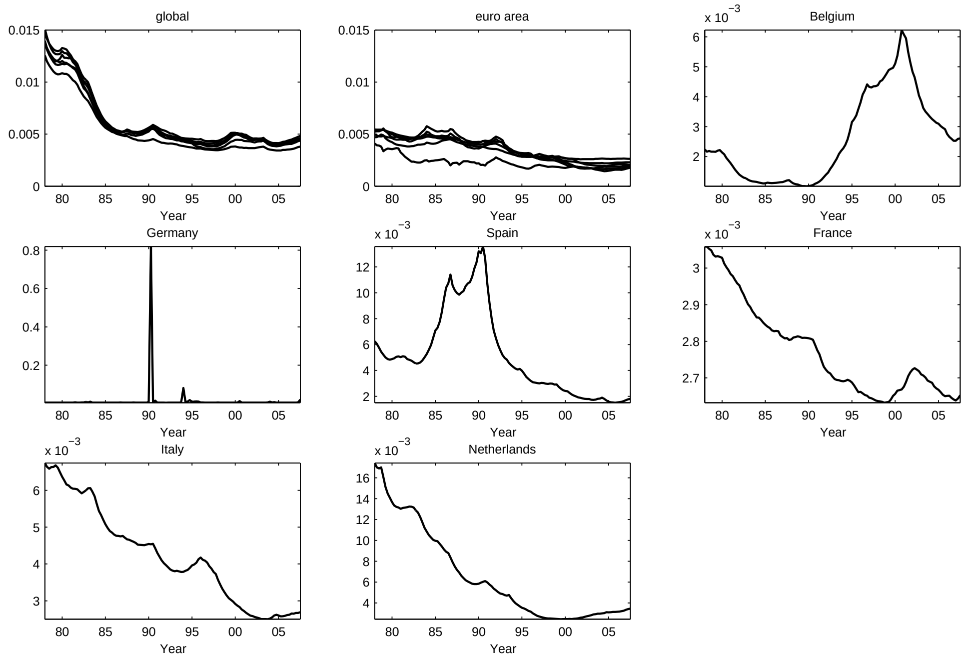


Figure 4.5: Standard deviation of shocks

tapers off and declines recently to levels lower than what we observe at the beginning of the sample period. While the gradual decline observed for the standard deviations of the country-specific shocks of Italy and the Netherlands is also in line with our previous findings based on the fixed-coefficient SVAR and FSVAR models, the standard deviation estimate of the German shocks shows two spikes around 1990-1991 and 1994, which the SVAR and FSVAR model estimates did not show. Finally, the standard deviation of the French shock shows a steady decline since the 1980s, a pattern that had not been observed when estimating with the previous models.

Variance decompositions of output

In the TVC-SVAR context, we compute the process governing the motion of the output gap using a TVC version of the process in Equation (3.7) of Chapter 3, which is given by

$$\tilde{y}_{j,t} \approx \sum_{m=-\kappa}^{\kappa} \Psi_{j,US,m,t}\varepsilon_{US,t+m} + \sum_{m=-\kappa}^{\kappa} \Psi_{j,EA,m,t}\varepsilon_{EA,t+m} \sum_{m=-\kappa}^{\kappa} \Psi_{j,i,m,t}\varepsilon_{i,t+m}, \tag{4.9}$$

where $\Psi_{jk,m,t}$ for $k = US, EA, i$ stand for coefficients of the output gap process of country-j output for $j = US, EA, i$, with respect to structural shocks, and $\varepsilon_{k,t+m}$ for $k = US, EA, i$ stand for shocks at period $t + m$. The only difference between (4.9) and (3.7) is that $\Psi_{jk,m,t}$ are now time-varying and therefore have a time subscript. Hence, using TVC version of the formulas in (3.8) and (3.9), the variance of the cyclical component of country j's output, $var\left(\tilde{y}_{j,t}\right)$ for $j = US, EA, i$, is now time-varying and is given by

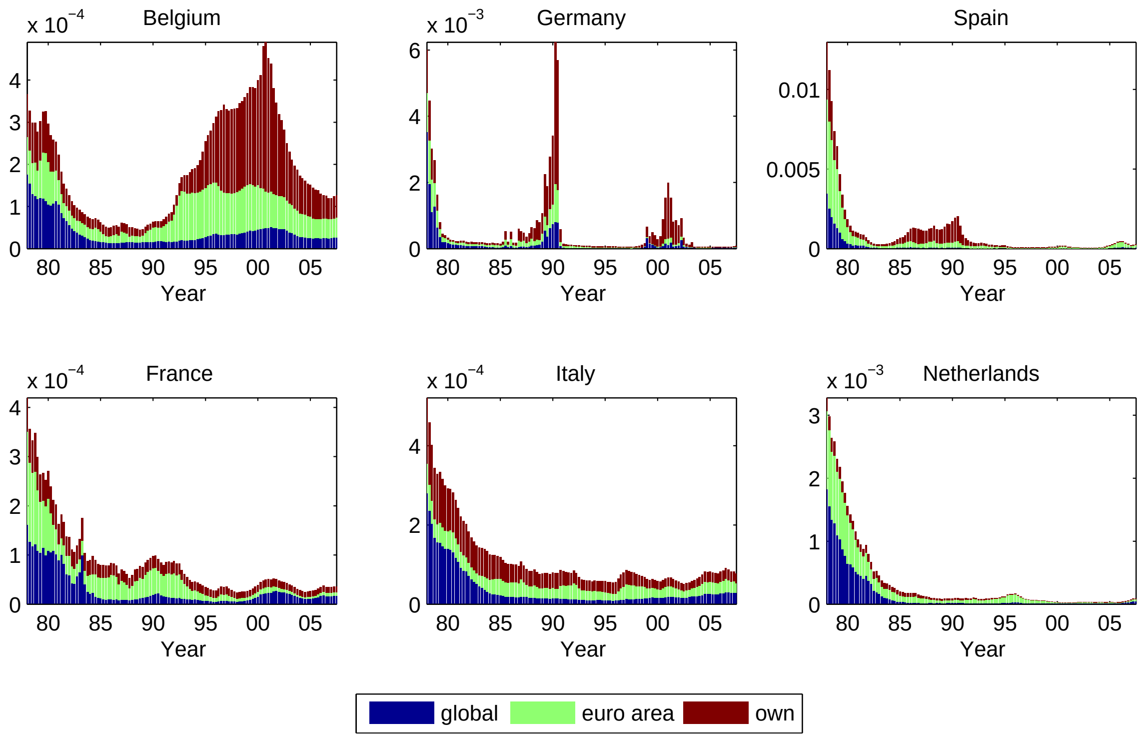
$$var\left(\tilde{y}_{j,t}\right) = \sum_{k}\left[\left(\sum_{m=-\kappa}^{m} \Psi^{2}_{jk,m,t}\right)\sigma^{2}_{k,t}\right], \tag{4.10}$$

where $\sigma_{k,t}$ for $k = US, EA, i$ stands for the standard deviation of the global, euro area or country-specific shock in the corresponding country-specific model at period t.

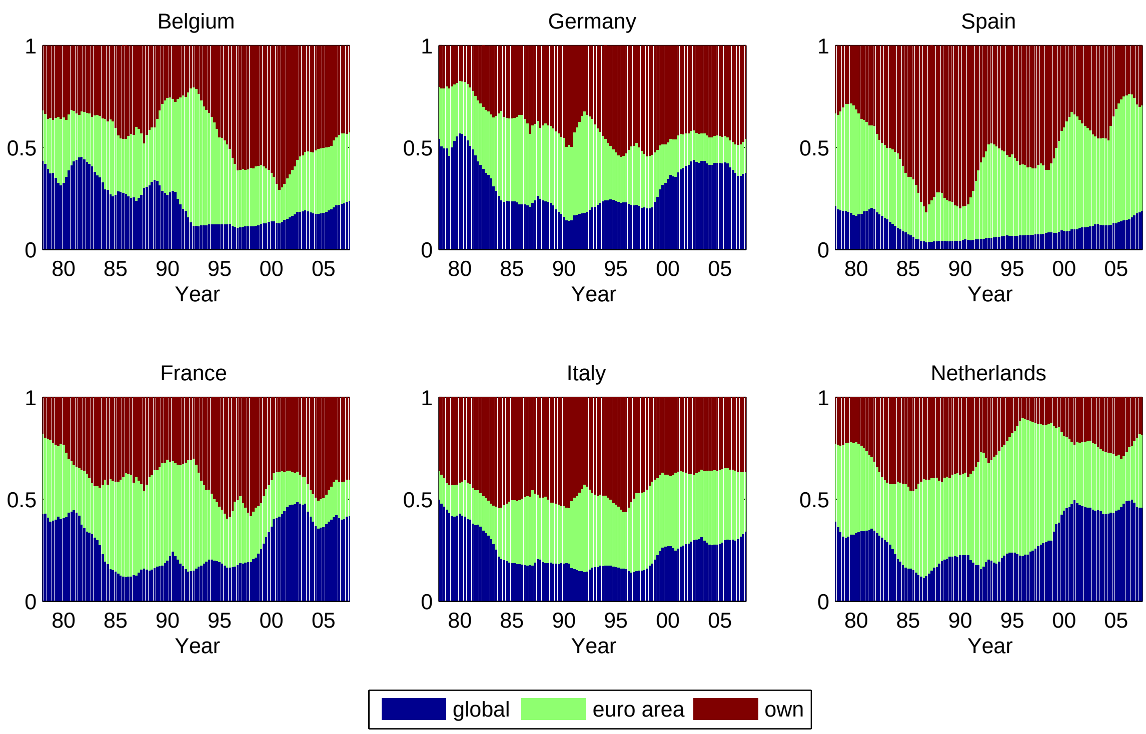
The evolution of the standard deviation of output gaps according to the TVC-SVAR estimations is displayed in Figure 4.6(a). These also differ from their rolling-window computation counterparts in Figure 3.8(a). While the rolling-window estimates point for most countries to a gradual decline, or at least (roughly) constant levels in more recent windows, the TVC-SVAR estimates have a different pattern for Belgium and Spain. The variance of the Belgian output gap reaches a peak around 2000 following a gradual increase starting around 1990 and returns to its (low) levels of the mid-1980s towards the end of our sample period. The volatility of the Spanish output gap decreases sharply from the beginning of the sample period until the mid-1980, and rises again from there on until a point in the first half of the 1990s. Afterwards it swiftly declines to historically low levels towards the end of the sample period. The output gap volatilities of Germany, France, Italy and the Netherlands decrease, however, steadily from roughly the beginning of the sample period until the latest period. The only exception to this rule is the small hike in Germany's output gap volatility around 1991, possibly due to the German reunification.

Using the expression in (4.10), the share of the structural shock k in the variance of the output cycles of country j for $j = US, EA, i$ at period t is given by

$$s^{i}_{jk,t} = \left[\left(\sum_{m=-\kappa}^{\kappa} \Psi^{2}_{jk,m,t}\right)\sigma^{2}_{k,t}\right] / \sum_{k}\left[\left(\sum_{m=-\kappa}^{m} \Psi^{2}_{jk,m,t}\right)\sigma^{2}_{k,t}\right], \tag{4.11}$$

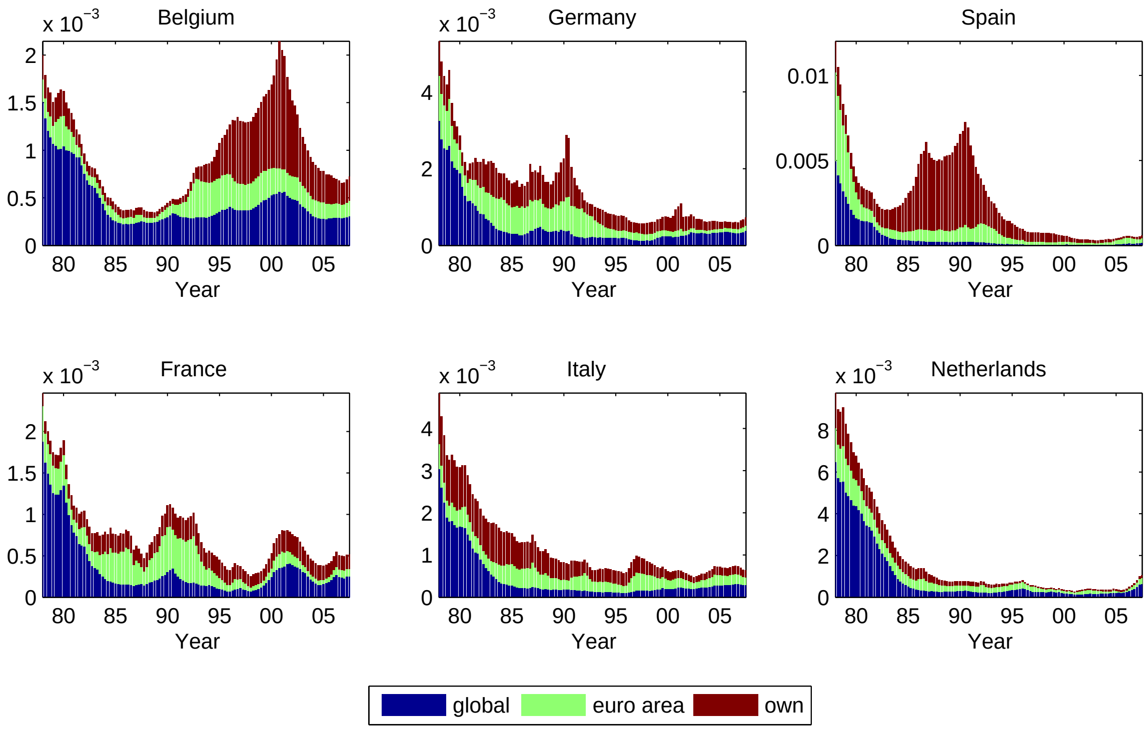


(a) Variance decomposition of output gap (absolute)

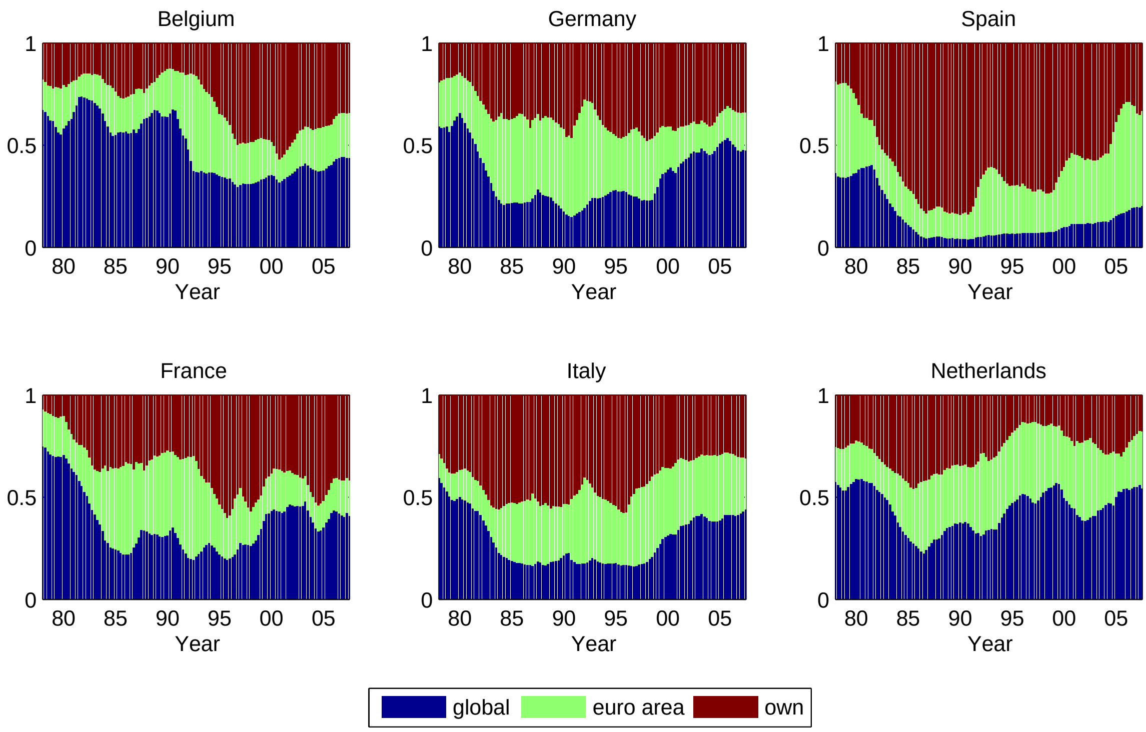


(b) Variance decomposition of output gap (relative)

Figure 4.6: Variance decomposition of output gap



(a) 12-quarters-ahead forecast error variance of output



(b) FEVD of output (relative)

Figure 4.7: FEVD of output

which follows from the country-specific trivariate model of country i. We display the evolution of the relative shares of shocks in output gap variance in Figure 4.6(b). The pattern of evolution of the shares of shocks is generally quite different from what we observed previously in terms of the rolling-window estimations of the fixed-coefficient SVAR model. However, TVC-SVAR models attribute non-negligible shares to common shocks in many quarters over the sample period just as the SVAR model did.

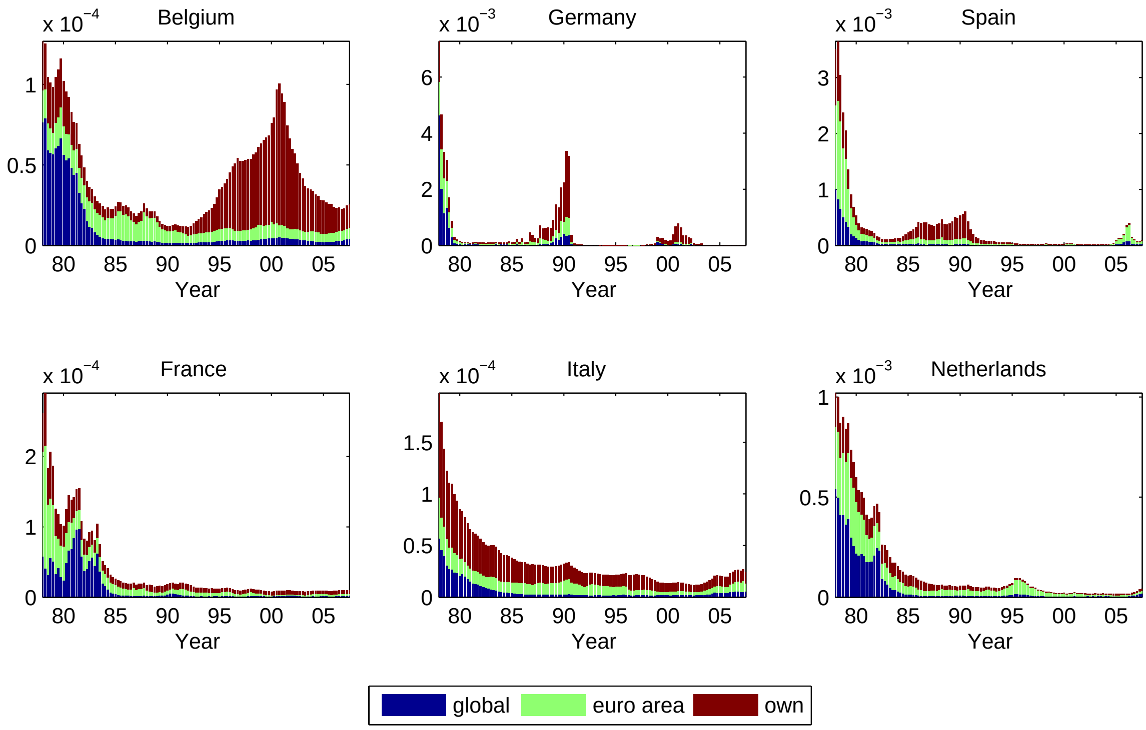
The increase over time in the share of euro area shocks in the Spanish output gap variance is especially striking. However, it is also not possible to establish a significantly increasing share of euro area shocks in output gap dynamics after the EMU process has been kicked off in 1990Q2. In the two biggest euro area economies, Germany and France, the share of euro area shocks declines to even lower levels after 1999 than before, which is accompanied by a rise in the share of global shocks in these countries. As such, the TVC-SVAR results are supportive of the findings in the literature that dynamics peculiar to the euro area exist and are non-negligible for the member countries, especially for smaller ones. However, these dynamics did not become more important after the initiation of the EMU process in the smaller economies and became even somewhat less important in the bigger economies.

Note that the evolution pattern of the output forecast error variance decomposition is quite similar to the evolution pattern of output gap variance decomposition. Therefore, we do not further interpret the output forecast error variance decompositions given in Figure 4.7(b). The most important difference between the two results is that the FEVD estimates emphasise the role of global shocks more and euro area shocks less relative to the output gap variance decomposition, as it was also the case with the fixed-coefficients SVAR model.

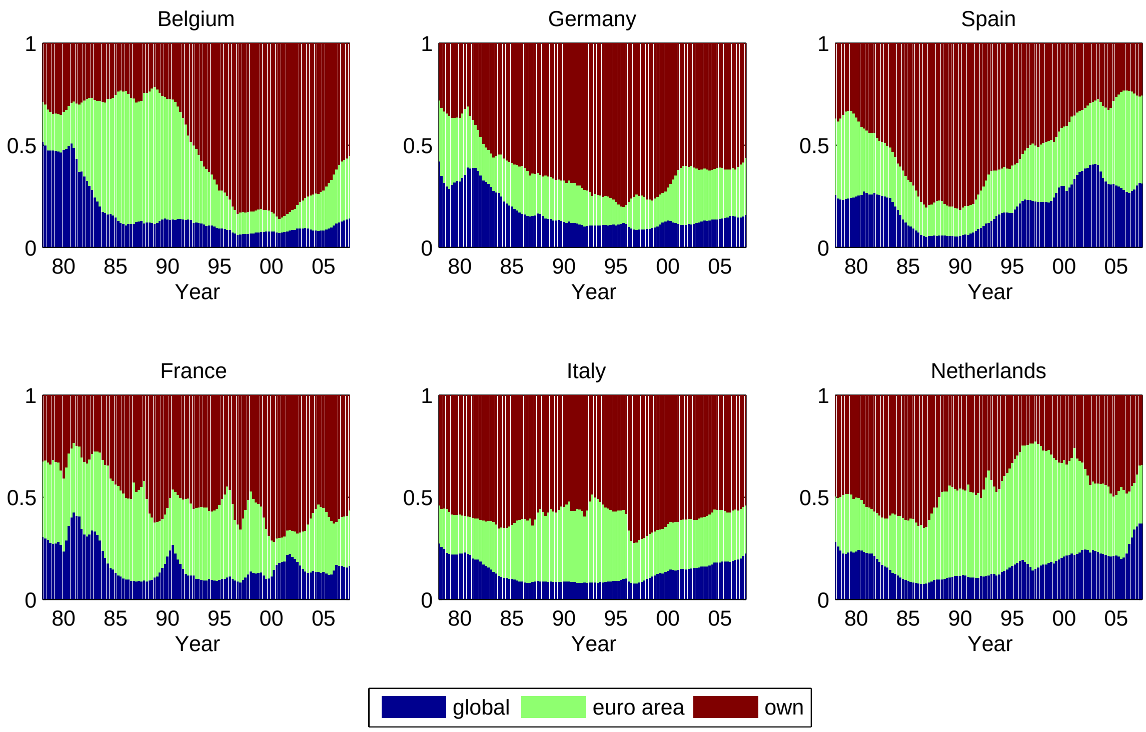
Variance decomposition of output gap differentials

Variance of output gap differentials of Belgium, Spain, Italy and the Netherlands, depicted in Figure 4.8(a), qualitatively follow a similar pattern to the standard deviation of the corresponding output gaps displayed in Figure 4.6(a). The volatilities of output gap differentials are half of or less than the volatilities of the corresponding output gaps, which is a byproduct of the positive correlations between euro area output gap and individual country output gaps. The sizes of output gap differentials—a measure of heterogeneity—between the output gap of the entire euro area and the output gaps of the individual countries decline gradually for all countries. Yet, there is a period—from the mid-1990s to the mid-2000s—during which the size of the Belgian output gap differential increases strongly and tapers off again towards the end of the sample period due to country-specific shocks in Belgium.

The relative shares of shocks in the output gap differential variances are displayed in Figure 4.8(b). Country-specific shocks are attributed very often shares above 0.50 as was the case with the SVAR and FSVAR models before, implying that these shocks are the main driving force of output gap differentials. Exceptions to this rule are the high total share of global and euro area shocks in Belgium until about 1993 as well as relatively high shares of euro area shocks in the Netherlands after the mid-1990s and in Spain after about 2003.

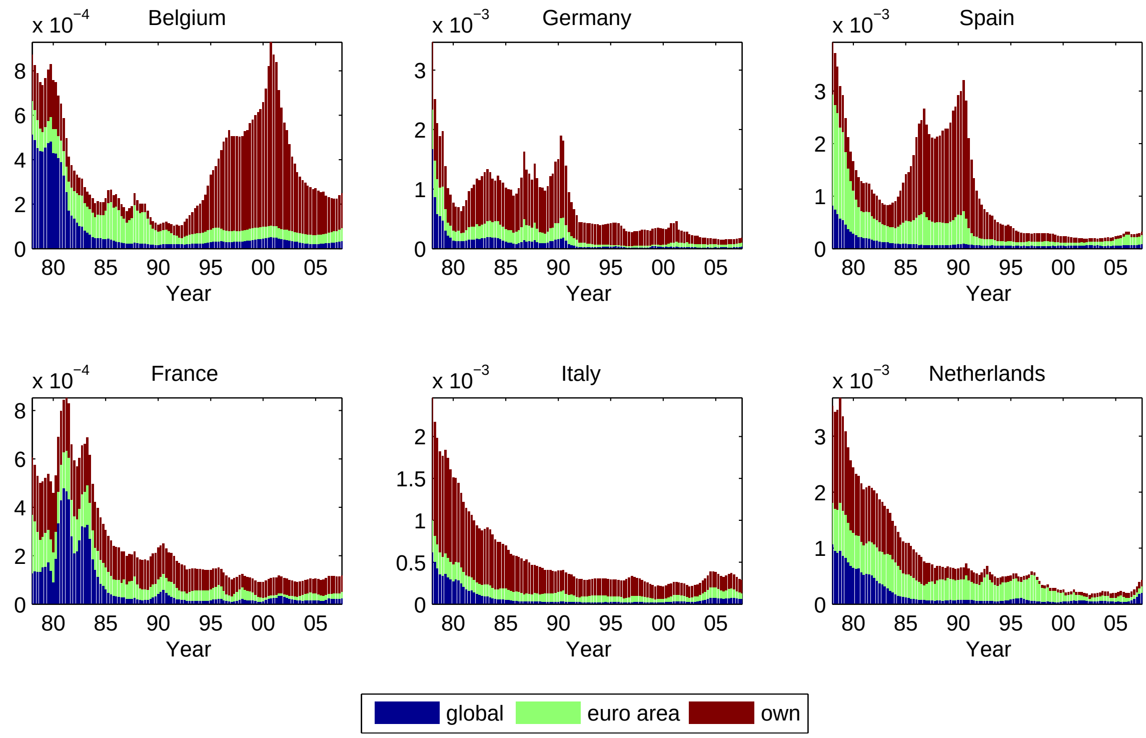


(a) Variance decomposition of output gap differential (absolute)

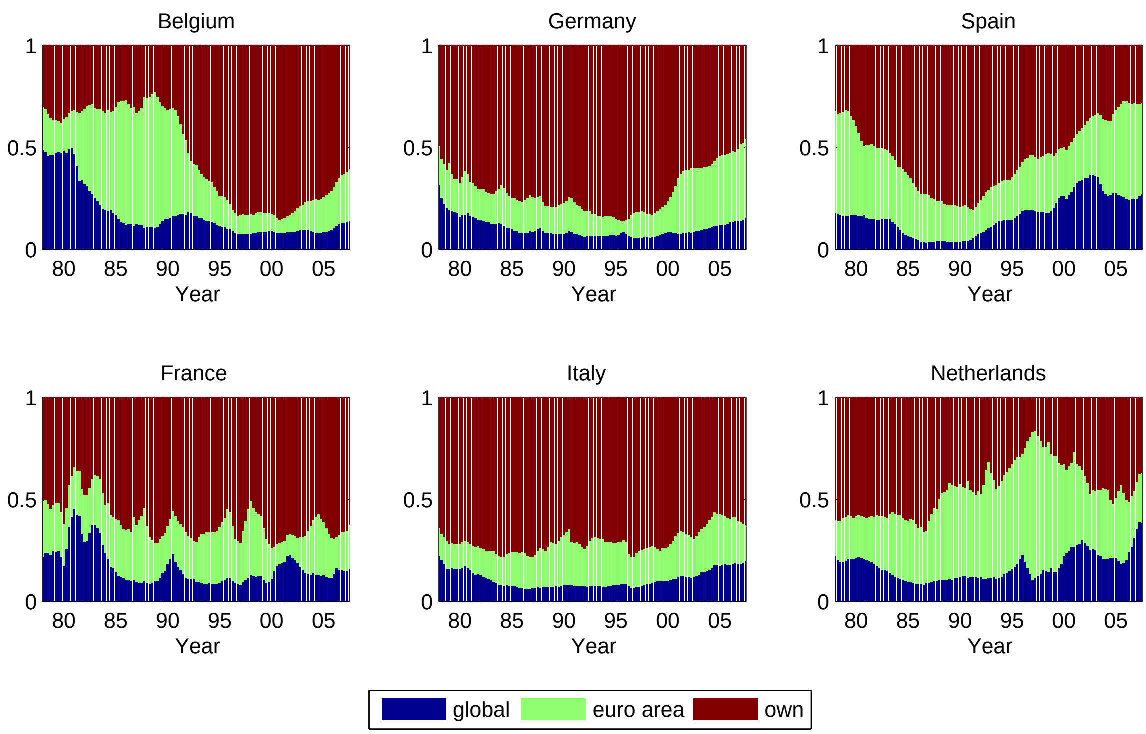


(b) Variance decomposition of output gap differential (relative)

Figure 4.8: Variance decomposition of output gap differential



(a) 12-quarters-ahead forecast error variance of output differential



(b) FEVD output differential (relative)

Figure 4.9: FEVD of output differential

4.3 Summary and remarks

Our discussion of the business cycle dynamics in the euro area started in Chapter 2 with a review of the literature, where two main issues were established. First, there is a series of factors that contribute to the synchronisation of national business cycles. While the establishment of a currency union is not necessarily found to be leading to more synchronised business cycles by itself, its byproducts such as an increase in international trade, higher financial integration and more similar fiscal policies do generally lead to a stronger synchronisation. This makes it possible to speak of international business cycles according to our literature review. However, a combination of various factors may in total have mixed effects on synchronisation such that, for example, an increase in international trade or higher financial integration may not result in more synchronised business cycles. In the case of the euro area countries, two developments—the globalisation and the EMU process—have contributed to a bigger role of these factors in macroeconomic developments. However, the empirical literature on business cycle synchronisation in the euro area is not united as to whether macroeconomic fluctuations became more synchronised in the euro area recently, and if they did so, as to whether the higher synchronisation was more due to the globalisation or the EMU process or both.

Second, industrialised countries' business cycles underwent a moderation in the two decades preceding the recent global macroeconomic turmoil. Our analysis in the previous and current chapters shows that this applies to the output fluctuations of euro area member countries in our sample. Although the change in output gap variance was seldom statistically significant, the size of output forecast errors corresponding to business cycle periodicities were found to have declined significantly. Furthermore, we obtained that output gap differentials—between each member country and the entire euro area as well as between all possible couples of member countries—and output differential forecast errors underwent a moderation, too, although a moderation of output gaps should not necessarily lead to a moderation of output gap differentials. Although each member country was found to have its own peculiar relationship with the entire euro area, we interpret the moderation in output gap differentials as another sign of increased commonality of euro area business cycles in more recent times preceding the latest economic crisis.

Given these findings, we investigated three issues related to business cycle dynamics in the euro area using a fixed-coefficient SVAR approach in Chapter 3 and FSVAR and TVC-SVAR approaches in Chapter 4. First, instead of asking whether there is a seperate euro area business cycle (in addition to a global business cycle) explicitly like many other studies, we explored the share of global and euro area shocks in output fluctuations corresponding to business cycle frequencies. Variance decompositions were employed to this end. While the SVAR and TVC-SVAR approaches did not allow spillovers of country-specific shocks between individual member countries, the FSVAR approach obtained that spillovers from other euro area countries played a non-negligible role in business cycle fluctuations of the member countries. Although the quantitative estimates vary to an important degree across the different empirical approaches and countries, the general implication of all models is that euro area countries' output gaps are driven to a large extent by common shocks. The role of euro area shocks has been found to be more important for the output gap fluctuations (measured by the CF-filter), while forecast error variance decomposition at business cycle frequencies hinted more often at a higher share of global shocks—especially when it was based on SVAR and FSVAR models.

Second, we explored the driving forces of the existing heterogeneity in terms of business cycles in the euro area. This issue attracted attention from academics and politicians alike, since, in particular, being subject to a common monetary policy in a monetary union can be beneficial for the member countries most when their own cycles do not deviate much from the cycle of the entire monetary union. Two extreme forms of heterogeneity exists: (i) heterogeneity because of differing responses to common macroeconomic shocks; (ii) heterogeneity resulting from exposure to asymmetric shocks which are not shared by other members of a monetary union. Both counterfactual correlation analysis and variance decomposition of output gap differentials pointed to a significant role of country-specific (asymmetric) shocks in the existing heterogeneity. It should be noted, however, that common shocks sometimes also had a non-negligible contribution to heterogeneity, although they were rarely dominant in the estimations we carried out.

Third, we found only weak statistical support for a moderation in output gaps and output gap differentials. Although point estimates of the change over time in the variance of output gaps and output gap differentials were negative, these were rarely statistically significant, possibly due to the short sub-samples at hand. Decline in the forecast error variance of output *level* differentials at business cycle periodicities were, on the other hand, usually found to be significant. We obtained with both SVAR and FSVAR models that changes in the size of shocks alone, i.e., if there were no changes in shock transmission, would have led to a statistically significant moderation of output gaps and output gap differentials in some cases. The same channel was also the main driving force behind the moderation of output and output differential forecast errors. This finding supports the so-called good luck hypothesis.

Chapter 5

Business cycle dynamics of the G7 countries*

This chapter is devoted to an analysis of the structural sources of business cycle dynamics in industrialised countries. The term "structural source" refers here to exogenous shocks that trigger dynamics in economies. In Chapters 3 and 4, the identified shocks were not structural in the sense that they were not given an economic interpretation related to macroeconomic theory. Shocks were merely identified with respect to their geographical origin. In this chapter, we estimate neutral technology, news, preference and monetary shocks as potential driving forces of macroeconomic fluctuations. The identification of these shocks occurs by referring to macroeconomic theory.

The first section of this chapter provides a review of the literature on the sources of business cycle fluctuations. Various types of shocks have been brought forward as important sources of cyclical fluctuations by the macroeconomic literature that has evolved since the first half of the 1980s. The primary contribution came from the so-called real business cycle (RBC) paradigm, the proponents of which claimed that neutral technology shocks were the dominant driving force behind business cycle fluctuations. The RBC paradigm brought with itself an important tool for macroeconomic analysis, the so-called dynamic stochastic general

*This chapter is partly based on Seymen and Kappler (2009). Most of the estimations and calculations in this chapter are carried out using MATLAB codes written by the author. JMulTi is used for model specification. The MATLAB code included in the Spatial Econometrics Toolbox of James P. LeSage is used for the estimation of the structural form. The GAUSS codes of Stock and Watson (2005) have been translated into MATLAB for the estimation of the common factor model.

equilibrium (DSGE) model, which has been improved by researchers during the course of years following the seminal contribution of Kydland and Prescott (1982). While the basic RBC model (see King, Plosser, and Rebelo (1988a)) comprised only neutral technology shocks as an exogenous source of fluctuations, it has been modified extensively in various directions. On the one hand, more sources of shocks have been added to the basic model, while, on the other hand, models with more variables and macroeconomic mechanisms have been introduced. Whether technology shocks or—perhaps to state it more properly—shocks related to technology represent the main driving force of cyclical fluctuations is still an issue discussed vigorously by economists.

A recent literature emphasised the importance of news shocks—shocks reflecting future technological improvements—as an important source of macroeconomic fluctuations.[1] This literature is in stark contrast to the findings of another literature initiated by Gali (1999) and surveyed by Gali and Rabanal (2004), which finds a dominant role for non-technology shocks in business cycle fluctuations. Our empirical framework presented in the second section of this chapter is closely related to the benchmark empirical framework of Beaudry and Lucke (2009). It augments the empirical framework of Gali (1999). The main difference to the latter model is the inclusion of stock price and nominal interest rate in addition to labor productivity and hours worked included in the framework of Gali (1999). The inclusion of these additional variables allows us to distinguish between two different types of technology shocks—neutral technology and news—as well as to refine the non-technology shocks as preference and monetary shocks. Another important difference of our model to Galí's model is that cointegration is allowed in former case. Note that Gali (1999) provides results for the G7 group for an early sample, whereas the analysis of Beaudry and Lucke (2009) is carried out with a recent sample but covers only the US economy. We include all G7 economies in our analysis using a recent sample.

The third section is devoted to the estimation of country-specific SVECMs, while the

[1] See, e.g., Beaudry and Portier (2005), Beaudry and Portier (2006), Haertel and Lucke (2008), Schmitt-Grohe and Uribe (2009) and Beaudry and Lucke (2009).

fourth section provides an analysis of international linkages within the G7 group. The point of departure is the estimated country-specific SVECM for each G7 country. An important contribution of our analysis is the assessment of the extent to which the business cycle dynamics in the G7 group is driven by *structural* common shocks, given that a multitude of studies, which investigate the driving forces of international business cycles, distinguish between common and country-specific shocks, while such shocks are rarely given an economic interpretation.[2] A common factor framework is imposed on the estimated structural shocks following from the G7 countries' SVECMs along the lines of Chapter 4 in order to distinguish between common (international) and country-specific structural shocks and to investigate the role of international shocks in output fluctuations of the G7 countries. We follow Chamie, DeSerres, and Lalonde (1994), Stock and Watson (2005), Xu (2006) and Seymen and Kappler (2009) in doing this.

The chapter closes with a summary of the main findings and a discussion of further related issues that cannot be addressed within the given model framework.

5.1 Related literature

We divide our review of the literature on the driving forces of business cycles into two parts. The first part discusses the literature on the role of technology shocks in cyclical fluctuations. The dispute on the role of technology shocks in business cycle fluctuations has been going on since a very long time among macroeconomists. Moreover, two types of technology shocks—investment-specific technology and news shocks—exist in addition to conventional neutral technology shocks, which makes the dimensions of the whole discussion even larger. Therefore, it makes sense to devote an independent sub-section to this issue. The literature

[2]Stock and Watson (2005) and Canova, Ciccarelli, and Ortega (2007) estimate, for example, common shocks and country-specific shocks with spillover effects within the G7 group. Perez, Osborn, and Artis (2006) identify US, EU15 and country-specific shocks. Crucini, Kose, and Otrok (2008) model common G7, nation-specific and idiosyncratic factors. While following different approaches to identification, none of these studies pursue a structural identification. Clearly, this list is far from being exhaustive.

on the role of other shocks is reviewed in the second part.

5.1.1 Technology shocks and business cycles

Neutral technology shocks

The RBC literature starts with the seminal contributions of Kydland and Prescott (1982) and Long and Plosser (1983).[3] Two innovations of this new strand of literature are particularly important for macroeconomists. First, it introduces a new approach to macroeconomic modelling; models of this class are called DSGE models. Second, it introduces technology shocks in the form of shocks hitting the total factor productivity, which is itself an exogenously evolving process. The standard RBC model comprises a production function of Cobb-Douglas type, which is given by

$$Y_t = A_t N_t^{\alpha} K_t^{1-\alpha}, \tag{5.1}$$

where Y_t, A_t, N_t, K_t and α stand for output, total factor productivity, labor input, capital stock and the share of labor in output, respectively. The log total factor productivity is typically modelled as an $AR\,(1)$ process given by

$$\log A_t = \gamma + \rho \log A_{t-1} + \varepsilon_{at}, \tag{5.2}$$

where ε_{at} is an i.i.d. process and represents a "technology shock". A common practice in the early RBC literature is to estimate the parameter ρ in (5.2) and the standard deviation of ε_{at} for a certain sample period, and to simulate the RBC model in order to generate macroeconomic series of interest such as output, consumption, investment, etc. Then, (particularly) second moments of such data are computed and compared with reality.[4] This basic one-shock model structure is kept in a number of studies belonging to the early RBC literature.

[3]See for a review of the basic RBC model and its various extensions King, Plosser, and Rebelo (1988a) and King, Plosser, and Rebelo (1988b) inter alia.

[4]See, e.g., Prescott (1986).

Since the seminal study of Nelson and Plosser (1982), macroeconomists often assume that the majority of macroeconomic time series follow unit-root processes. In order to be able to reproduce this statistical property with theoretical models, the parameter ρ in (5.2) is typically set to one. Note that this assumption is also in accordance with the widely-accepted view that long-run movements in macroeconomic data are determined by the production possibilities and hence the supply side of the economy.

It is not surprising that the (S)VAR literature, which grew concurrently with the RBC literature after the seminal contribution of Sims (1980), has also shown interest to the issue of the role of technology shocks in business cycle fluctuations. A prominent early study in this context is Blanchard and Quah (1989). These authors argue on the basis of a variant of the model in Fischer (1977), which contains two exogenous unit-root processes—productivity and money supply—that only shocks to productivity, i.e., technology shocks, have a long-run impact on output. In line with this model, Blanchard and Quah (1989) employ a long-run identification scheme in a bivariate SVAR framework consisting of first-differenced log output and unemployment rate (in level) to identify supply shocks. Formally, their model can be summarised by

$$Y_t = \begin{bmatrix} \Delta y_t \\ U_t \end{bmatrix}, \ \Phi(1) = \begin{bmatrix} * & 0 \\ * & * \end{bmatrix}, \tag{5.3}$$

where Δy_t and U_t stand for the first-differenced log output and the unemployment rate (in level), and $\Phi(1)$ shows the matrix of the long-run multipliers of the shocks. Blanchard and Quah (1989) label the second shock a demand shock (represented by the money supply shock in the theoretical model) since it has no long-run impact on output, and the first shock a supply shock (represented by the shocks to productivity) with a long-run impact on output.

The study by King, Plosser, Stock, and Watson (1991) is another important contribution to the SVAR literature on the role of technology shocks. Based on a VECM, the authors distinguish between structural shocks with permanent effects and reduced-form shocks with only transitory effects on the variables of the model. King et al. are interested in the estimation of structural shocks with permanent effects only and their implications. Those are ordered as technology, inflation and real interest rate shocks according to the classification in their six-variable model, and the (last) three transitory shocks are left without economic interpretation. Their six-variable model is described by

$$\Delta Y_t = \begin{bmatrix} \Delta y_t \\ \Delta c_t \\ \Delta i_t \\ \Delta m_t - \Delta p_t \\ \Delta R_t \\ \Delta^2 p_t \end{bmatrix}, \ \Theta(1) = \begin{bmatrix} * & 0 & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 \end{bmatrix}, \tag{5.4}$$

where $\Delta y_t, \Delta c_t, \Delta i_t, \Delta m_t - \Delta p_t, \Delta R_t$ and $\Delta^2 p_t$ stand for first-differenced log-output, log-consumption, log-investment, log-real-balances, nominal interest rate and inflation, $\Theta(1)$ shows the matrix of the long-run multipliers of the shocks. Given that the technology shock is ordered first in the model, $\Theta(1)$ in (5.4) implies that only technology shocks can affect the level of output in the long run. The six-variable model of King, Plosser, Stock, and Watson (1991) also has the balanced-growth property of RBC models, i.e., the consumption-output and investment-output ratios stay constant in the long run when only technology shocks occur in their model.[5]

Using a stylised model with monopolistic competition, Gali (1999) argues that it is more appropriate to consider the long-run effects on labor productivity rather than output for identifying technology shocks. He gives examples of theoretical models, which allow shocks other than technology also to have permanent effects on output. Baxter and King (1993) consider, for instance, the effects of permanent changes in government purchases. Another example can be found in Shapiro and Watson (1989), who allow both permanent labor-supply shocks and permanent productivity shocks to affect output in the long run. As a last example, the sticky-price model with labor market dynamics in Gali (1999) contains a second stochastic trend, an exogenous random-walk money supply process. Gali shows that such a framework implies that both technology and money supply can affect output,

[5]See Chapter 1 for a description of such cointegrated models with permanent and transitory shocks.

while only technology shocks can affect labor productivity in the long run. Therefore, he suggests estimating a bivariate model containing labor productivity and hours worked with the latter implication in order to distinguish between technology and nontechnology shocks. The bivariate SVAR is given by

$$\Delta Y_t = \begin{bmatrix} \Delta x_t \\ \Delta n_t \end{bmatrix}, \ \Theta(1) = \begin{bmatrix} * & 0 \\ * & * \end{bmatrix}, \tag{5.5}$$

with Y_t containing the log of labor productivity (x_t) and hours worked (n_t). The long-run effect of the second shock on labor productivity is set to zero in the system, which implies, according to the motivation of Gali (1999), that the first and second shocks should be labelled technology and non-technology, respectively.

Investment-specific technology shocks

The approach to identification of technology shocks and results of Gali (1999) initiated a vigorous discussion in the macroeconomic literature.[6] An important contribution to this discussion is the study by Fisher (2006), which suggests that another type of technology shocks, namely investment-specific technology (IST) shocks, could be an important source of macroeconomic fluctuations. This idea was first introduced to the literature by Greenwood, Hercowitz, and Huffman (1988) and further developed in Greenwood, Hercowitz, and Krusell (1997). Such shocks are embedded into an otherwise standard capital accumulation rule such that

$$K_{t+1} = (1-\delta) K_t + V_t I_t, \tag{5.6}$$

where δ, V_t and I_t respectively stand for depreciation rate, level of investment-specific technology and investment. While $V_t = 1$ holds in standard formulation of capital accumulation equations, Fisher (2006) suggests it be of the form

$$\log V_t = \nu + \log V_{t-1} + \varepsilon_{vt} \tag{5.7}$$

[6] A review of this literature can be found in Gali and Rabanal (2004).

where ν is a constant, the log of IST is a random walk with drift, and ε_{vt} is an i.i.d. process and represents an "investment-specific technology shock".

Greenwood, Hercowitz, and Krusell (1997) find an important role for IST shocks in growth. In a more recent study, Justiniano, Primiceri, and Tambalotti (2009a) estimate a model of the US economy comprising several shocks and find IST shocks to be of great importance for macroeconomic fluctuations at business cycle frequencies. Fisher (2006) introduces such type of shock into a SVAR model and obtains a dominant role for them in macroeconomic fluctuations. His SVAR model is a modified version of the bivariate model in Gali (1999) given in (5.5) and can be summarised by

$$Y_t = \begin{bmatrix} \Delta pi_t \\ \Delta x_t \\ n_t \end{bmatrix}, \; \Phi(1) = \begin{bmatrix} * & 0 & 0 \\ * & * & 0 \\ * & * & * \end{bmatrix}, \tag{5.8}$$

where pi_t, x_t and n_t stand for the log of real investment price, the log of labor productivity and the log of hours worked.[7] The identified structural shocks are ordered (and labelled) as IST shocks, neutral technology shocks and non-technology shocks.[8] $\Phi(1)$ in (5.8) shows the long-run impact of the structural shocks on the variables. While the real price of investment can be affected by only IST shocks in the long run, Gali's identification scheme is augmented by allowing both IST shocks and neutral technology shocks to have a long-run impact on labor productivity. Note that an important difference between the models of Gali (1999) and Fisher (2006) is that hours worked enters the VAR of Gali in first difference, whereas Fisher assumes it to be stationary. Indeed, this seems to be an important driver of the findings in Fisher (2006) as shown by Gali and Rabanal (2004): when hours worked enters the model in (5.8), IST shocks are attributed much smaller shares in cyclical fluctuations.[9]

Schmitt-Grohe and Uribe (2009) estimate a DSGE model containing among others also IST shocks and obtain a negligible role for these shocks in cyclical fluctuations. An important

[7]Some additional endogenous variables also enter the SVAR of Fisher (2006), which we skip here for the ease of presentation.

[8]The labelling of the latter shock is done by us.

[9]See also our discussion below on how hours worked should enter such type of VARs.

feature of their model is that it includes news shocks that we discuss below as an additional potential source of fluctutions. Justiniano, Primiceri, and Tambalotti (2009b) consider, in addition to IST shocks (that affect the transformation of consumption into investment goods), marginal efficiency of investment (MEI) shocks that affect the transformation of invesment goods into productive capital. The authors find a negligible contribution of IST shocks in such a framework. Beaudry and Lucke (2009) estimate a SVECM including neutral technology, IST and news shocks within one framework and also obtain a negligible role for IST shocks in macroeconomic fluctuations. The studies of both Schmitt-Grohe and Uribe (2009) and Beaudry and Lucke (2009) at the same time emphasise the importance of news shocks as the dominant factor behind fluctuations, to which we turn our attention next.

News shocks

Recently, another type of technology shock has been suggested in, among others, Beaudry and Portier (2004, 2006). These authors argue and present evidence for the view that positive shocks to stock prices—labelled as news shocks—represent advances in future technology and are thus another type of supply shock. Beaudry and Portier (2006) motivate their approach to identification in the SVAR context of news shocks with a New Keynesian model, where the stock market value of firms is the discounted sum of profits of intermediate good producers. The technology process is assumed to consist of transitory and permanent components in this model. The latter component follows a so-called diffusion process given by

$$D_t = \sum_{i=0}^{\infty} d_i \eta_{t-i} \tag{5.9}$$

with

$$d_i = 1 - \delta^i, \ 0 \leq \delta < 1, \ \text{and } d_0 = 0$$

so that the effect of technological innovation η has no immediate effect on the level of technology, while its effect grows over time, its long-run effect being normalised to one. Forward-looking variables such as stock prices bear information on future technological developments even before these are realised and expand the economy's production possibilities.

Haertel and Lucke (2008) motivate news shocks with a model taken from Long and Plosser (1983), which is aggregated to a single sector. However, the production technology is extended to a multi-period setting. The total factor productivity consists of a random walk component, ζ_t, and a stationary component, v_t,

$$\log A_t = \zeta_{t-1} + v_t, \tag{5.10}$$

where,

$$\zeta_t = \zeta_{t-1} + \eta_{1t}, \tag{5.11}$$

$$v_t = \rho v_{t-1} + \eta_{2t}, \tag{5.12}$$

with η_{1t} and η_{2t} being unit-variance white noise innovations. They compute stock prices as the discounted sum of expected returns to capital, of which productive use extends over many periods. Thus, the delayed response of total factor productivity to permanent innovations in this model as well as in Beaudry and Portier (2006) is a key element for the motivation and identification of news-shocks. This property is embedded to the SVECMs in Beaudry and Portier (2005), Beaudry and Portier (2006), Haertel and Lucke (2008) and Beaudry and Lucke (2009). All of these studies find an important role of news shocks in macroeconomic fluctuations.

5.1.2 Other shocks

The subject of the effects of monetary policy shocks on economic activity has attracted a lot of interest in the literature, and monetary policy shocks are also a part of the empirical framework that we use for the analysis of G7 business cycles. Meanwhile, there seems to be a consensus on the identification of monetary policy shocks. The well-established assumption for identifying monetary policy shocks is that the monetary authority sees the development of economic activity within a period (a quarter) before setting the policy (see, e.g., Christiano, Eichenbaum, and Evans (1999) and Bagliano and Favero (1998)). The implication of this assumption is that shocks to monetary policy can affect (most of) the economic activity only with a time lag. The benchmark model in Christiano, Eichenbaum, and Evans (1999) contains, for example, seven variables and is restricted by only short-run restrictions that impose this assumption. The model can be summarised by

$$Y_t = \begin{bmatrix} y_t \\ p_t \\ pcom_t \\ ff_t \\ tr_t \\ nbr_t \\ m_t \end{bmatrix}, \; A = \begin{bmatrix} * & 0 & 0 & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 & 0 \\ * & * & * & * & 0 & 0 & 0 \\ * & * & * & * & * & * & * \\ * & * & * & * & * & * & * \\ * & * & * & * & * & * & * \end{bmatrix}, \tag{5.13}$$

where $y_t, p_t, pcom_t, ff_t, tr_t, nbr_t$ and m_t denote the log of real GDP, the log of implicit GDP deflator, the smoothed change in an index of sensitive commodity prices, the federal funds rate, the log of total reserves, the log of non-borrowed reserves plus extended credit, and the log of money supply (either M1 or M2) at period t, respectively. The matrix A in (5.13) shows the contemporaneous relationships among the variables in this system, where ff_t is taken to be the policy instrument. This structure implies that the monetary authority cannot affect the economic activity variables y_t, p_t and $pcom_t$ through surprise changes in the the policy rate, whereas tr_t, nbr_t and m_t can be affected by surprise changes in the policy at the impact period. Note that other shocks are not given an economic interpretation in the framework of Christiano, Eichenbaum, and Evans (1999).

Demand shocks represent another general class of shocks that have often been put forward in the SVAR literature. As mentioned above, Blanchard and Quah (1989) claim to identify a demand shock, a shock with no long-run impact on output, with the model summarised in (5.3). The model they use to motivate their empirical approach implies that shocks to money supply belong to the class of demand shocks. Gali (1999) also uses money-supply shocks as an ingredient of the model that he uses as a motivation for his empirical approach.

Christiano and Eichenbaum (1992) add government consumption shocks to an otherwise prototypical RBC model in order to enable it to generate a weak correlation between hours worked and the return to working. As a last example, preference shocks can be seen as real demand shocks that lead to shifts in marginal utility of consumption, changes in relative prices, etc. Two examples of such type of shocks can be found in Bencivenga (1992) and Weder (2006). One of the shocks in our forthcoming SVECMs is labelled preference, whereas it could possibly also be labelled any demand shock which is orthogonal to different types of technology and monetary policy shocks.

Note that all hitherto reviewed shocks are related to our empirical analysis in the subsequent sections, and the list of other types of shocks considered in the SVAR literature is long. While we acknowledge that the list we are providing is far from being exhaustive, we find it appropriate to confine the discussion to a convenient size. We turn our attention now to the econometric methodology underlying our forthcoming analysis of business cycles in the G7.

5.2 Econometric methodology

The model we employ in order to investigate the sources of the G7 countries' business cycle fluctuations is a modified version of the model used by Beaudry and Lucke (2009) in the context of the US economy. Therefore, we first present the model of Beaudry and Lucke, and then discuss the modification of it in the following.

5.2.1 The model of Beaudry and Lucke (2009)

The business cycle analysis of Beaudry and Lucke (2009) is based on an SVECM of the B-form,

$$\Delta Y_t = bd_t + \Pi Y_{t-1} + D_1 \Delta Y_{t-1} + \cdots + D_{p-1} \Delta Y_{t-p+1} + B\varepsilon_t. \qquad (5.14)$$

Note that (5.14) is the structural version of the reduced form in (1.6). The same notation applies here. The model comprises five endogenous variables in the following order: total factor productivity (tfp_t), inverse of relative investment price (pi_t), stock price index (sp_t), activity and federal funds rate (int_t). Beaudry and Lucke (2009) estimate various versions of their model with different activity variables. The activity variable in the benchmark model is the hours worked (h_t), while Beaudry and Lucke substitute it with output, consumption and investment in other estimations. We focus on the benchmark case in the following.[10]

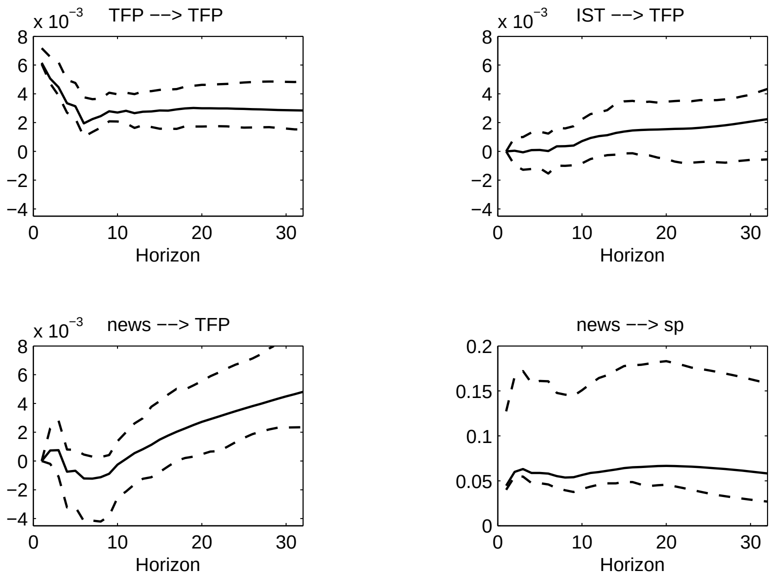
Beaudry and Lucke (2009) impose a set of short-run and long-run restrictions together with the conventional orthogonality restrictions on the covariance matrix of the structural shocks. The vector of endogeonus variables as well as the corresponding short-run and long-run restrictions are given by

$$\Delta Y_t = \begin{bmatrix} \Delta tfp_t \\ \Delta pi_t \\ \Delta sp_t \\ \Delta h_t \\ \Delta int_t \end{bmatrix}, B = \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix}, \Theta(1) = \begin{bmatrix} * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}, \tag{5.15}$$

where $\Theta(1)$ stands for the matrix of long-run multipliers as described in Chapter 1.

The restrictions in (5.15) that follow from recent macroeconomic literature reviewed above allow Beaudry and Lucke to identify five shocks, which are ordered as TFP-shock, IST shock, news shock, preference shock and monetary shock. Hence, the first three shocks are different sorts of technology shocks. According to (5.15), total factor productivity is affected by only TFP-shocks in the short-run, and all types of technology shocks are allowed to have an impact on it in the long run, while preference shocks and monetary shocks do not have a long-run effect on total factor productivity. Furthermore, news shocks and preference shocks are restricted not to have contemporaneous effects on the relative price of investment. Finally, monetary shocks have only delayed effects on three variables—total factor productivity, relative price of investment and hours worked—in accordance with the

[10] I thank Bernd Lucke for kindly providing me the data set used by Beaudry and Lucke (2009).



Note: The area between the dashed lines shows the 95-percent confidence interval.

Figure 5.1: Impulse responses from the original BL model

literature on monetary policy shocks discussed above. Note that stock prices are allowed to react to surprise innovations to monetary policy at the impact period they occur, which is plausible.

It is common practise in the SVAR literature to check whether the signs of impulse response functions coincide with the expectations that follow from theory. Since macroeconomic theory is pretty clear about the long-run effects of positive technology shocks of all sorts on total factor productivity, we focus here on the response of TFP to a TFP-shock, an IST-shock and a news shock. Moreover, the expected effects of positive news shocks on stock prices is also clear-cut. Figure 5.1 displays these impulse responses from the benchmark model of Beaudry and Lucke (2009). While the effects of different sorts of technology shocks on TFP differ in the short-run, the long-run effects of all technology shocks is positive, as expected by the theory. Similarly, positive news shocks have significantly positive short-run and long-run effects on stock prices.

5.2.2 A modified version of the Beaudry-Lucke model

It follows from the findings of the five-variable model of Beaudry and Lucke that the inclusion of the relative price of investment in the SVECM is redundant, at least when the aim is to explain business cycle fluctuations. The role of IST-shocks in macroeconomic fluctuations is negligible. Therefore, the authors drop the relative price of investment from their model and estimate a four-variable SVECM, which is described by

$$Y_t = \begin{bmatrix} tfp_t \\ sp_t \\ h_t \\ int_t \end{bmatrix}, \; B = \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & * & * \\ * & * & * & 0 \\ * & * & * & * \end{bmatrix}, \; \Theta(1) = \begin{bmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix}. \tag{5.16}$$

(5.16) is obviously analogous to (5.15). After dropping IST-shocks from the model, the other shocks have the same order as in the previous model. We introduce one more modification to this framework and include labor productivity (x_t) instead of total factor productivity so that

$$Y_t = \begin{bmatrix} x_t & sp_t & h_t & int_t \end{bmatrix}'. \tag{5.17}$$

This modification brings us three advantages for the forthcoming empirical analysis. The first advantage is practical: total factor productivity is more difficult to calculate due to the lack of a directly observable quarterly capital stock data. Second, this modification is a natural extension of the bivariate model advocated by Gali (1999) and allows us direct comparison with the model of Gali. Third, output is also indirectly included in this type of a model as the sum of labor productivity and total hours worked.

The disadvantage of substituting total factor productivity with labor productivity in the model is that labor productivity responds to changes in the capital stock, which cannot be accounted for by the modified model. In order to check the importance of this issue, we compare the shocks estimated with the five-variable and four-variable models. Their correlations are reported in Table 5.1. While IST-shock of the five-variable model is virtually not correlated with the other shocks of the four-variable models, all other shocks in the

Table 5.1: Correlations of shocks from four- and five-variable models

	TFP	IST	news	pref.	mon
TFP	0.81	-0.05	-0.12	-0.04	0.05
	(0.03)	(0.07)	(0.08)	(0.07)	(0.06)
news	0.13	0.07	0.86	-0.29	-0.30
	(0.08)	(0.07)	(0.02)	(0.06)	(0.06)
pref.	0.02	0.08	0.32	0.89	0.06
	(0.07)	(0.07)	(0.06)	(0.02)	(0.07)
mon.	0.00	0.01	0.28	-0.17	0.92
	(0.06)	(0.07)	(0.06)	(0.07)	(0.01)

Notes: Standard errors in parentheses.

five-variable model are highly correlated with their counterparts in the four-variable model. Thus, we think it is legitimate to include the labor productivity instead of the total factor productivity in (5.16) when investigating the macroeconomic fluctuations of the G7 countries with that model.

5.3 Country-specific models

The findings of Beaudry and Lucke (2009) point to a dominant role of news shocks in US macroeconomic fluctuations. In the following, we extend their analysis to other G7 countries by estimating the model summarised by (5.16), where Y_t is replaced by (5.17). We include the US in our estimations as well, since we are interested in investigating the international linkages in the next section.

5.3.1 Data and model specification

The data set we use has been retrieved from Datastream. The entire sample covers the period 1971Q1–2006Q4. While we initially report results from the entire sample period in the following, the literature on the business cycle dynamics of the G7 countries suggests that it makes sense to consider estimates from various sub-periods as well.[11] For example, Stock and Watson (2005) split their sample at 1983Q4, which, they argue, is particularly valid for the US economy, although the authors acknowledge that "when modelled as a single break the reductions [in business cycle volatility] generally are neither concurrent nor of similar magnitudes". Another convenient break date could be 1990Q2, after which the EMU process has been kicked off along the plan suggested in the Delors report as we discussed in Chapter 2, and which we used in the empirical analysis of the previous two chapters. Moreover, Stock and Watson (2005), as well as various other studies mentioned therein, point to the emergence of a cyclically coherent euro area group, which has possibly to do with the EMU process. Hence, we report results from sub-periods by splitting our sample in 1990Q2. A practical reason behind this decision is that it splits the sample almost at the middle. Other break-date candidates, such as 1983Q4, would result in one very short sample given the number of parameters to be estimated. The four-variable SVECMs of this chapter suffer even more from estimation uncertainty than the models considered in Chapters 3 and 4, since there are more coefficients and parameters to estimate in the SVECMs, which should not be exacerbated further by estimating with short sub-samples such as 1971Q1–1983Q4.

There are three important decisions concerning the specification of the VECMs that underlie our structural estimation. First, we set the lag order to 4 for each country, since different information criteria support different lag orders within and across country-specific models. We find it important to set the lag order to a uniform value for all countries for the sake of comparison in the forthcoming analysis of international linkages. However, the lag order choice does not have an important impact on our conclusions.

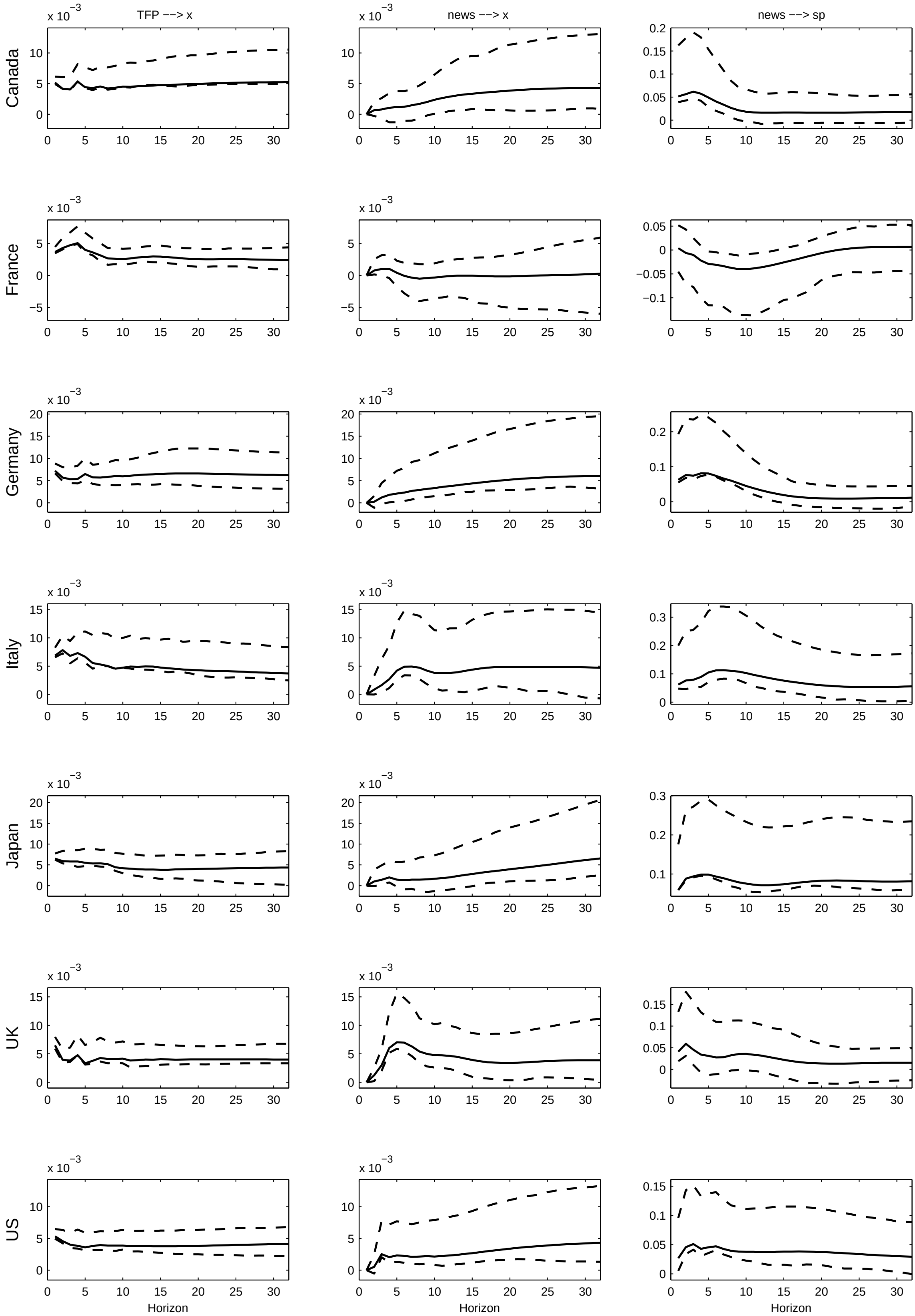
Second, attention must be paid to the specification of hours worked. Gali (1999) assumes in his specification that total hours worked is a nonstationary variable, while the majority of macroeconomic models include hours worked as a stationary variable. However, the latter property must not necessarily be taken for granted on the basis of macroeconomic theory,

[11] See also our discussion about the break in the data in Chapter 2 in the context of the euro area business cycle dynamics.

since, as Gali (2005) shows, there may be reasons for hours worked to be nonstationary without changing the balanced-growth property of theoretical models. Chang, Doh, and Schorfheide (2007) work with a DSGE model, in which hours worked contains a stochastic trend due to labor-supply shocks which follow a non-stationary process. The importance of the issue comes from the fact that findings are affected importantly by how hours worked enter into VAR models. While Gali (1999) obtains a negative contemporaneous response of hours worked to a technology shock, Christiano, Eichenbaum, and Vigfusson (2004) show that this finding is not supported when hours worked is assumed to be stationary and enters the bivariate VAR of Gali (1999) in level. Fisher (2003, 2006) finds that technology shocks, particulary investment-specific technology shocks, matter for business cycle fluctuations with hours worked specified to be stationary, whereas Gali and Rabanal (2004) show that this finding changes when hours worked is taken to be nonstationary and hence enters the estimation in first difference. An important advantage of estimating a VECM with unrestricted cointegrating relationships is that, as noted by Beaudry and Lucke (2009), "we do not need to impose any assumptions on the stationarity properties of hours, for if hours were in fact stationary, one of the cointegrating vectors would give a nonzero weight only to the hours variable."

Third, the number of cointegrating relationships must be determined. Beaudry and Lucke (2009) refer to recent macroeconomic theory to determine the number of stochastic trends in their SVECM. Their system must be driven by two types of stochastic trends corresponding to disembodied and investment-specific technological processes according to their argument. We stick to their assumption in the following and assume a cointegration rank of 3 in our benchmark model, which implies only one stochastic trend. Note that the second source of stochastic trend, the investment-specific technological progress, does not exist in the modified framework presented above. A cointegration rank of 3 generates estimates that are in line with our conjecture that the response of labor productivity to a positive technology shock is positive in the short-run as well in the long-run in all G7 countries and over our entire sample period as well as sub-periods as displayed in the first column of the three panels of Figure 5.2. Moreover, the interpretation that positive news shocks announce future technological progress is also supported by the estimated model, see the second column of all panels of the same figure. Finally, positive news shocks are generally found to have a positive effect on stock prices, while this rule is partly not valid for the corresponding impulse response function of France in the entire sample period and in the first sub-period (see the last columns of Figure 5.2(a) and Figure 5.2(b)) and Japan in the second sub-period (see the last column of Figure 5.2(c)).

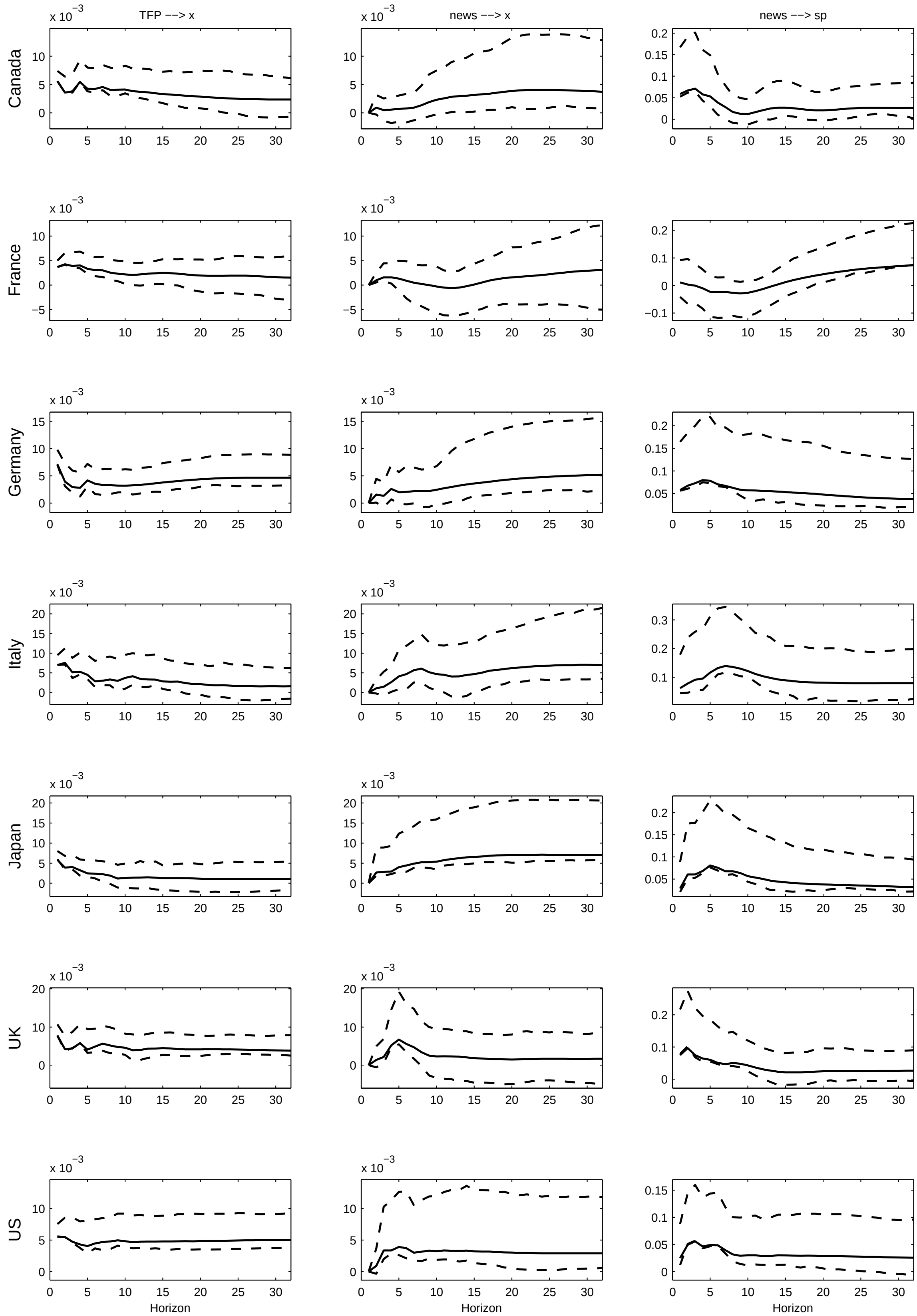
Johansen cointegration tests, of which results are reported in Table 5.2, do unfortunately not support the same rank of cointegration across countries and time periods. The tests suggest a cointegration rank of 0, 1 or 2 (at the 5-percent significance level) in different countries at different periods. The first implication of this result is that differing number of stochastic trends must be included in the country-specific models, which suggests that theory-based analyses of these countries' macroeconomic dynamics must differ from each other. Second, our theoretical prior of three cointegrating relationships is rejected by the data. As we show later, our results are sensitive to the choice of the cointegration rank. We report and discuss the results from country-specific models with a cointegration rank of two later in this chapter.



(a) Sample: 1971Q1–2006Q4

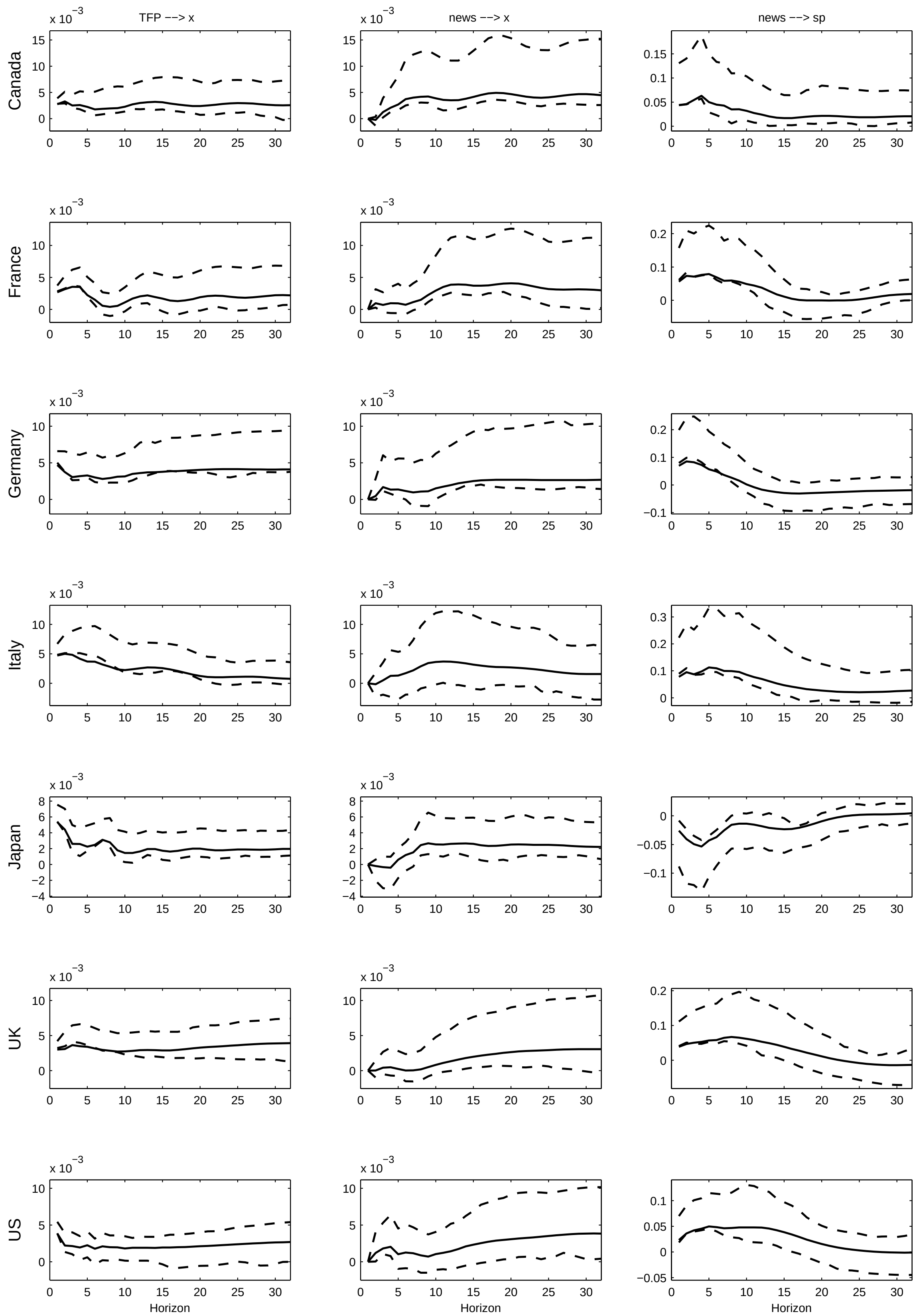
Note: The area between the dashed lines shows the 95-percent confidence interval.

Figure 5.2: Impulse responses from country-specific models



(b) Sample: 1971Q1–1990Q2

Figure 5.2: Impulse responses from country-specific models (cont.)



(c) Sample: 1990Q3–2006Q4

Figure 5.2: Impulse responses from country-specific models (cont.)

Table 5.2: Johansen cointegration rank tests

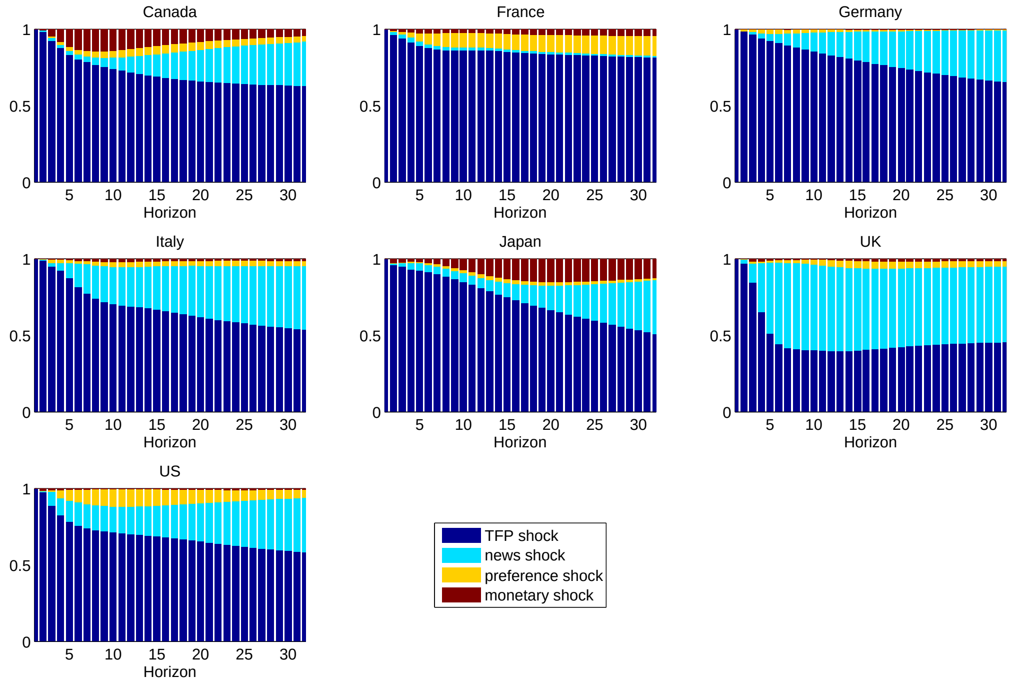
		71Q1–06Q4		71Q1–90Q2		90Q3–06Q4	
	rank	statistic	p-value	statistic	p-value	statistic	p-value
Canada	0	44.50	0.10	52.31	0.02	59.70	0.00
	1	24.21	0.20	19.27	0.48	34.92	0.01
	2	9.26	0.35	8.21	0.45	14.68	0.06
France	0	66.08	0.00	49.71	0.03	49.39	0.03
	1	38.61	0.00	17.36	0.62	28.84	0.06
	2	18.61	0.01	9.99	0.29	14.54	0.07
Germany	0	70.14	0.00	62.08	0.00	52.97	0.01
	1	31.14	0.03	29.29	0.06	29.52	0.05
	2	13.36	0.10	7.66	0.51	11.91	0.16
Italy	0	49.53	0.03	54.51	0.01	49.62	0.03
	1	31.23	0.03	19.44	0.47	31.31	0.03
	2	17.35	0.02	8.25	0.45	17.65	0.02
Japan	0	57.08	0.00	53.80	0.00	62.13	0.00
	1	27.10	0.10	36.37	0.01	13.85	0.85
	2	9.28	0.35	6.28	0.67	6.07	0.69
UK	0	53.42	0.01	51.47	0.02	71.53	0.00
	1	15.19	0.77	23.12	0.25	30.56	0.04
	2	5.70	0.73	4.93	0.81	10.91	0.22
US	0	34.16	0.50	43.20	0.13	48.30	0.04
	1	18.40	0.55	20.27	0.42	26.01	0.13
	2	7.08	0.58	5.36	0.77	11.21	0.20

Notes: Four lags are included in each model.

5.3.2 Forecast error variance decomposition

Since we are interested in capturing changing dynamics of business cycles over time, we report FEVD estimates for the sub-periods mentioned above in addition to entire-sample estimates. The FEVD of labor productivity, displayed in Figure 5.3, yields results across the G7 countries that are very similar to what Beaudry and Lucke (2009) report for total factor productivity of the US: neutral technology shocks, labelled TFP shocks in Figures 5.3 to 5.6, are an important driving force of labor productivity fluctuations at business cycle horizons. Moreover, the share of news shocks in the forecast error variance of labor productivity generally increases with longer forecast horizon similar to the case of the TFP in the five-variable model of Beaudry and Lucke. This finding is in line with the interpretation that news shocks contain information about future technological developments. An important exception to this rule is seen in the estimations for France in the entire sample period as well as the first sub-period (see Figures 5.3(a) and 5.3(b)). Note that the FEVD of the labor productivity in Japan in the second sub-period, given in Figure 5.2(c), is in accordance with our conjecture that the share of news shocks—news about future technological improvement—increases in longer forecast horizons, although we had reported a negative response of stock prices to a positive news shock in Japan in the second sub-period in Figure 5.2(c).

The picture is more heterogeneous when it comes to the driving forces of stock price fluctuations. According to the benchmark model of Beaudry and Lucke (2009), the sole driving force of US stock price fluctuations is news shocks, while other shocks play a negligible role. Our finding displayed in Figure 5.4(a) is that news shocks are similarly the main driving force of stock price fluctuations in the US, while monetary shocks are also of some importance in the entire sample period. News shocks are clearly dominant in the stock price fluctuations of Germany and Japan and explain also about half of stock price forecast error variance in Canada and Italy when the entire sample is used for the estimation. Monetary shocks are important in Italy and the UK at the business cycle horizon, whereas preference shocks have a non-negligible share in Canada and the UK over the entire sample period.

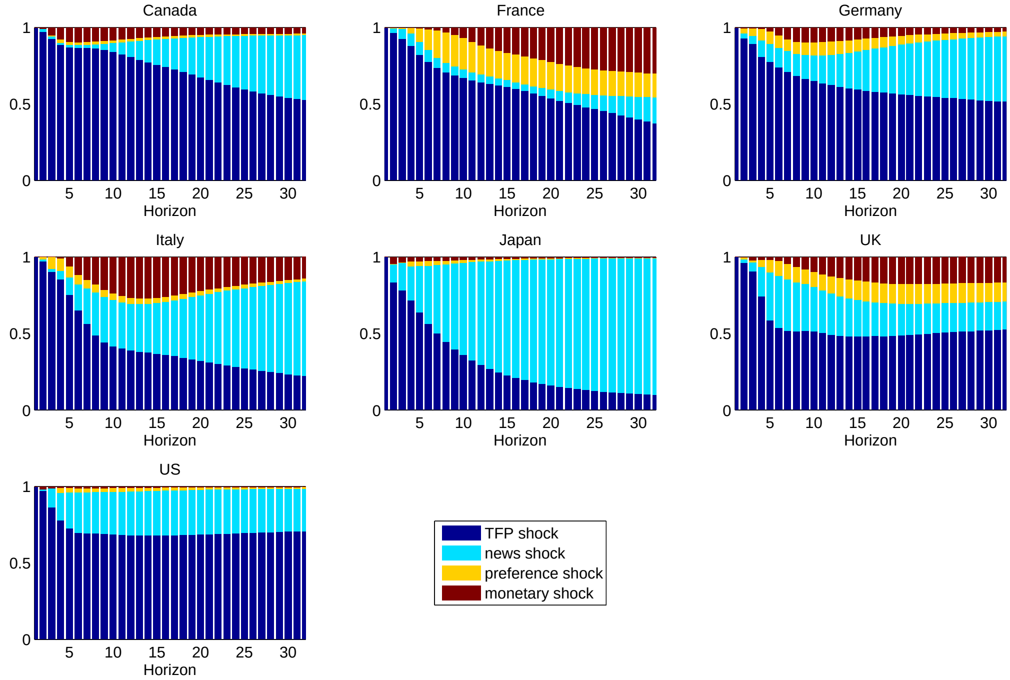


(a) Sample: 1971Q1–2006Q4

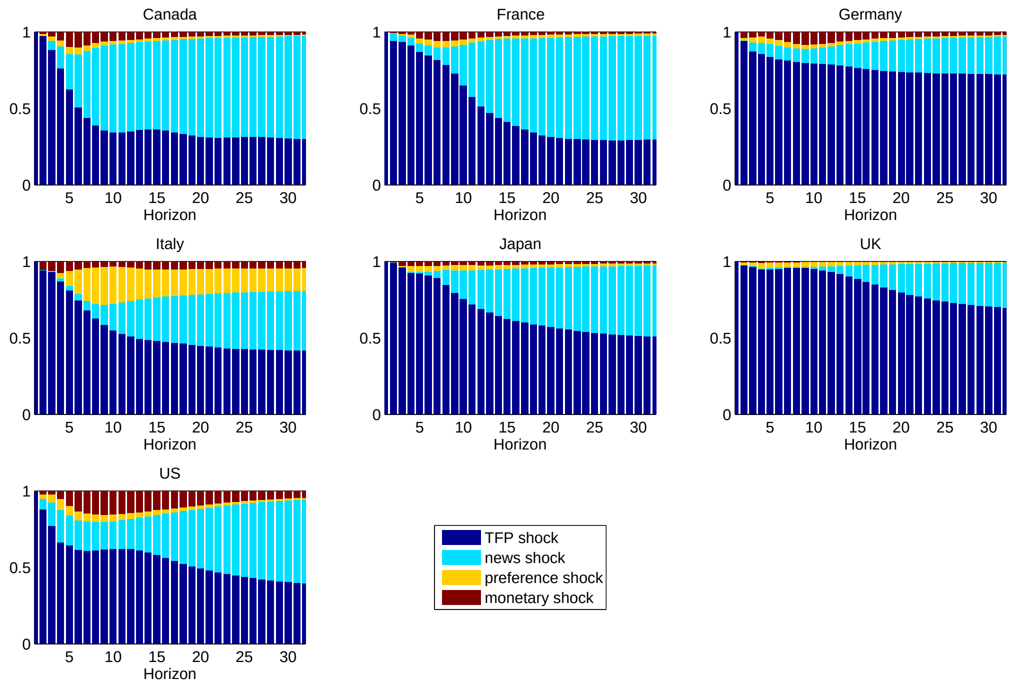
Figure 5.3: FEVD of labor productivity

The FEVD of labor productivity in the entire sample period as well as in the first sub-period had casts doubt on our interpretation of news shocks as news about future technological improvements for the French economy. The FEVD of stock prices further strengthen this doubt: the forecast error variance of stock prices in France is dominated by monetary shocks with shares far above 0.50 in the estimations based on the entire sample and the first sub-sample. Furthermore, in Japan in the second sub-period, for which we had reported a negative response of stock prices to positive news shocks, the share of news shocks is confined to equal to or less than 0.40. Other than that, news shocks are the main driver of stock price fluctuations in Figures A.2(a) and A.2(b). TFP, preference and monetary shocks play only a minor (often insignificant) role.

Hours worked is a variable that is often used as a proxy for capacity utilisation (see, e.g., Basu, Fernald, and Kimball (2006)), a variable deemed to be closely related to business cycles. Figure 5.5 shows the FEVD of hours worked in the G7 countries. Like stock prices,

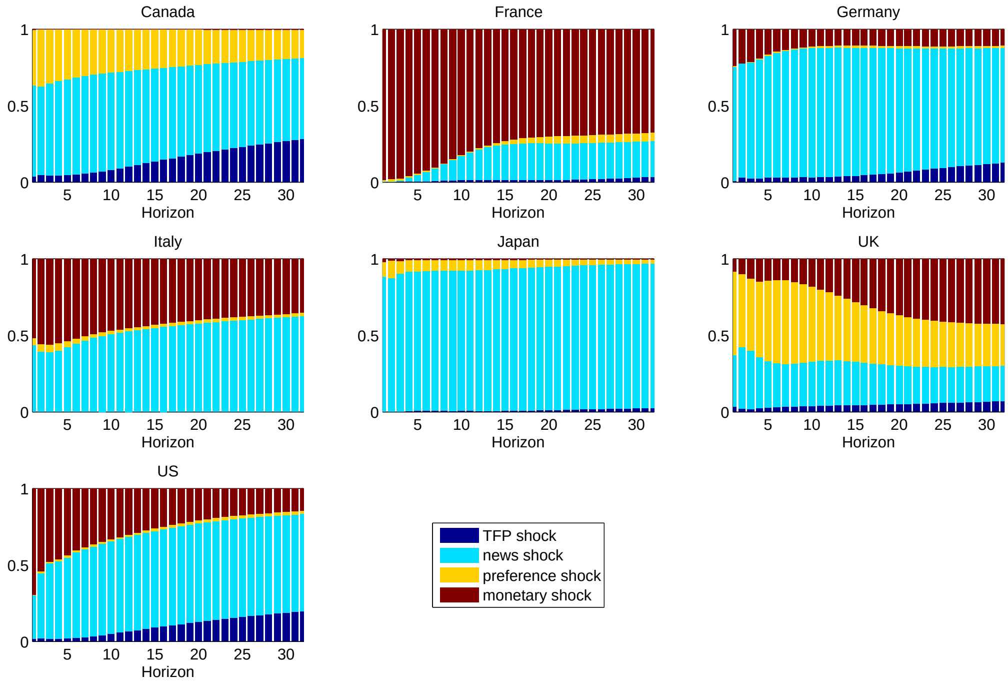


(b) Sample: 1971Q1–1990Q2



(c) Sample:1990Q3–2006Q4

Figure 5.3: FEVD of labor productivity (cont.)

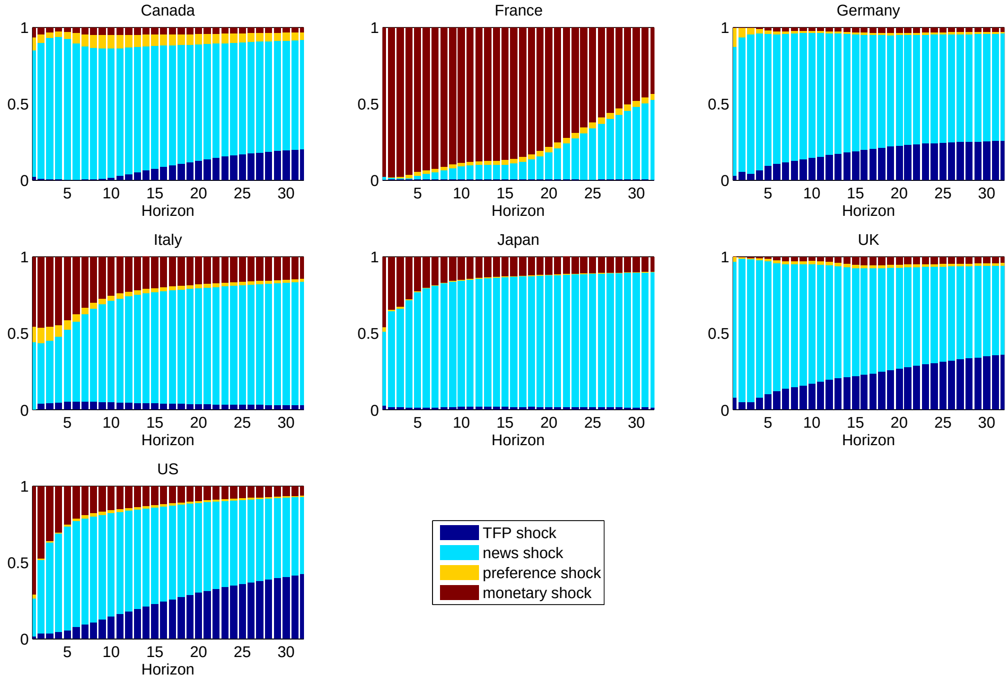


(a) Sample: 1971Q1–2006Q4

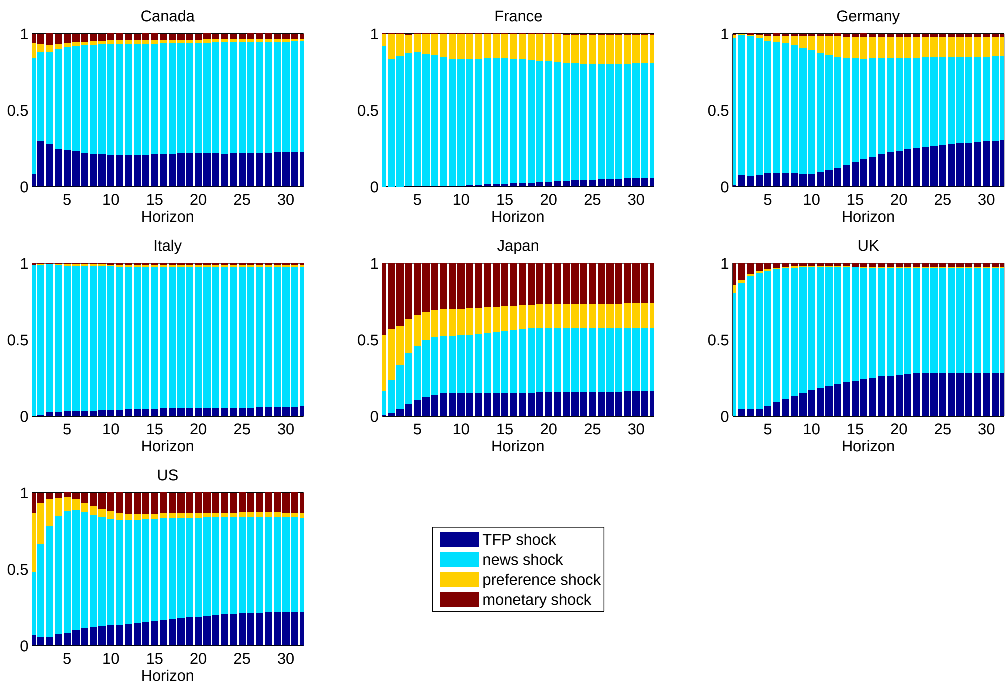
Figure 5.4: FEVD of stock prices

the driving forces of hours worked forecast errors also vary across countries. According to the entire-sample estimates, displayed in Figure 5.5(a), news shocks dominate the fluctuations of hours worked in France, Japan and the US, while they are also of some importance in Germany and the UK. Preference shocks are dominant in Canada and Italy and are also important at some forecast horizons in all other G7 countries when the entire sample is used for the estimation, whereas the role of TFP and monetary shocks is generally much smaller and often negligible.

Substantial changes occur in findings when FEVD of hours worked is carried out with sub-sample data. For example, monetary shocks are non-negligibly important (and sometimes dominant) for hours worked fluctuations in Canada, Germany, Italy and the UK in the first sub-period. News shocks explain an important chunk of hours worked variability in France, Italy, Japan and the US in the first sub-period, while the shares attributed to preference shocks (in terms of point estimates) are in general relatively lower in the first sub-period

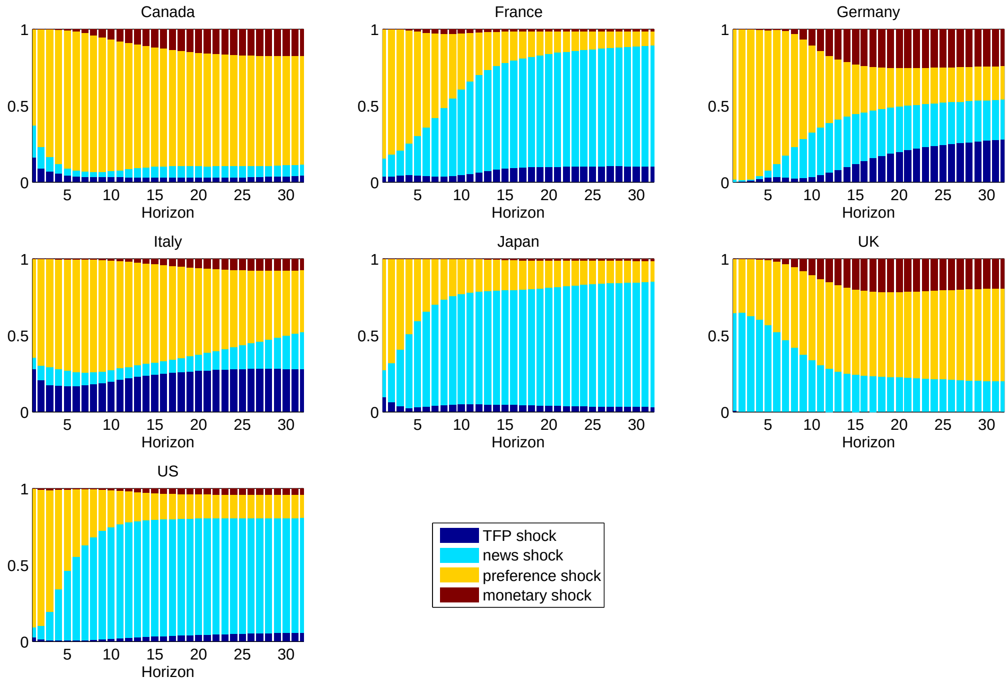


(b) Sample: 1971Q1–1990Q2



(c) Sample:1990Q3–2006Q4

Figure 5.4: FEVD of stock prices (cont.)



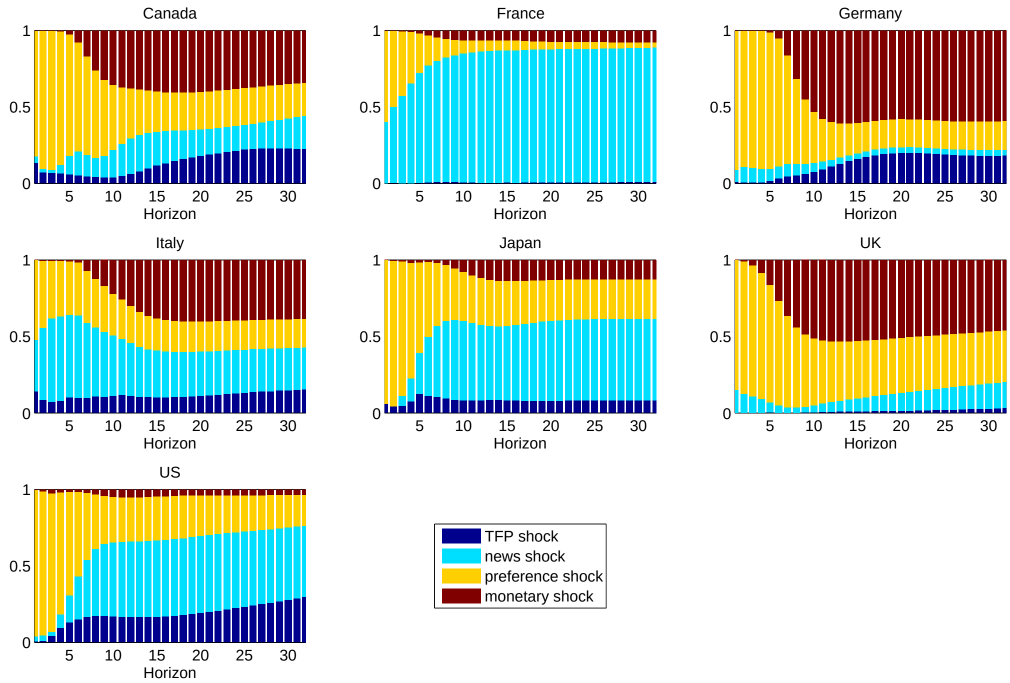
(a) Sample: 1971Q1–2006Q4

Figure 5.5: FEVD of hours worked

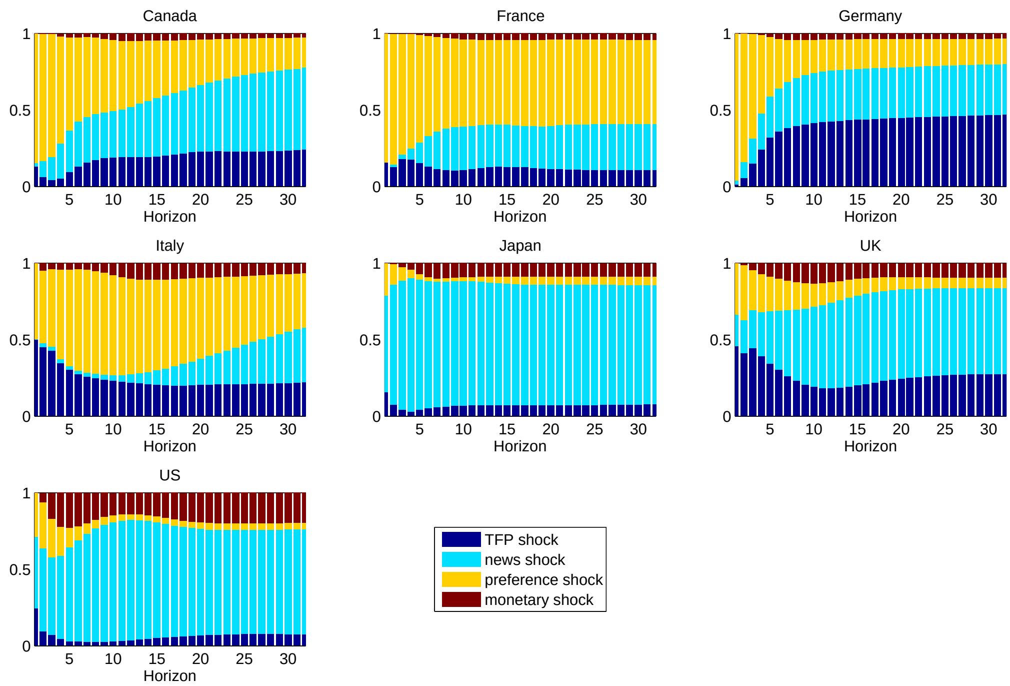
estimates than in the entire-sample estimates.

The shares attributed to monetary shocks are minor in the second sub-period, while the shares of TFP shocks become non-negligible in Germany, Italy and the UK. News shocks dominate the hours worked fluctuations of Japan and the US in the second sub-period as well and are not unimportant in the other G7 countries with the exception of Italy. Finally, preference shocks have a large share in France and Italy, while having more moderate but still important shares in Canada and Germany in the second sub-period.

Finally, we display FEVD graphs for output in Figure 5.6. The commonality in the FEVD results of output is that technology shocks, i.e. TFP-shocks and news shocks, dominate the output fluctuations of all G7 countries, particularly in the second sub-period. The role of preference and monetary shocks in output fluctuations is secondary according to our FEVD estimates. We observe some importance of preference shocks in Canada in all estimates displayed in Figure 5.6. These shocks play a role also according to the entire-sample estimates

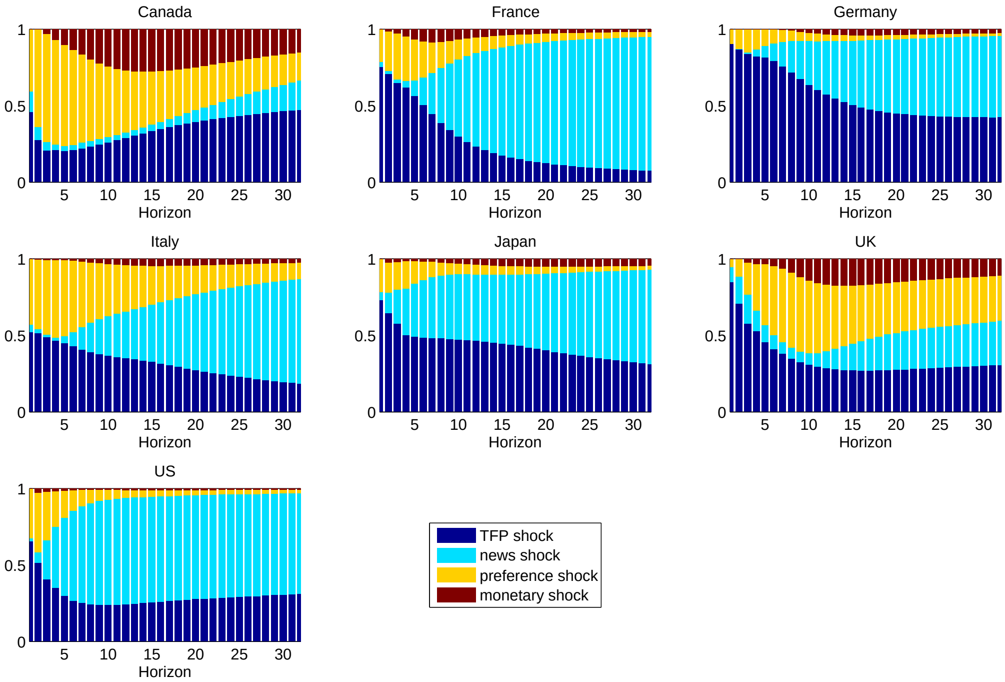


(b) Sample: 1971Q1–1990Q2



(c) Sample:1990Q3–2006Q4

Figure 5.5: FEVD of hours worked (cont.)

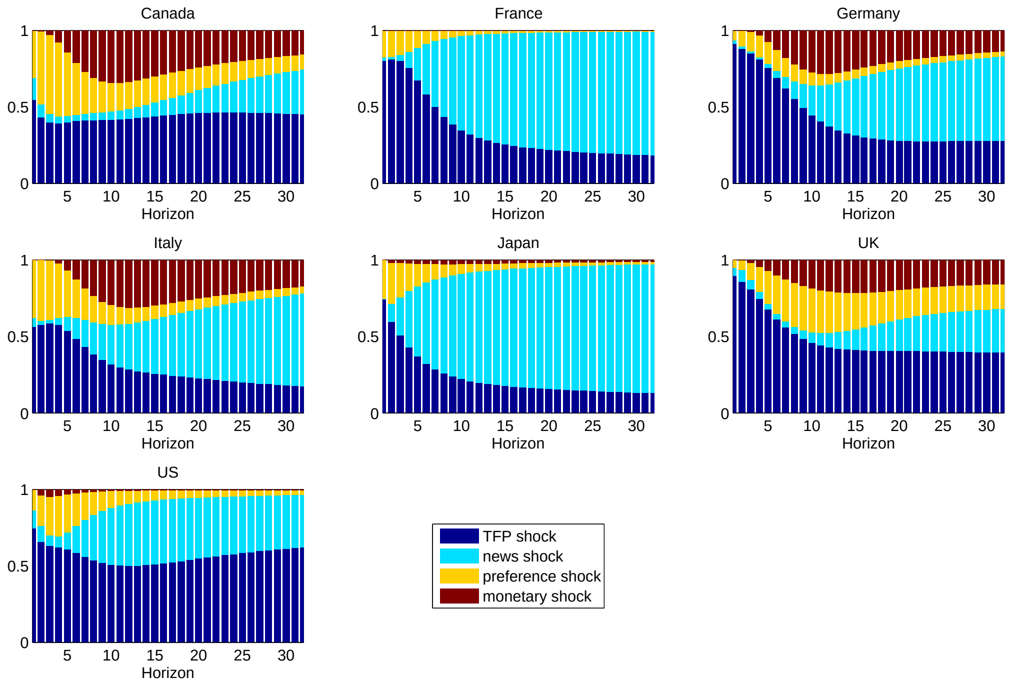


(a) Sample: 1971Q1–2006Q4

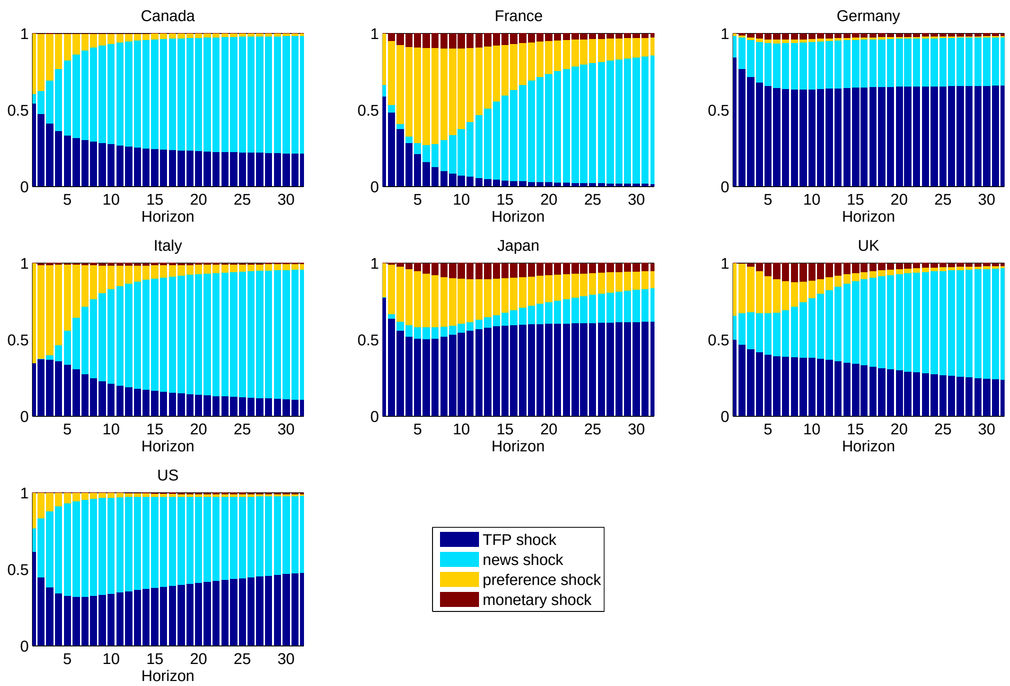
Figure 5.6: FEVD of output

for Italy and the UK, and in the second sub-period estimates for France and Italy.

The FEVD analysis shows that important differences exist across the G7 economies in terms of absorbing exogenous shocks. It is not possible to identify sub-groups of countries of which macroeconomic variables persistently show similar FEVD patterns across them. In particular, the existence of English-speaking and euro area groups as suggested by some studies (see, e.g., Stock and Watson (2005) and the references therein) in terms of their variables showing similar FEVD patterns cannot be established.



(b) Sample: 1971Q1–1990Q2



(c) Sample:1990Q3–2006Q4

Figure 5.6: FEVD of output (cont.)

5.3.3 Robustness: cointegration

Cointegration equations

Cointegration relationships are long-run relationships among variables. Estimation of cointegrated systems are notorious for producing unreliable results when the sample underlying the estimation is short. In order to detect the importance of this issue for our conclusions, we have re-estimated our models with sub-period data by imposing on them the coefficients of the cointegration equations that are estimated using the entire data set, while the coefficients of the VECMs corresponding to the first-differenced terms were left unrestricted. The results of the first sub-period are marginally sensitive to this restriction, the majority of them being in accordance with the findings reported above. The results of the second sub-period show more sensitivity. Particularly, the reported shares of shocks in stock prices, hours worked and output fluctuations are affected. There is a larger role, for example, for preference shocks in the hours worked fluctuations of Canada, Germany and the UK and a smaller role in the hours worked fluctuations of France, when entire-sample estimates are used as the coefficients of the cointegration equations in the VECM. Monetary shocks play a non-negligible role in the output fluctuations of France and Italy according to our modified estimation, while these shocks are unimportant according to our previous estimations of the model. Since most of our other conclusions are, however, the same as before, we present our new estimates in the appendix for the interested reader.

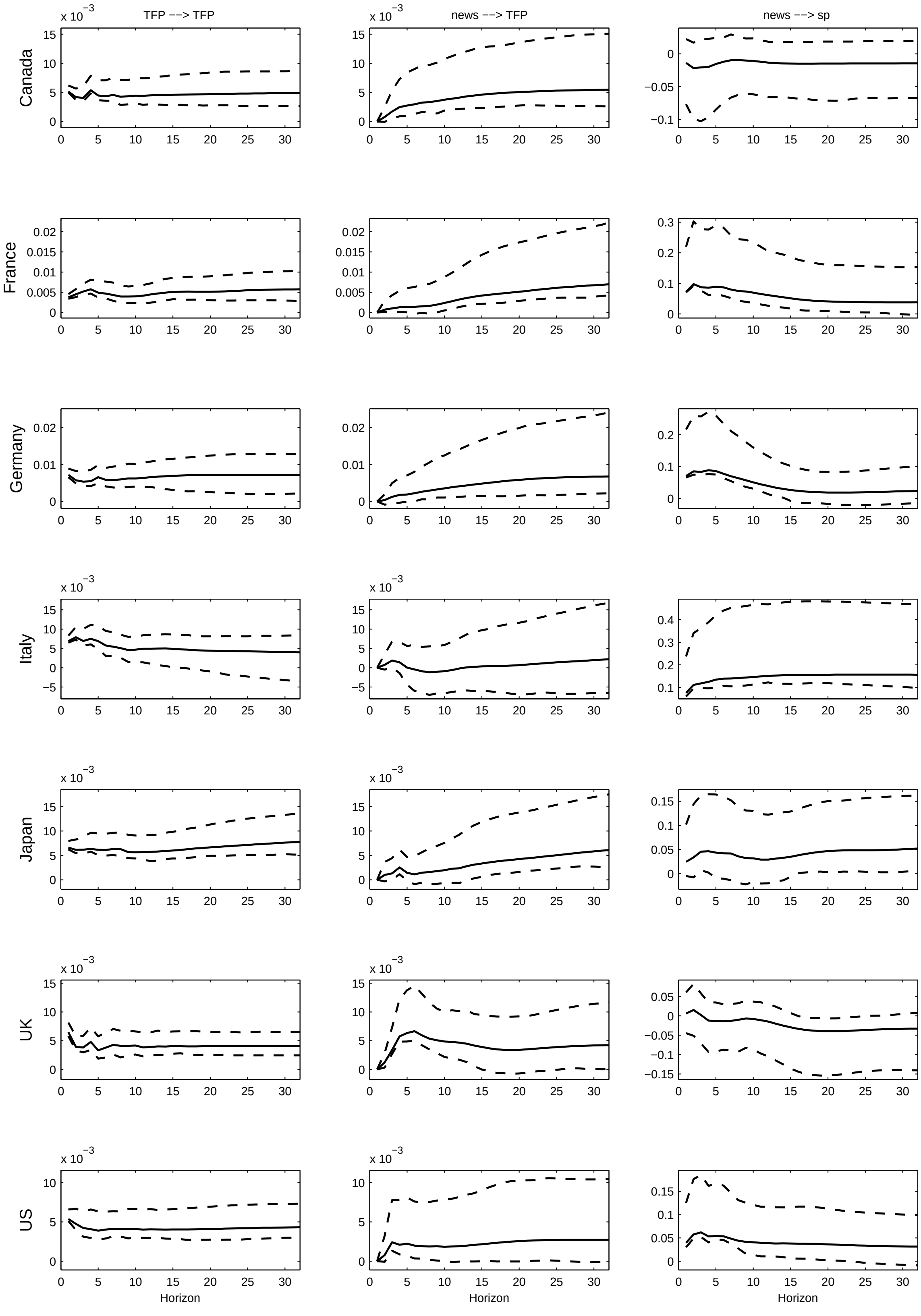
Cointegration rank

We followed Beaudry and Lucke (2009) when setting the cointegration rank to 3 in our hitherto estimations, which implies that our country-specific SVECMs contain only one stochastic trend. This assumption is in line with the theory, which typically assumes that the total factor productivity follows a unit root process. However, it is often not supported by our data, as shown before in Table 5.2. We check the implications of assuming a cointegration rank of 2 in this sub-section.[12] We display the response of labor productivity to a one-standard-deviation TFP shock and the responses of labor productivity and stock prices to a one-standard-deviation news shock in Figure 5.7, which is analogous to Figure 5.2. Labor productivity reacts positively to a positive TFP shock in the short run as well as in the long run in estimations corresponding to both sub-periods as shown in the first column of all panels of Figure 5.7.

In the second column of all panels of Figure 5.7, we display the response of labor productivity to news shocks. The interpretation of a positive news shock corresponding to improvements in future technology requires that the long-run response of labor productivity is positive to such a shock, which is indeed the case in Figure 5.7. Note that whether this sign restriction holds is trivial, since the SVECM is identified only up to a certain sign restriction as discussed at the end of Chapter 1. In case the sign of labor productivity response is negative in the long run, the sign is changed by multiplying the impulse response function by minus one and interpreting the underlying shock to be a positive technology shock.

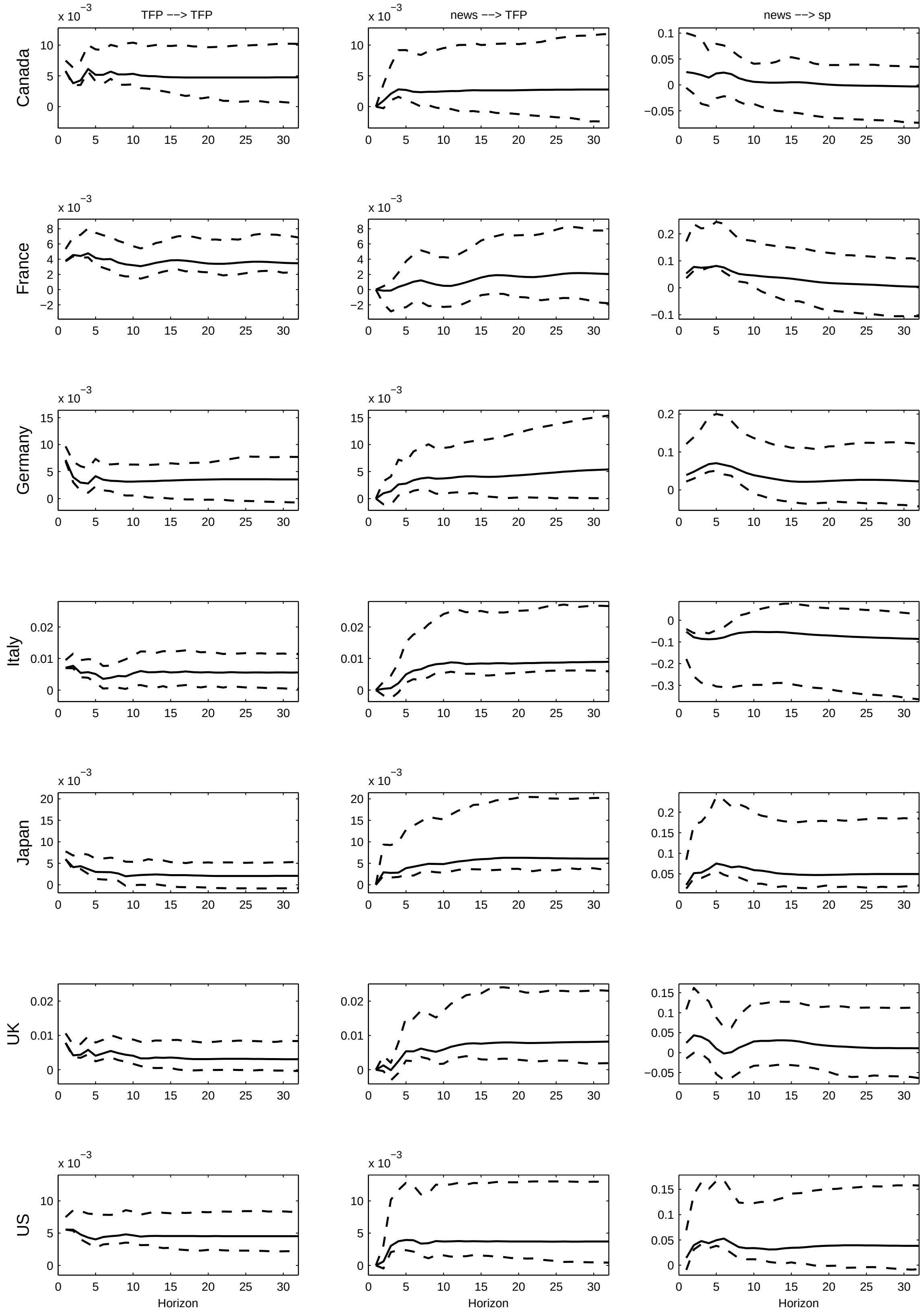
Once we set the sign of the labor productivity response to news shocks such that it can be interpreted as a positive shock to technology, particularly in the long run, we are bound by this restriction and cannot alter the sign of other variables' responses to a "positive" news shock. Keeping this in mind, our SVECM estimations now imply that the response of stock prices, shown in the last column of all panels of Figure 5.7, is negative to a positive news shock in Canada and the UK for the estimations with the entire sample, in Italy in the first sub-period, and in Italy, Japan, the UK and the US in the second sub-period. Note that a negative response of stock prices to positive news shocks is theoretically possible. Jaimovich and Rebelo (2006) argue, for example, that such shocks affect the value of a firm through two channels: while a news shock increases, on the one hand, the value of a firm's investment, it decreases, on the other hand, the value of its existing capital stock. If the latter channel is

[12] Note that we have also tried out a cointegration rank of one in the country-specific models. It generated the implausible result that stock prices fluctuations are solely due to monetary shocks in five of the G7 countries (the ones except France and the US). Therefore, we do not report results from that model.



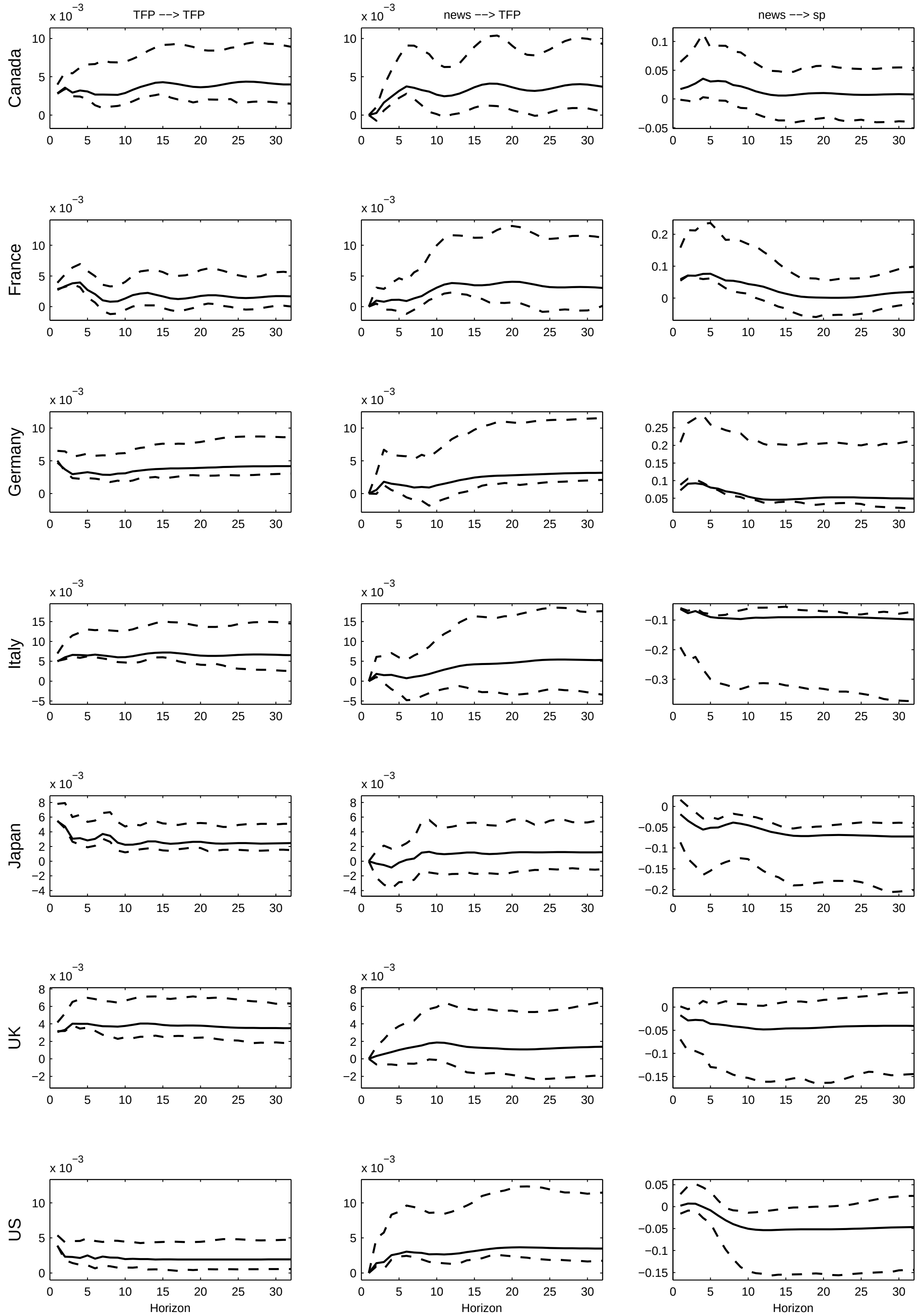
(a) Sample: 1971Q1–2006Q4

Figure 5.7: Impulse responses from country-specific models



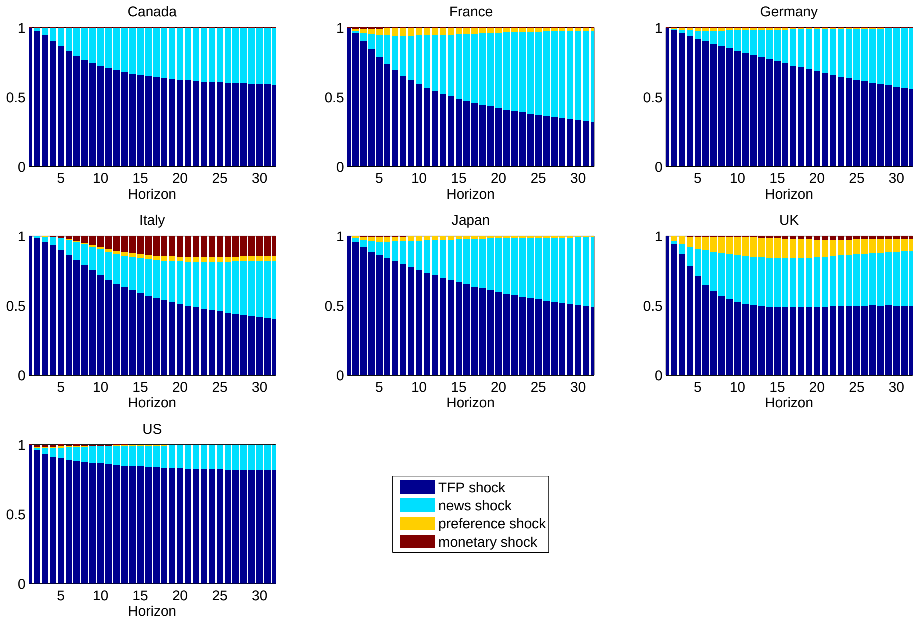
(b) Sample: 1971Q1–1990Q2

Figure 5.7: Impulse responses from country-specific models (cont.)



(b) Sample: 1990Q3–2006Q4

Figure 5.7: Impulse responses from country-specific models (cont.)



(a) Sample: 1971Q1–2006Q4

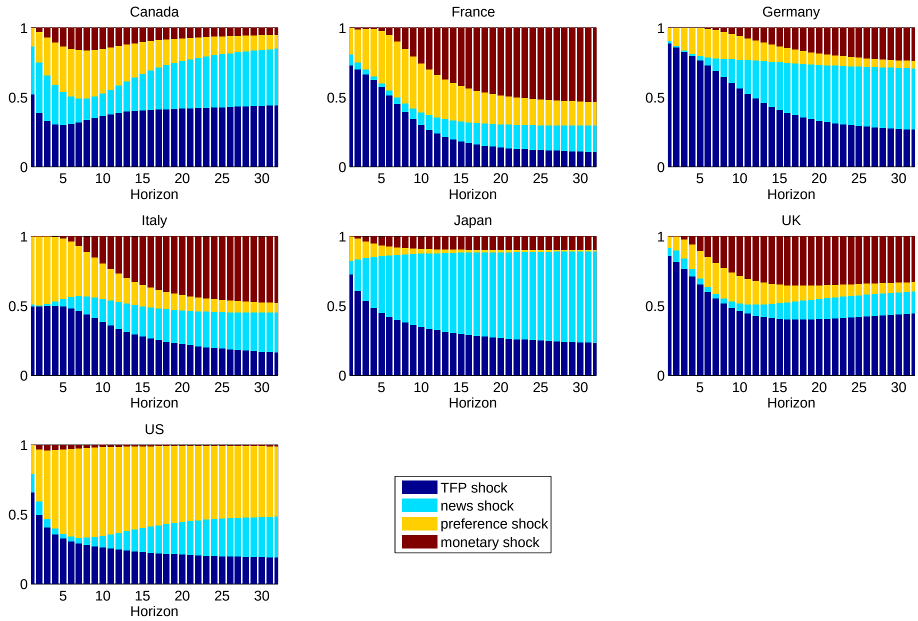
Figure 5.8: FEVD of labor productivity

stronger than the former channel, a news shocks decreases the firm's value according to the model of Jaimovich and Rebelo (2006).

Note that a cointegration rank of two gives results that are also in accordance with the hypothesis that news shocks stand for future technological improvements: the share of news shocks in the fluctuations of labor productivity increase with increasing forecast horizon according to the FEVD of labor productivity, displayed in Figure 5.8, from our SVECMs with two cointegrating equations.[13] However, our other results are not totally insensitive to this choice. For example, the weight of news shocks in the FEVD of output decreases substantially in France and the US according to the entire-sample estimate of the model with two cointegrating equations in comparison to the former case with three cointegrating relationships, cf. Figure 5.9, although the differences between the two models are not so large for the other G7 countries.

Our hitherto findings may point to one of several possible conclusions. For example, it

[13]We report only the entire-sample results, but sub-sample results are similar.



(a) Sample: 1971Q1–2006Q4

Figure 5.9: FEVD of output

may well be the case that a cointegration rank of two is inappropriate for our SVECMs, and a cointegration rank of three gives the correct specification of the model. Cointegration tests are after all notorious for their low power, particularly in short samples, and a cointegration rank of three is also in line with the assumptions of a class of theoretical models. Another possibility is that, a cointegration rank of two is correct, i.e., data is driven by more than one stochastic trend, and theoretical models must be extended or modified in this direction. After all, whether there are two or three stochastic trends in the theoretical model of, e.g., Fisher (2006), is not an implication of the model, but an assumption. There is no a priori reason to reject the hypothesis that monetary shocks or preference shocks do not feed exogenous processes with a unit root. Gali (1999), for example, assumes in the stylised model he uses as a motivation for his SVAR identification scheme that money supply is a unit root process. In this context, more refining of news shocks may be necessary. Schmitt-Grohe and Uribe (2009) consider, for example, different sources of news shocks corresponding not only to (stationary and nonstationary) productivity, but also to investment-specific technology and government spending. Obviously, other sources of shocks could be added to this list.

5.4 International linkages

As mentioned in the introduction to this chapter, while linkages of the G7 countries' business cycles has already been the subject of the macroeconomic literature, most of this literature does not give an interpretation to estimated shocks that corresponds to macroeconomic theory. In this section, we tackle this issue by assuming that structural shocks of individual countries consist of common (international) and country-specific components. The previous empirical framework of country-specific SVECMs is extended with international shocks, the role of which in output fluctuations of the G7 countries is assessed.

5.4.1 Data

We focus only on output fluctuations in the following, which is the main subject of interest in the majority of studies on international business cycles. The correlation of output gaps computed with per capita output data of the G7 countries employing the asymmetric CF-filter are reported in Table 5.3. Some aspects of this table deserve emphasis. First, the correlations computed using the entire sample data are positive and statistically significant. However, differences exist in these correlations when the sample is split. The average correlation is lower in the second sub-period (0.30) than in the first sub-period (0.62). Both of these findings are in line with the previous literature (see, e.g., Stock and Watson (2005)). Second, the output gap of Japan is positively correlated with the output gaps of the other G7 countries in the first sub-period, whereas the picture changes significantly in the second sub-period where Japanese output gap is generally much less related to the output gaps of the other G7 members.

The emergence (or existence) of a euro area sub-group within the G7 group in terms of coherent output gaps can be detected in our data, too. Particularly in the second sub-period,

Table 5.3: Output gap correlation

Sample: 1971Q1–2006Q4						
	can	fra	deu	ita	jap	uk
fra	0.50	1.00				
	(0.19)	(0.00)				
deu	0.48	0.59	1.00			
	(0.14)	(0.08)	(0.00)			
ita	0.50	0.67	0.52	1.00		
	(0.11)	(0.08)	(0.15)	(0.00)		
jap	0.21	0.45	0.60	0.33	1.00	
	(0.19)	(0.14)	(0.16)	(0.18)	(0.00)	
uk	0.52	0.72	0.45	0.36	0.49	1.00
	(0.17)	(0.11)	(0.14)	(0.12)	(0.12)	(0.00)
us	0.72	0.56	0.64	0.30	0.50	0.62
	(0.10)	(0.16)	(0.14)	(0.12)	(0.13)	(0.16)

	Sample: 1971Q1–1990Q2						Sample: 1990Q3–2006Q4					
	can	fra	deu	ita	jap	uk	can	fra	deu	ita	jap	uk
fra	0.40	1.00					0.62	1.00				
	(0.19)	(0.00)					(0.19)	(0.00)				
deu	0.78	0.72	1.00				0.23	0.66	1.00			
	(0.11)	(0.09)	(0.00)				(0.15)	(0.10)	(0.00)			
ita	0.57	0.66	0.60	1.00			0.25	0.68	0.79	1.00		
	(0.17)	(0.12)	(0.07)	(0.00)			(0.09)	(0.15)	(0.10)	(0.00)		
jap	0.57	0.63	0.79	0.29	1.00		-0.25	0.08	0.41	0.49	1.00	
	(0.20)	(0.17)	(0.10)	(0.19)	(0.00)		(0.18)	(0.25)	(0.25)	(0.20)	(0.00)	
uk	0.43	0.77	0.72	0.29	0.78	1.00	0.71	0.34	0.18	0.35	-0.15	1.00
	(0.23)	(0.12)	(0.15)	(0.12)	(0.12)	(0.00)	(0.14)	(0.25)	(0.24)	(0.17)	(0.21)	(0.00)
us	0.77	0.59	0.89	0.38	0.78	0.70	0.64	0.42	-0.12	-0.11	-0.17	0.29
	(0.05)	(0.20)	(0.07)	(0.12)	(0.10)	(0.15)	(0.14)	(0.17)	(0.20)	(0.18)	(0.33)	(0.33)

Notes: The output gap measure is the CF-filter. Standard errors in parentheses. *Abbreviations*: can: Canada, fra: France, deu: Germany, ita: Italy, jap: Japan.

where the average correlation in the G7 group is much lower than in the first sub-period, the correlations in the euro area group are roughly at least as high as in the first sub-sample, while the correlation between each euro area country and other countries is lower than in the first sub-sample. Moreover, the output gap of each euro area country has the highest correlation with the output gaps of the other two euro area countries. The emergence (or existence) of an English-speaking group is, however, less evident. While Canadian output gap is strongly related to the output gaps of the UK and the US in both sub-periods, the output gap correlation of the US and the UK is only 0.29 in the second sub-period.

5.4.2 Common factors

The generally positive and significant correlations reported in Table 5.3 suggest that common (international) shocks play a certain role in business cycle dynamics of the G7 countries. We follow Chamie, DeSerres, and Lalonde (1994), Xu (2006) and Seymen and Kappler (2009) for modelling common and country-specific components of previously estimated structural shocks of the G7 countries. The estimated shocks of all countries are collected in a state-space model, where each country's structural shocks are assumed to comprise an unobserved component common to all countries and an unobserved country-specific component, which are orthogonal to each other by construction. Formally, the j^{th} block for $j = TFP, news, preference, monetary$—with respect to the j^{th} structural shock—of the measurement equation reads

$$\begin{bmatrix} \varepsilon^j_{1,t} \\ \vdots \\ \varepsilon^j_{7,t} \end{bmatrix} = \begin{bmatrix} \alpha^{j,1}_{10} & \cdots & \alpha^{j,\kappa}_{10} \\ \vdots & \ddots & \vdots \\ \alpha^{j,1}_{70} & \cdots & \alpha^{j,\kappa}_{70} \end{bmatrix} \begin{bmatrix} \xi^{j,1}_{0t} \\ \vdots \\ \xi^{j,\kappa}_{0t} \end{bmatrix} + \begin{bmatrix} \xi^j_{1t} \\ \vdots \\ \xi^j_{7t} \end{bmatrix}, \tag{5.18}$$

where $\alpha^{j,k}_{i0}$ is the loading for the i^{th} country, corresponding to the k^{th} common factor of the j^{th} structural shock, $\xi^{j,k}_{0t}$ is the k^{th} common factor for the j^{th} structural shock, and ξ^j_{it} for $i = 1, \ldots, 7$ is the country-specific component of the j^{th} structural shock for the i^{th} country. Hence, $\alpha^{j,k}_{i0}\xi^{j,k}_{0t}$ gives the k^{th} common component of the j^{th} structural shock for the i^{th}

country. Note that there are κ common factors in this framework. Both types of unobservable components are modelled as white noise errors due to the assumption of no autocorrelation and no cross-correlation of the structural shocks and their zero-mean property. We also assume that structural shocks of different countries are not correlated across time. This condition is necessary for excluding the possibility that future shocks can be estimated. We estimate the loadings, factors, country-specific shocks and the corresponding variances by maximising the Gaussian maximum likelihood using the expectations-maximisation (EM) algorithm following Stock and Watson (2005).

Our empirical strategy is in line with many theoretical international business cycle models, which connect different economies through exogenous processes. For instance, in a typical two-country model, both countries are assumed to show a similar structure with different parameter values. The models considered by Backus, Kehoe, and Kydland (1992) and Baxter and Crucini (1993) provide a good example. The authors assume that two economies are linked through technology, which is a part of the production function and is modelled as an exogenous process:

$$\begin{bmatrix} \log A_t \\ \log A_t^* \end{bmatrix} = \begin{bmatrix} \rho_A & \rho_{A^*} \\ \rho_A^* & \rho_{A^*}^* \end{bmatrix} \begin{bmatrix} \log A_{t-1} \\ \log A_{t-1}^* \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \varepsilon_t^* \end{bmatrix}, \tag{5.19}$$

where $\log A_t$ and $\log A_t^*$ stand for the log levels of technology in the home and foreign countries, respectively, ρ and ρ^* are the coefficients corresponding to the lag of the technology level in the home and foreign countries, respectively, and ε_t and ε_t^* are the technology shocks of both countries with a non-zero covariance matrix. It is straightforward to think of a structure similar to (5.19) for other types of shocks. The factor structure in (5.18) reflects the view that the correlation between the structural shocks of the individual countries considered within the framework of (5.19) is due to the common factors.

Recall that we initially estimate country-specific SVECMs, which are not connected to each other. This amounts to assuming that $\rho_{A^*} = \rho_A^* = 0$ in terms of our example in (5.19). In other words, no spillovers are allowed across the countries in our framework. Hence, while common shocks hit all countries at the same time, their transmission on the individual countries are independent from each other. Our empirical model reflects an environment, where the coefficients corresponding to the lagged level of exogenous processes, ρ_A and $\rho^*_{A^*}$ are embedded into the structural matrix polynomial $\Theta(L)$ in terms of the moving average representation of our SVECM in (5.14).

We carry out likelihood ratio tests in order to determine the number of factors to be included in (5.18) for each structural shock estimated with country-specific SVECMs, i.e., TFP, news, preference and monetary shocks. We conjecture four different factor structures. Factor Model I and Factor Model II respectively contain unrestricted one and two factors, i.e., unrestricted 7×1 and 7×2 loading matrices in (5.18). Factor Model III comprises two factors, the first factor being unrestricted for all G7 countries, i.e., a global factor, the second factor applying only to euro area countries, i.e., a euro area factor. Factor Model IV consists of two global and one euro area factors. Ordering the G7 countries as Canada, France, Germany, Italy, Japan, the UK and the US, the factor structure corresponding to these four specifications is respectively given by

$$\begin{bmatrix} \alpha_{10}^{j,1} \\ \alpha_{20}^{j,1} \\ \alpha_{30}^{j,1} \\ \alpha_{40}^{j,1} \\ \alpha_{50}^{j,1} \\ \alpha_{60}^{j,1} \\ \alpha_{70}^{j,1} \end{bmatrix}, \quad \begin{bmatrix} \alpha_{10}^{j,1} & \alpha_{10}^{j,2} \\ \alpha_{20}^{j,1} & \alpha_{20}^{j,2} \\ \alpha_{30}^{j,1} & \alpha_{30}^{j,2} \\ \alpha_{40}^{j,1} & \alpha_{40}^{j,2} \\ \alpha_{50}^{j,1} & \alpha_{50}^{j,2} \\ \alpha_{60}^{j,1} & \alpha_{60}^{j,2} \\ \alpha_{70}^{j,1} & \alpha_{70}^{j,2} \end{bmatrix}, \quad \begin{bmatrix} \alpha_{10}^{j,1} & 0 \\ \alpha_{20}^{j,1} & \alpha_{20}^{j,2} \\ \alpha_{30}^{j,1} & \alpha_{30}^{j,2} \\ \alpha_{40}^{j,1} & \alpha_{40}^{j,2} \\ \alpha_{50}^{j,1} & 0 \\ \alpha_{60}^{j,1} & 0 \\ \alpha_{70}^{j,1} & 0 \end{bmatrix}, \quad \begin{bmatrix} \alpha_{10}^{j,1} & \alpha_{10}^{j,2} & 0 \\ \alpha_{20}^{j,1} & \alpha_{20}^{j,2} & \alpha_{20}^{j,3} \\ \alpha_{30}^{j,1} & \alpha_{30}^{j,2} & \alpha_{30}^{j,3} \\ \alpha_{40}^{j,1} & \alpha_{40}^{j,2} & \alpha_{40}^{j,3} \\ \alpha_{50}^{j,1} & \alpha_{50}^{j,2} & 0 \\ \alpha_{60}^{j,1} & \alpha_{60}^{j,2} & 0 \\ \alpha_{70}^{j,1} & \alpha_{70}^{j,2} & 0 \end{bmatrix}. \tag{5.20}$$

The results of tests on the four different factor structures are reported in Table 5.4. The unrestricted one-factor model is rejected for preference shocks in the first sub-period and for news shocks in the second sub-period, while the unrestricted two-factor model is rejected for preference shocks in the first sub-period. However, Factor Model III and Factor Model IV find support at 5-percent significance level. We stick to Factor Model III specification in the following when reporting variance decomposition findings. Its main implications are

Table 5.4: Test of number of common factors

	Factor Model I p-values			
	TFP	news	pref.	mon.
1971Q1–2006Q4	0.26	0.04	0.15	0.03
1971Q1–1990Q3	0.88	0.23	0.03	0.18
1990Q3–2006Q4	0.15	0.04	0.20	0.25

	Factor Model II p-values			
	TFP	news	pref.	mon.
1971Q1–2006Q4	0.58	0.15	0.51	0.28
1971Q1–1990Q3	0.78	0.40	0.03	0.38
1990Q3–2006Q4	0.12	0.82	0.29	0.43

	Factor Model III p-values			
	TFP	news	pref.	mon.
1971Q1–2006Q4	0.16	0.01	0.24	0.01
1971Q1–1990Q3	0.80	0.13	0.06	0.17
1990Q3–2006Q4	0.23	0.24	0.19	0.14

	Factor Model IV p-values			
	TFP	news	pref.	mon.
1971Q1–2006Q4	0.47	0.06	0.85	0.13
1971Q1–1990Q3	0.54	0.20	0.08	0.39
1990Q3–2006Q4	0.60	0.34	0.47	0.20

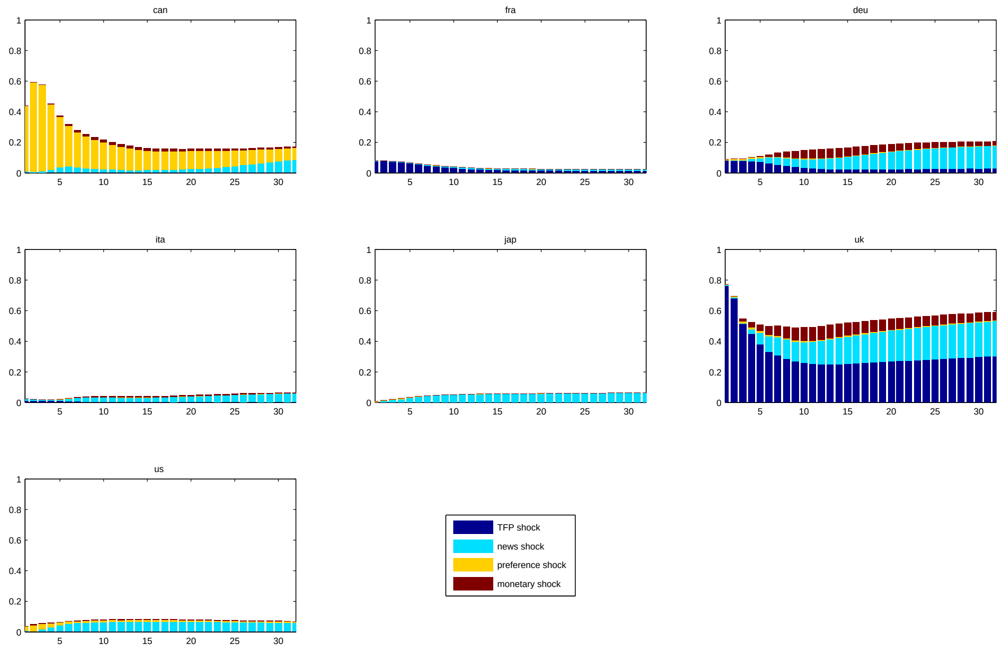
similar to Factor Model IV specification, while the global factors are attributed a higher share, particularly in the first sub-period, in output fluctuations by the latter model.

5.4.3 Forecast Error Variance Decomposition

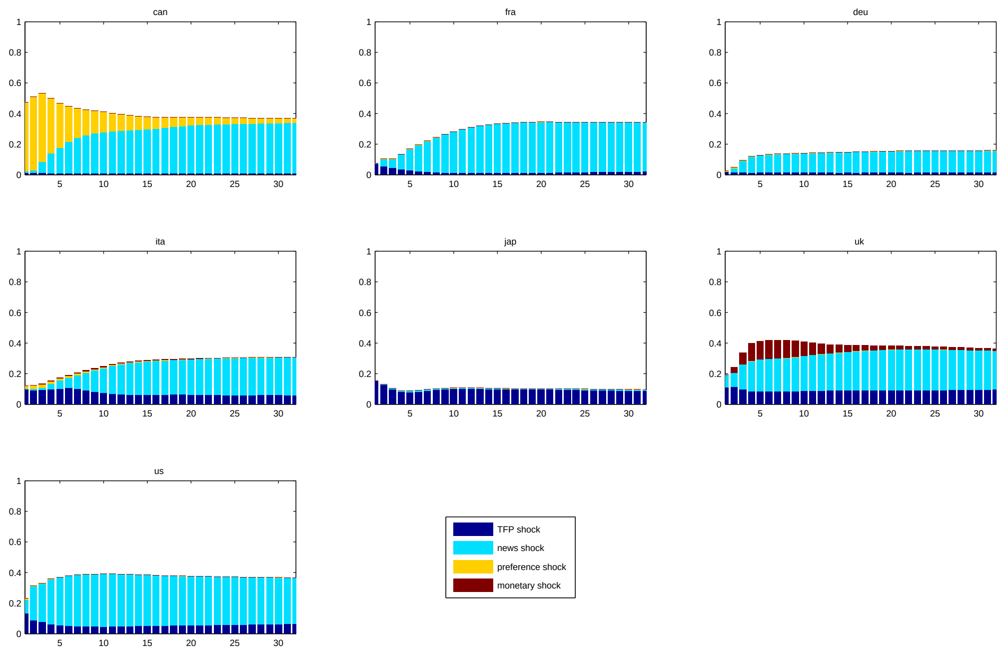
The factor structure in (5.18) can be fed back to the moving average representation of country-specific SVECMs in (5.14), which allows us to compute FEVD as hitherto done in this study. Note that each structural shock of each G7 country comprises three components now: a global component (the first factor), a euro area component (the second factor applying only to euro area members), and a country-specific component given by ξ_{it}^{j} for $i = 1, \dots 7$ in (5.18). Hence, there are altogether 12 different shock sources in our empirical model, 8 of which are of international origin.

In Figure 5.10, we show the total FEVD shares of global component of each structural shock over our two sub-periods. Shocks of global nature become more important in the second sub-period than in the first sub-period for the output fluctuations of France, Italy and the US. International shocks play an important role in the fluctuations of Canada and the UK over both periods, FEVD shares of international shocks become somewhat lower in the second sub-period. The shares of global shocks is quite low in the output fluctuations of Japan over both sub-periods. A striking feature of the FEVDs illustrated in Figure 5.10 is that global news shocks become a non-negligible factor in the output fluctuations of all G7 countries but Japan. This finding suggests that theoretical models investigating international business cycles could improve their performance in terms of matching the reality by including news shocks as a stochastic source of fluctuations. Global TFP, preference and monetary shocks are generally of negligible importance for the output fluctuations of the G7 countries. Note that this finding is valid also when we assume one or three factors (in the latter case two global factors and one euro area factor).

In Figure 5.11, we show the total FEVD shares of the euro area factor in the output fluctuations of the corresponding countries. The share of the euro area factor is higher in the output fluctuations of France and Italy in the second sub-period than in the first sub-period. The structural euro area factors that are important for the output cycles of Italy changes from preference shocks to TFP shocks, albeit it is not possible to claim that these shares are statistically significant. In the case of Germany, the total share of euro area factors decreases to virtually zero in the second sub-period from shares above 0.4 in the first sub-period, whereas the total share of euro area factors is virtually zero in the first sub-period for the output cycles of France. Recall, however, from Table 5.3 that euro area countries' cycles are highly correlated in both sub-periods. The latter finding combined with our FEVD findings in Figure 5.11 implies that euro area countries must be react to global shocks and euro area shocks in a similar way and that global shocks are, at least partly, an important



(a) Sample: 1971Q1–1990Q2



(b) Sample:1990Q3–2006Q4

Figure 5.10: FEVD shares of global shocks for output

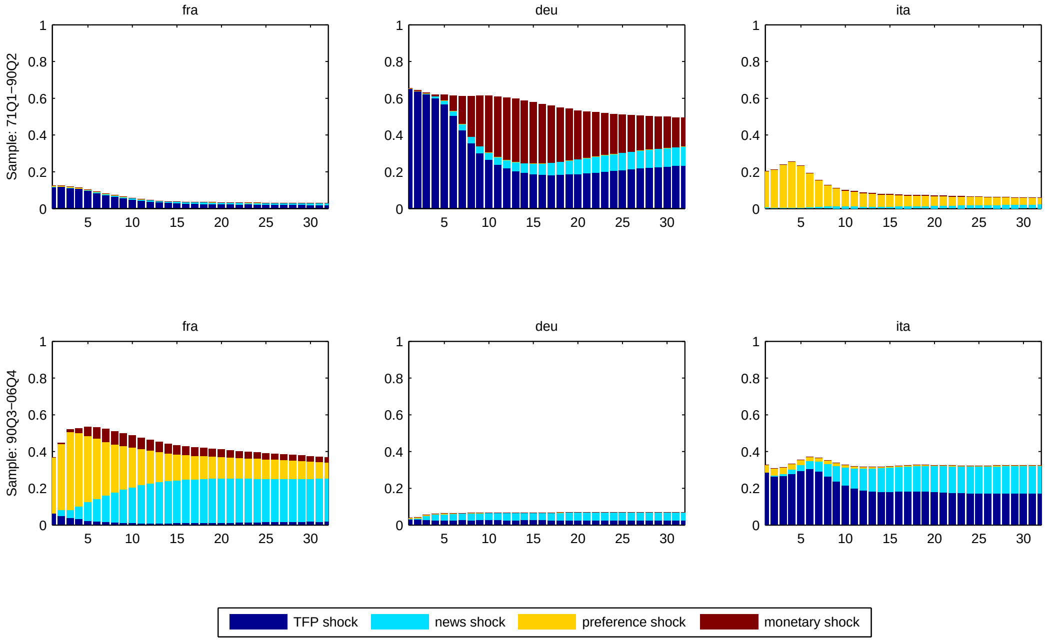


Figure 5.11: FEVD shares of euro area shocks for output

driving force of output fluctuations of the euro area countries so that we can observe the high correlations within the euro group over both sub-periods in Table 5.3.

5.5 Summary and remarks

In this chapter, we carried out an analysis of the G7 countries' business cycle dynamics. We started with a review of prominent macroeconomic views on the sources of macroeconomic fluctuations, which was followed by the presentation of the benchmark SVECM of Beaudry and Lucke (2009). The latter model has the property of containing competing contemporary views on the sources of cyclical fluctuations in a unified framework. We modified the basic model of Beaudry and Lucke to analyse the driving forces of the G7 countries' business cycles. Our modification was shown to make little difference to the benchmark model of Beaudry and Lucke (2009) in the case of the US economy.

An important finding of Beaudry and Lucke (2009) is that news shocks, which reflect information on future developments in technology, are the most important driving force behind the fluctuations of economic activity, represented by hours worked and output among others. Although our data set differs from the one of Beaudry and Lucke and, moreover, we report estimates from two different sub-periods, our findings with respect to these two variables are broadly in line with the findings of those authors, at least in terms of establishing the importance of news shocks in the macroeconomic fluctuations of the US economy. With respect to the output fluctuations of the other G7 countries, we found that, particularly in our second sub-period that covers the period from 1990Q3–2006Q4, TFP and news shocks are generally the main driving forces of output fluctuations at business cycle frequencies. While some studies report the emergence of two cyclically coherent groups of countries—euro area countries and English-speaking countries—within the G7, we were not able to establish similar patterns in terms of FEVD of the macroeconomic variables comprised by the country-specific SVECMs we estimated. This suggests that, in spite of generally high and positive output gap correlations in the G7 group, structural differences exist across the countries in terms of absorbing shocks.

We conjectured a factor structure for each type of structural shock included in the country-specific SVECMs, i.e., neutral technology (TFP), news, preference and monetary shocks, such that these consist of common and country-specific components for each G7 country. Likelihood ratio tests did not reject the constellation that all types of shocks consist of global, euro area and country-specific components. Hence, the likelihood ratio tests provide an indirect support for the hypothesis of the emergence or existence of a euro area of sub-group within the G7. With the exception of Japan in both sub-periods that we consider and Germany in the latter sub-period, we found that international shocks are an important source of cyclical fluctuations. While the finding corresponding to Germany might be related to the adjustment process due to the reunification, and the finding corresponding to Japan in the second sub-period might be due to the crisis that Japan underwent in the 1990s, the finding corresponding to Japan in the first sub-period may be due to a misspecification in our empirical framework, because Japanese output gap was indeed found to be highly related to the output gaps of other G7 countries in the first sub-period. Finally, abstracting from Japan, we found that international news shocks are the most important international source of fluctuations in the second sub-period, suggesting that theoretical business cycle models investigating international business cycles must include this type of a shock.

We estimated the country-specific SVECMs under the assumption of a cointegration rank of three, which implied for our model only one stochastic trend in the data, in line with recent macroeconomic theory. However, Johansen tests often pointed to a cointegration rank of two or one. We showed that a cointegration rank of two is also in line with the interpretation that positive news shocks represent future technological developments. We believe that this issue must be further investigated in the future. In particular, the model implies two stochastic trends when the cointegration rank is two. While there is a consensus on what the first stochastic trend must be, a technology-related process, there may be different potential candidates for a second trend. One line of research may deal with distinguishing between different sources of news shocks, as suggested, for example, in a recent study by Schmitt-Grohe and Uribe (2009). Another possibility could be to check whether estimated TFP shocks and news shocks do really represent shocks to technological progress by following a similar strategy to Alexius and Carlsson (2005), who compare the estimated technology shocks of King, Plosser, Stock, and Watson (1991) and Gali (1999) SVAR models with technology shocks estimated using production function approaches such as, e.g., in Basu, Fernald, and Kimball (2006). In particular, given that SVECMs with both two and three cointegrating relationships usually support the future technology shock interpretation of news shocks, additional support from comparison with production function residuals could strengthen the case for one of these options.

As mentioned above, connecting our country-specific SVECMs in the way we do in order to estimate international shocks yields a misspecification, at least for Japan in the first sub-period. One source of misspecification could be that we do not allow for bilateral spillovers of shocks across countries. If spillovers are, however, an important source of macroeconomic fluctuations, our model may lead to wrong conclusions. Yet, the problem is that currently no method exists that allows to model spillovers of shocks stemming from an individual country. While the global VAR (GVAR) approach, recently introduced to the literature by Pesaran, Schuermann, and Weiner (2004), provides a tool for estimating interrelationships among a large number of countries, it may prove hard to be suitable for our subject of interest for two reasons. First, GVAR models are estimated only in reduced form, and no study that deals with structural shocks within the GVAR framework exists. Second, even if it were possible to identify structural shocks in the GVAR framework, the method does not include global shocks or shocks affecting only a group of countries like the euro area shocks in the application of this chapter. However, we believe that estimating a structural GVAR model would still provide another valuable source of assessing the data.

We carried out our estimations over two sub-periods in order to capture changes in business cycle dynamics over time. While we imposed the same single break date, 1990Q2, for all G7 countries' models, we acknowledge that this choice may have an impact on our conclusions. There were two motivations behind sticking to a single, and in particular to this, break date. First, we were interested in investigating the emergence or existence of euro area and English-speaking country sub-groups, and 1990Q2 is a convenient break date for, at least, the euro area as argued in Chapters 2 to 4. Second, choosing a break date that applies to all countries was necessary for conducting our analysis of international linkages. The common break date allowed us to impose our factor structure on all G7 countries over both sub-periods. It is clear that we could have chosen other break dates, such as 1983Q4 as in Stock and Watson (2005) or 1993Q4 after which the Maastricht treaty came into force. Yet, a technical problem with both of these proposals is that they would lead to sub-samples, one of which would be very short, which would lead to less reliable results. Moreover, the element of arbitrariness in the choice of the break date would still not be eliminated, since it is known from the literature that break dates chosen based on statistical tests typically differ across countries. A solution to this problem could be to estimate models with time-varying coefficients as suggested recently by, e.g., Primiceri (2005) and Gali and Gambetti (2009), and done also in Chapter 4 of this study, where change in the parameters of the models is handled for each quarter in the sample. However, two problems exist with respect to such an application in our framework. Time-varying coefficients have been estimated only for stationary VARs in the literature, whereas we estimate VECMs in this chapter. The methodology would have to be extended such that it can be applied also with cointegrated VARs. One possibility in this context is to proceed as we did in Chapter 4, by estimating the cointegrating relationships using the full-sample data and then using the resulting error correction terms in the OLS estimation of VECMs. Second, we could not impose the international factor structure on the estimated structural shocks any more, since the statistical properties of the estimated shocks differ over time (over each quarter in our data set) and we would have only one observation from each country for each quarter. The implementation of the time-varying VAR strategy in the GVAR framework is also not possible.

All in all, our findings point to the importance of news shocks as a driving force of macroeconomic fluctuations, not only for the US, but for other G7 countries too. Moreover, our analysis of international linkages suggests that news shocks are also an important source of international business cycle linkages and must therefore be included in theoretical models working on the topic. While our empirical approach, as every empirical approach, is not perfect, our discussion above suggests some interesting future research topics on the issues that were the subject of this chapter.

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Appendix A

Appendix

A.1 Coefficients of a filtered process

This section derives the coefficients in Equation (1.34) of the main text, which shows the approximate process governing the cyclical component of the j^{th} variable in a SVAR. Let the macroeconomic data of interest be generated by the process given in Equation (1.14) of the main text,

$$Y_t = Y_0 + ct + \sum_{i=0}^{t-1} \Theta_i^* \varepsilon_{t-i}, \tag{A.1}$$

with the only deterministic term being a constant so that $d_j = 1$. We can write the process governing the motion of the j^{th} variable in Y_t as

$$Y_{j,t} = Y_{j,0} + c_j t + \sum_{k=1}^{K} \sum_{i=0}^{t-1} \Theta_{jk,i}^* \varepsilon_{k,t-i}, \tag{A.2}$$

where $Y_{j,t}$ stands for the j^{th} variable in Y_t at period t, c_j is the constant term corresponding to the j^{th} variable in Y_t, $\Theta_{jk,i}^*$ is the (j,k) element of the i^{th} coefficient matrix in (A.1), and $\varepsilon_{k,t-i}$ is the k^{th} shock at period $t-i$.

We know from Baxter and King (1999) and Christiano and Fitzgerald (2003) that the ideal band-pass filter used for extracting the business cycle component of the data is of the form

$$x_t^c = \sum_{m=-\kappa}^{\kappa} a_m x_{t-m}, \tag{A.3}$$

where x_t is the process of interest, with $\kappa = \infty$, while the ideal band-pass filter is approximated by setting κ to a finite number in practice. We impose this filter to the process $Y_{j,t}$ in order to extract the cyclical component of it, $Y^c_{j,t}$, hence

$$Y^c_{j,t} = \sum_{m=-\kappa}^{\kappa} a_m Y_{j,t-m} \text{ for } t \geq \kappa + 1, \tag{A.4}$$

which is obtained by substituting x^c_t and x_{t-m} with $Y^c_{j,t}$ and $Y_{j,t}$ in (A.3). Note that both filters we consider, the BK-filter and the CF-filter, are symmetric, i.e., $a_m = a_{-m}$ and, $\sum_{m=-\kappa}^{\kappa} a_m = 0$. These properties imply that the cyclical component of the first two terms of $Y_{j,t}$ in (A.2) are equal to zero. Hence, the sub-component of $Y^c_{j,t}$ with respect to the k^{th} structural shock, $Y^c_{jk,t}$ is given by

$$\begin{aligned}
Y^c_{jk,t} &= a_{-\kappa}\left(\Theta^*_{jk,0}\varepsilon_{k,t+\kappa} + \Theta^*_{jk,1}\varepsilon_{k,t+\kappa-1} + \cdots + \Theta^*_{jk,t+\kappa-1}\varepsilon_{k,1}\right) \\
&\quad + a_{-\kappa+1}\left(\Theta^*_{jk,0}\varepsilon_{k,t+\kappa-1} + \Theta^*_{jk,1}\varepsilon_{k,t+\kappa-2} + \cdots + \Theta^*_{jk,t+\kappa-2}\varepsilon_{k,1}\right) \\
&\quad + \cdots \\
&\quad + a_{\kappa}\left(\Theta^*_{jk,0}\varepsilon_{k,t-\kappa} + \Theta^*_{jk,1}\varepsilon_{k,t-\kappa-1} + \cdots + \Theta^*_{jk,\tau+1}\varepsilon_{k,1}\right)
\end{aligned} \tag{A.5}$$

for $t \geq \kappa + 1$ and $\kappa < \tau < \infty$, where τ shows the number of observations that exist before the period $t - \kappa$. Rewriting (A.5) gives

$$Y^c_{jk,t} = \sum_{i=1}^{\tau-\kappa-1} \Psi_{-\kappa-i}\varepsilon_{t-\kappa-i} + \Psi_{-\kappa}\varepsilon_{t-\kappa} + \cdots + \Psi_{\kappa}\varepsilon_{t+\kappa} \text{ for } t \geq \kappa + 1 \tag{A.6}$$

with

$$\begin{aligned}
\Psi_{-\kappa-i} &= a_\kappa \Theta^*_{jk,i} + \cdots + a_{-\kappa}\Theta^*_{jk,i+2\kappa}, \text{ for } i = 1, \ldots, \tau - \kappa - 1 \\
\Psi_{-\kappa} &= a_\kappa \Theta^*_0 + \cdots + a_1 \Theta^*_{\kappa-1} + a_0 \Theta^*_\kappa + a_{-1}\Theta^*_{\kappa+1} + \cdots + a_{-\kappa}\Theta^*_{2\kappa} \\
\Psi_{-\kappa+1} &= a_{\kappa-1}\Theta^*_0 + \cdots + a_1 \Theta^*_{\kappa-2} + a_0 \Theta^*_{\kappa-1} + a_{-1}\Theta^*_\kappa + \cdots + a_{-\kappa}\Theta^*_{2\kappa-1} \\
&\vdots \\
\Psi_\kappa &= a_{-\kappa}\Theta^*_0.
\end{aligned}$$

We approximate (A.6) by

$$Y^c_{jk,t} \approx \Psi_{-\kappa}\varepsilon_{t-\kappa} + \cdots + \Psi_\kappa \varepsilon_{t+\kappa} \tag{A.7}$$

in our applications. The quality of this approximation depends on the quality of the approximation

$$\sum_{i=1}^{\tau-\kappa-1} \Psi_{-\kappa-i}\varepsilon_{t-\kappa-i} \approx 0. \tag{A.8}$$

Note that, for a sufficiently big i, $\Psi_{-\kappa-i}\varepsilon_{t-\kappa-i} \approx 0$ is a good approximation due to the fact that $\Theta^*_{jk,i} \approx \Theta^*_{jk,i+1} \approx \cdots \approx \Theta^*_{jk,i+2\kappa}$.[1] While the quality of the approximation may not be good when i is not sufficiently big, $\kappa = 60$ generates for both CF-filter and BK-filters results that are very close to the one implied by the ideal band-pass filter, see, the application in Section ??.

Finally,

$$Y^c_{j,t} = \sum_{k=1}^{K} Y^c_{jk,t}, \tag{A.9}$$

which implies Equation (1.34) of the main text.

A.2 FEVD of the variables in Chapter 5

Since estimation of cointegrated systems are notorious for producing unreliable results when the sample underlying the estimation is short, we have re-estimated our models in Chapter 5 with sub-period data by imposing on them the coefficients of the cointegration equations that are estimated using the entire data set, while the coefficients of the VECMs corresponding to the first-differenced terms were left unrestricted. The results are provided in the following.

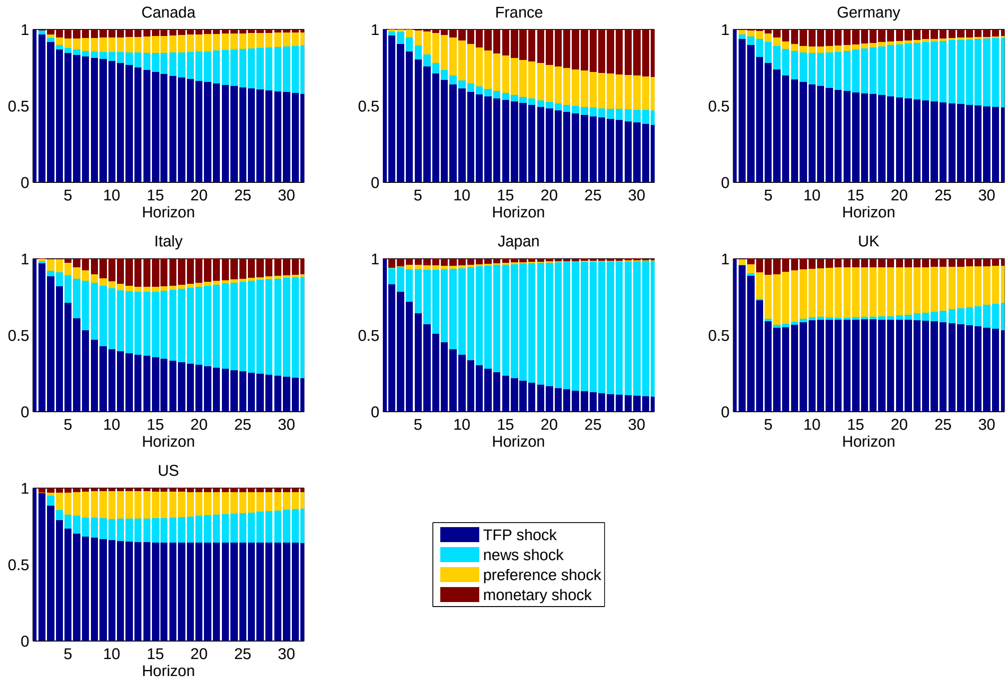
[1] We know from Chapter 1 that $\Theta^*_i = \sum_{j=0}^{i} \Theta_i$. The condition $\lim_{i\to 0} \Theta_i = 0$, which follows from the stationarity property of (1.13), implies that $\lim_{i\to 0} \Theta^*_i < \infty$. It follows that $\Theta^*_i \approx \Theta^*_{i-1}$ is a good approximation for sufficiently big i. In such a case, a good approximation of $\Psi_{-\kappa-i}$ is given by

$$\Psi_{-\kappa-i} \approx \left(\sum_{m=-\kappa}^{\kappa} a_m \right) \Theta^*_{jk,i},$$

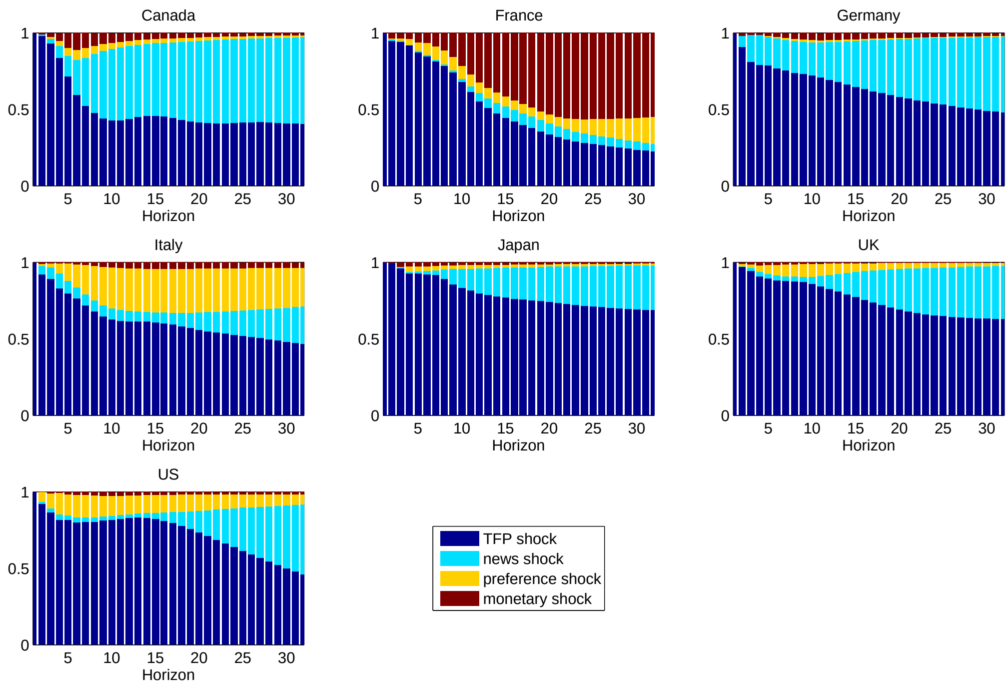
where $\Theta^*_{jk,i+1}, \ldots, \Theta^*_{jk,i+2\kappa}$ are substituted by $\Theta^*_{jk,i}$. Hence,

$$\Psi_{-\kappa-i} \approx 0$$

is also a good approximation due to $\sum_{m=-\kappa}^{\kappa} a_m = 0$.

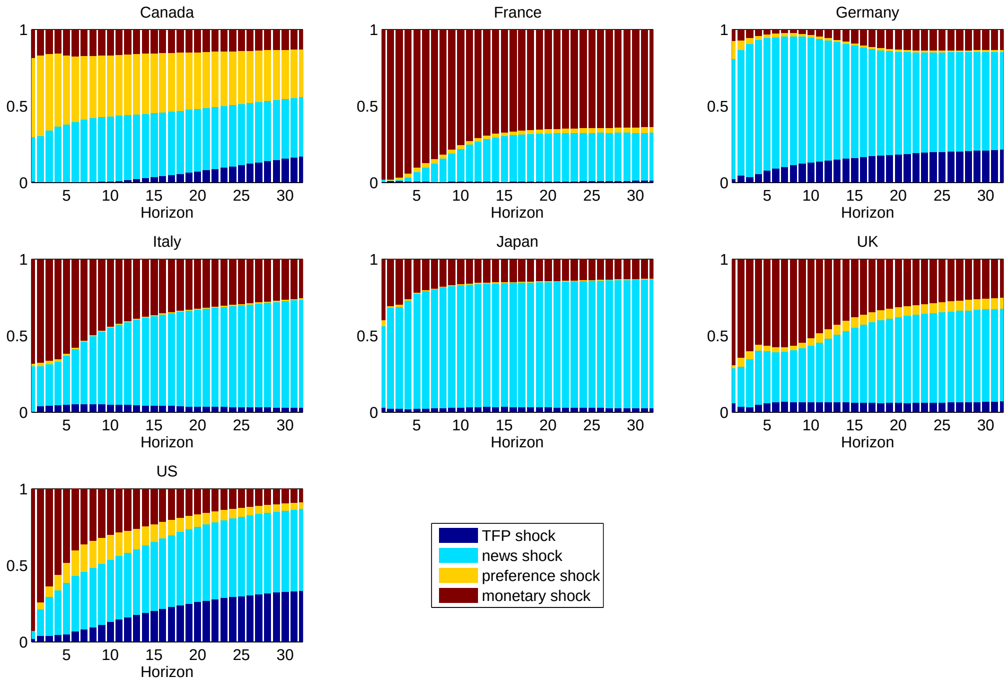


(a) Sample: 1971Q1–1990Q2

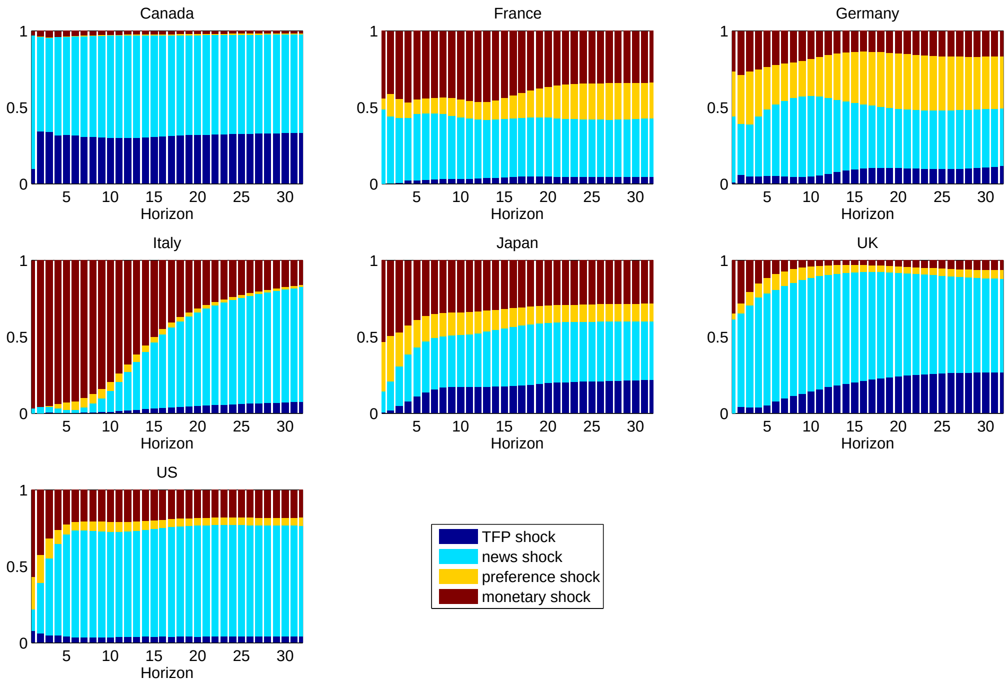


(b) Sample:1990Q3–2006Q4

Figure A.1: FEVD of labor productivity

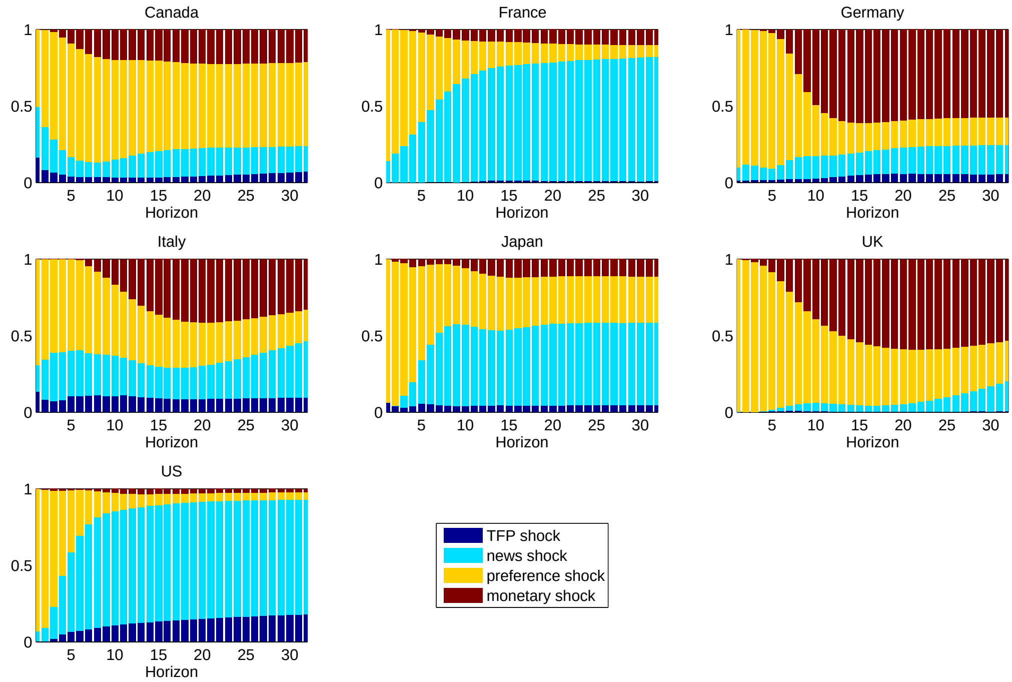


(a) Sample: 1971Q1–1990Q2

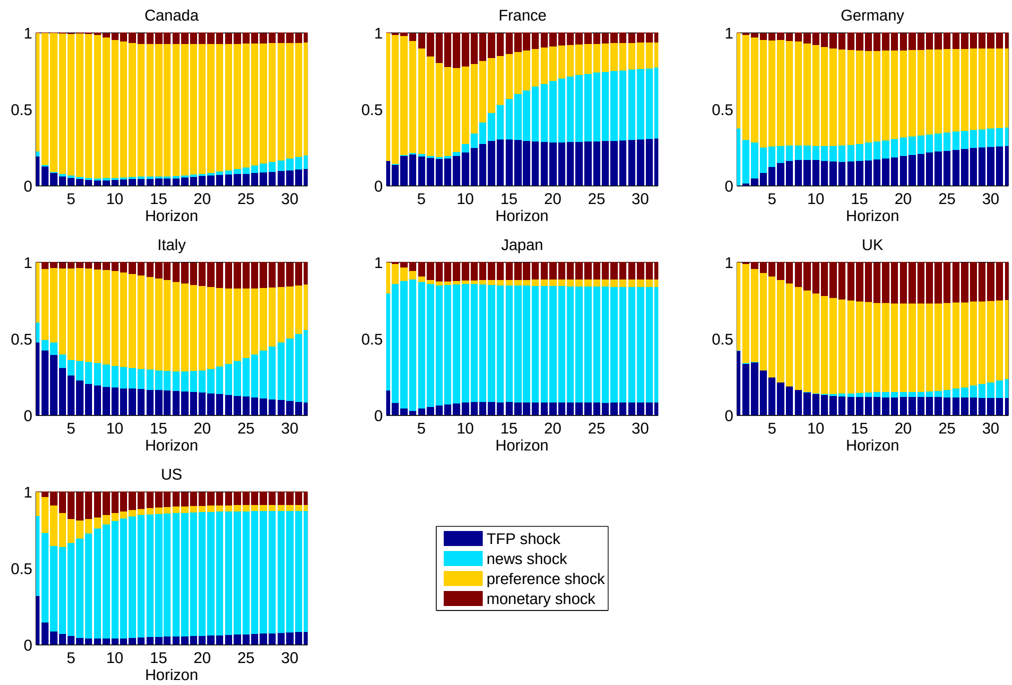


(b) Sample:1990Q3–2006Q4

Figure A.2: FEVD of stock prices

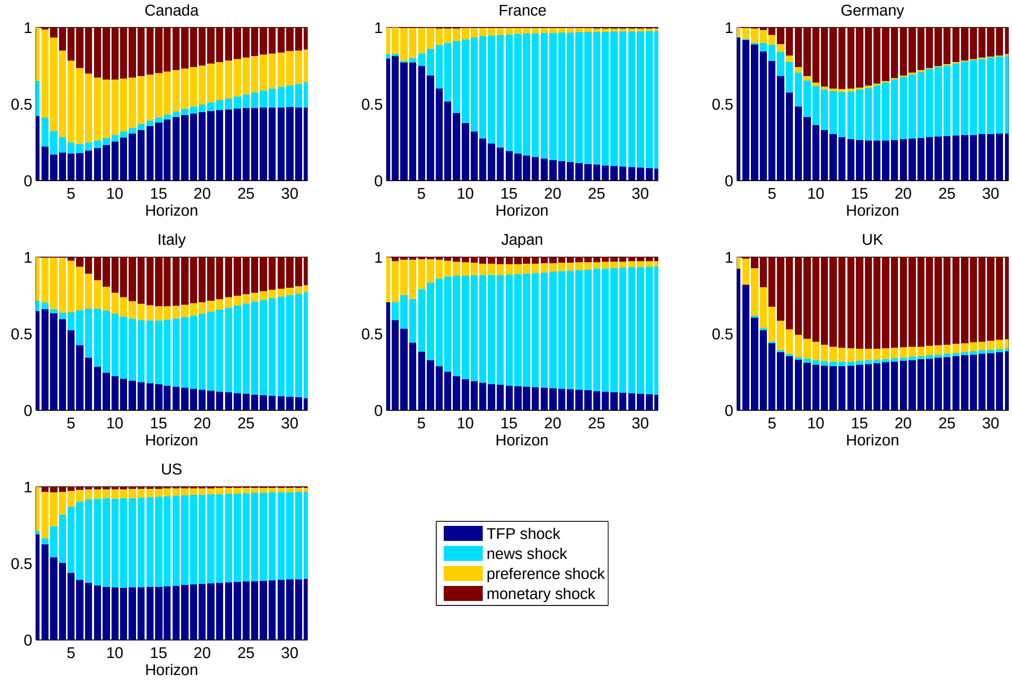


(a) Sample: 1971Q1–1990Q2

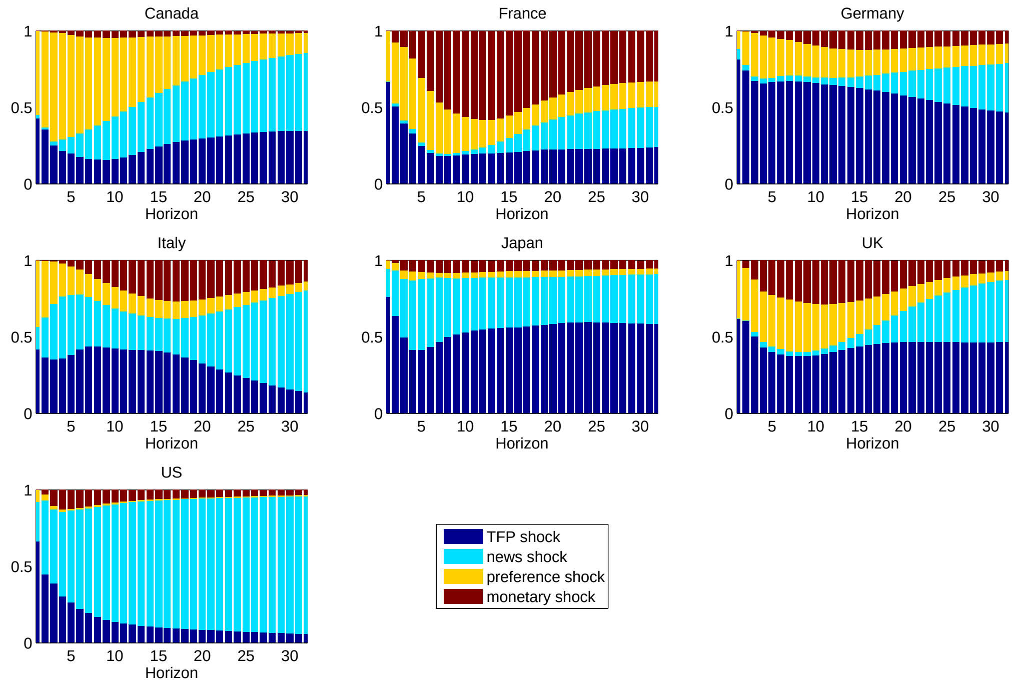


(b) Sample:1990Q3–2006Q4

Figure A.3: FEVD of hours worked



(a) Sample: 1971Q1–1990Q2



(b) Sample:1990Q3–2006Q4

Figure A.4: FEVD of output