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„The Dynamic Interrelations Between Unequal Neighbors: An Austro-German Case Study“

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Contents

1 Introduction

The motivation for this thesis is twofold. First of all the dynamic interrelations between two closely related asymmetric economic areas are of interest, since it is often the case that the economic performance of a small country is determined by a large neighbor. The transmission channels which ensure such an interrelation should be identified in this thesis. The countries investigated are Austria and Germany as they are highly integrated, but nevertheless represent distinct nations. They are both member states of the European Union, they share a common currency and a common language. There are a lot of important sectors where developments in Germany influence the performance of the Austrian economy. Important examples include: The bulk of Austrian exports goes to Germany (see Statistik Austria (2006)), many Germans spend their vacations in Austria, and lots of German workers supply their skills on the Austrian labor market and vice versa. The latter effect has become more and more important during recent years, when the German economy has suffered from a high unemployment rate (see for example Biffl (2006)). Similar models could prove useful in analyzing interactions between Canada and the United States, between Mexico and the United States, or between Portugal and Spain, to mention only a few examples. Some regional adaptations would be needed because Canada and the United States share a common language but no common currency, the converse holds true for Portugal and Spain, while Mexico shares neither a common language nor a common currency with the United States.

Secondly, as the resulting framework contains most of the relevant information for predicting the economic performance of the small country, it could be a useful forecasting tool. Since the model only involves two economies, difficulties with respect to data collection and aggregation of different time series are small. Consequently, it should produce reliable forecasts that involve as much information and as few distortions as possible. Therefore we expect that our model can complement existing forecasting procedures for the Austrian economy.

The first challenge is to find an accurate modeling framework. Various approaches are described in the literature of macroeconometric modeling: Large-scale models with a huge number of behavioral equations that are used most frequently in policy simulation but are subject to some serious criticism described later on; Dynamic Stochastic General Equilibrium (DSGE) Models, which recently became popular but are more suited for analyzing transmission channels of monetary policy shocks; Vector Autoregressive (VAR) models, which are purely statistically motivated, and consequently are immune against theoretical critiques; and Structural Vector Autoregressive (SVAR) models, which combine elements of short-run economic theory in the form of restrictions on the contemporaneous coefficients with purely statistically motivated VARs. However, there is a lack of consensus among economists on the validity of short-run economic theory and therefore Structural Vector Error Correction models (SVECMs) which have become a widely used tool in macroeconometric modeling in the recent years (see for example Vlaar and Schuberth (1999), Baltensperger et al. (2001), Garratt et al. (2003), Vlaar (2004), Garratt et al. (2006), Gaggl et al. (2008)) seem to be the most promising model class regarding our research questions. The main advantage of this class of models lies in the possible combination of two features. On the one hand, the long-run behavior of the economy is described with the help of theoretically motivated steady state conditions. On the other hand, the short-run behavior is analyzed statistically without guidance from economic theory. In contrast to SVAR models (see for example Blanchard and Quah (1989), Christiano et al. (1999)), which use short-run economic theory to derive identifying restrictions, SVECMs therefore do not necessarily need these restrictions. This is a clear advantage because of the lack of a consensus among economists regarding the validity of theoretical short-run relationships. Moreover, if one has to investigate data with a high frequency, for example monthly series, economic theory is unable to provide short-run restrictions on the contemporaneous dependency between variables.

Basically, Vlaar and Schuberth (1999), Baltensperger et al. (2001) and Vlaar (2004) concentrate their analyses on transmission channels of monetary shocks. These channels are identified with the help of impulse response functions. While Vlaar and Schuberth (1999) and Vlaar (2004) use long-run and short-run restrictions, the SVECM of Baltensperger et al. (2001) uses long-run restrictions, but solely relies on the Choleski decomposition for identifying short-run shocks.

The other authors mentioned above analyze open economies and interactions between the home and foreign country. Garratt et al. (2006) concentrate on the United Kingdom, where the "rest of the world", in this case all other OECD countries, represents the foreign economy. In their work the main task was to develop a model which is able to forecast the most important time series of the British economy and not so much weight is put on the interaction with the foreign region. In contrast, Gaggl et al. (2008) investigate the dynamics between the European Monetary Union and the United States, currently representing the dominant economic areas among developed countries. This is done by comparing impulse response functions of a United States model with the eurozone as foreign economy, with those of a eurozone model where the United States represent the foreign economy. As such SVECM analyses proved useful when looking at two closely linked economic areas, it would be the natural framework to describe the common development of Austria and Germany as well.

However, there are a number of important methodological differences to Gaggl et al. (2008). First of all, monetary variables do not play such an important role in explaining differences between Austria and Germany, as the Schilling was coupled to the Deutsche Mark over the relevant periods. Furthermore, since 1998, both countries have been members of the European Monetary Union and have shared a common currency. Therefore money aggregates like M0 or M1 do not exist for the individual economies anymore and also the exchange rate has been fixed since 1998. For these reasons, attention has shifted from monetary aggregates to the labor market in this thesis. The advantage of doing so is that possible interrelations with respect to labor migration can be assessed as well.

Another difference concerns the construction of relevant aggregate variables in the foreign economy. Gaggl et al. (2008) construct data for the eurozone from time series of the individual member countries. There are some difficulties associated with such an approach, for instance the choice of accurate weights (see Beyer et al. (2001) for more details), the fact that measurement errors carry over to the constructed aggregates, and that the foreign aggregated series are very smooth as compared to the domestic ones, since shocks are averaged out. In examining the relations between two individual countries there is no need to choose accurate weights, measurement errors are far less important, and shocks are not averaged at all. Therefore one could expect to work with data of higher quality in this case. Regarding the forecasting performance, this could clearly lead to advantages of the two country model. Furthermore, at the time when forecasts should be performed, one needs to be less concerned about the availability of data, since fewer time series are needed.

In section 2, traditional macroeconometric approaches are described. In particular, the most important historical developments, methodological critiques, and reactions of model builders to circumvent these critiques are outlined. Section 3 describes the SVECM and possible identification procedures for the cointegrating vectors as well as for short-run shocks. Furthermore, the estimation procedure and the associated specification tests are outlined. Section 4 includes the dynamic optimization model of households which makes it possible to derive three potential long-run restrictions. Two more potential restrictions can be derived using the steady state properties of neoclassical growth models and characteristics of the interactions between the two labor markets. Section 5 is dedicated to the description of the underlying time series. Visual inspection as well as unit root tests reveal that all series fulfill statistical properties such that they can be included in the SVECM. In sections 6 and 7 the model is estimated and has to undergo various specification tests. These tests indicate that the model performs well in describing the underlying data series, so it is used to study different shocks to German variables and their effects on Austrian counterparts. Section 8 investigates the forecasting properties of the SVECM. In addition, the model is combined with other forecasting procedures, which results in a useful tool for predicting changes in Austrian inflation, changes in the Austrian interest rate, changes in the Austrian unemployment rate and levels of Austrian output growth. This tool could be extended in various ways, for example to include the predictions of the large-scale models used by the Austrian Central Bank (OeNB), the Institute for Advanced Studies (IHS), and the Austrian Institute of Economic Research (WIFO). Additionally, the judgment of experts and future results of the DSGE model developed in the OeNB could be part of a combined forecasting procedure. Finally section 9 summarizes the results, draws various conclusions and highlights scope for further research.

2 The Main Macroeconometric Approaches

2.1 Large-scale Models

Large-scale models, which typically consist of a huge number of simultaneous equations, are the workhorses in macroeconometric modeling. Their roots go back to the work of Tinbergen (1937), which was the first approach to explain business cycle movements with the help of behavioral equations (see also Bårdsen et al. (2005)). Later the probabilistic foundations of econometrics, introduced by Haavelmo (1944), were explicitly implemented in a model for the United States economy by Klein (1950). Most research at that time concentrated on linking economic theory to mathematics in general and to statistics in particular and was performed by members of the so called Cowles Commission.

During the 1970s large-scale models lost a lot of their popularity as they had to face enormous critiques:

- First of all they were not able to forecast the dramatic impacts of the oil crises in 1973 and 1979 on the economies under consideration

- Secondly, the well known Lucas critique (Lucas (1976)) stated that policy simulations cannot be performed with the aid of large-scale models, since estimated parameters of the model itself would change in response to policy shocks. The reason for this is that the economic environment changes after an exogenous shock and consequently also agents with rational expectations would change their behavior to respond optimally

- Thirdly, Sims (1980) argued that the assumed distinction between endogenous and exogenous variables in large-scale models relies on incredible restrictions derived from the economic theory of the short-run. Such identification schemes are seen as quite arbitrary, since there are lots of doubts on the validity of short-run economic theory

Over the following decades there were a lot of attempts to strengthen large-scale models against such critiques by implementing rational expectations and by trying to formulate microfoundations of the behavioral equations. In addition, short-run restrictions became less and less relevant since due to advances in cointegration analysis modeling the long-run became increasingly popular (Engle and Granger (1987); see also Garratt et al. (2006)). Although some skepticism remained among researchers with respect to the use of large-scale models in policy analysis, this approach is still the most widely used in practice.

Examples of large-scale macroeconometric models now in use are the Fair Model (Fair (1998)) for the United States and the OECD Interlink Model (see for example Dalsgaard et al. (2001)). In case of Austria the IHS uses the model LIMA (Hofer and Kunst (2004)), the OeNB uses the model AQM (Fenz and Spitzer (2004)) and WIFO uses WIFO-Macromod (Baumgartner et al. (2004)).

2.2 Vector Autoregressive Models

Another way to circumvent the theoretical critiques was proposed by Sims (1980) and involved the application of unrestricted vector autoregressive (VAR) models to macroeconomic data. Contrary to large-scale models, VARs are purely statistically motivated and therefore they do not need to draw on economic theory to find identifying restrictions. VARs are also robust with respect to the Lucas critique (Lucas (1976)) because they are used for impulse response analysis, which is not deemed to be policy simulation since the data generating process does not consist of optimizing individuals whose underlying behavior could change.

There are nevertheless some points to be criticized: First of all the models have to stay quite small, both with respect to the lag length and with respect to the number of endogenous variables included. This is the case because otherwise the number of parameters to be estimated becomes very large and typically economic time series do not include enough observations to estimate them all in a meaningful way. Secondly, VARs require that the order of integration of all endogenous variables is the same. However, if some of the included series have to be differenced, one loses relevant information if cointegration is not accounted for. The third point is that in performing impulse response analysis one requires an identifying structure on the variance covariance matrix of the error terms. Sims (1980) used the Choleski decomposition, which imposes a causal ordering on the endogenous variables and therefore on the transmission of impulses. The application of a meaningful ordering would again require the use of economic theory but this is exactly what Sims wanted to avoid (see also Garratt et al. (2006)).

A solution to the third problem lies in the use of so called "generalized impulse response functions", described in section 3.2 (see Pesaran and Shin (1998), see also Koop et al. (1996)), which are invariant with respect to different orderings of endogenous variables. The relevant procedure is implemented in the software package used for estimating the model later on (see Eviews 6 (2007)).

2.3 Structural Vector Autoregressive Models

Most properties of VARs carry over to the SVARs. However, the latter approach solves the problem regarding the use of orthogonalized impulse response functions by assuming a structure for the variance-covariance matrix of the error terms, which again comes from short-run economic theory (see also Favero (2001)). In addition to the difficulties associated with such an approach and mentioned in section 1, one would have to deduce a very large number of restrictions for exact identification if the number of endogenous variables in the SVAR becomes large. However, economic theory is hardly able to provide so many restrictions. Examples of SVARs include Bernanke (1986), Blanchard and Quah (1989) and Christiano et al. (1999).

2.4 Dynamic Stochastic General Equilibrium Models

Dynamic Stochastic General Equilibrium (DSGE) models circumvent the Lucas critique (Lucas (1976)) by relying on the intertemporal optimization of agents in an economy. It is assumed that there exists a representative household which optimally allocates its income to consumption of the various goods and investment in various assets. The first order conditions of the household's optimization problem comprise an individual's optimal responses to different shocks in the economy. Therefore the approach is completely theory driven in the sense that equilibrium conditions are expressed in terms of the so-called "deep parameters" of the model (see also Garratt et al. (2006)). These parameters mainly represent the tastes of agents and are sometimes seen as the only parameters that could be reasonably estimated, since they do not change in response to exogenous shocks. These parameters typically enter the model via specific forms of utility functions. An example for a "deep parameter" would be the elasticity of substitution between different goods.

In the beginning, DSGE models were closely linked to the development of the Real Business Cycle theory. In particular, fluctuations were not considered as deviations from an equilibrium but as a Pareto optimal adjustment to exogenous real shocks (Garratt et al. (2006)). Consequently, market failures did not occur in these models, such that a social planner was unable to improve welfare and so welfare policies could not be investigated. Another disadvantage was that in earlier DSGE models nominal rigidities did not play any role and so monetary policy could not be addressed. In response to these shortcomings, adjustment costs, information heterogeneities, and also endogenous technological change were implemented in newer models. Nevertheless it was not until the 1990s that nominal rigidities of prices and wages were also considered in DSGE models. With the implementation of such frictions, DSGE models became more useful, especially for central banks, and they perform quite well in forecasting nowadays.

The solution of the system under rational expectations can be approximated by VAR models in case of closed economies. If open economies are the object of interest, one would have to generalize the VAR models to account for exogenous variables too. These models are called VARX models and are introduced in their vector error correction representation in section 3.

Examples of DSGE-models include the one used by the European Central Bank (Smets and Wouters (2003)). There are lots of attempts to implement DSGE models, especially in central banks of countries in the eurozone (see for example Pytlarczyk (2005)), but currently there is no operable model for the Austrian economy. For a basic treatment of this model class see for example Canova (2007).

3 The Structural Vector Error Correction Model

Macroeconometric models typically involve variables that are integrated of order one, i.e. are stationary in first differences. Taking first differences of the various time series in such models would result in a loss of information if cointegration were not taken into account. Cointegration defines long-run equilibrium relationships between variables in levels, such that linear combinations of these variables are stationary. In contrast to VARs and SVARs, vector error correction models (VECMs) account for cointegration because long-run deviations from stationary equilibrium relationships show up as regressors on the right hand side of the equations. Johansen (1995) (see also Lutkepohl (2005)) described maximum-likelihood estimators for vector error correction models where no overidentifying restrictions are imposed on the cointegrating relationships. In such a setting, the estimated parameters of the stationary linear combinations in levels, i.e. the adjustment parameters to deviations from long-run equilibria, do not exhibit an economically meaningful interpretation. In contrast, Garratt et al. (2006), (see also Garratt et al. (1999) and Garratt et al. (2003)) derive long-run restrictions from economic theory and apply them on the cointegrating vectors. In this set-up one can test for the validity of the theoretically implied overidentifying restrictions, which is not possible in SVAR models. Therefore in the case of a two country model, SVECMs allow to test which theoretically motivated long-run relations are likely to exist between these two countries.

3.1 General Model Formulation

If exogenous variables are allowed for, the most general form of a VECM with k endogenous variables can be written as (see Garratt et al. (2006)):

$$A\Delta z_t = \tilde{a} + \tilde{b}t + \tilde{\Pi} z_{t-1} + \sum_{i=1}^{\rho_1 - 1} \tilde{\Gamma}_i \Delta z_{t-i} + \sum_{i=0}^{\rho_2 - 1} \tilde{\Psi}_i \Delta x_{t-i} + \epsilon_t \qquad (1)$$

where A represents a $k \times k$ matrix containing the contemporaneous effects of a change in one endogenous variable to the other endogenous variables, Δ denotes the differencing operator, z_t is a $k \times 1$ vector containing the endogenous variables, $\tilde{a}$ is a $k \times 1$ vector of intercepts, the term $\tilde{b}$ describes the coefficients of the time trend, t, $\tilde{\Pi}$ is the matrix of adjustment coefficients to deviations from long-run equilibria defined by stationary linear combinations of endogenous variables in levels, $\tilde{\Gamma}_i$ is a $k \times k$ matrix containing the coefficients of the vector autoregressive part, $\tilde{\Psi}_i$ describes the coefficient matrix of exogenous variables included in the vector x_t and ϵ_t is a $k \times 1$ vector of error terms with variance covariance matrix Ω. Finally ρ_1 and ρ_2 are the optimal lag-lengths of endogenous and exogenous variables respectively. These numbers are obtained by estimating unrestricted VAR models with different lag specifications in levels and choosing the number of lags that corresponds to the model which is closest to the data generating process according to model selection criteria. Applications generally use $\rho_1 = \rho_2 > 1$ (see Gaggl et al. (2008)) or $\rho_1 > 1$ and $\rho_2 = 1$ (see Garratt et al. (2006)). Note that for exogenous variables a lag-length of zero in first differences is possible, i.e. they are allowed to affect endogenous variables contemporaneously. To get to the reduced form of equation (1) it has to be premultiplied by A^{-1}, such that

$$\Delta z_t = a + bt + \Pi z_{t-1} + \sum_{i=1}^{\rho_1 - 1} \Gamma_i \Delta z_{t-i} + \sum_{i=0}^{\rho_2 - 1} \Psi_i \Delta x_{t-i} + u_t \tag{2}$$

where $a = A^{-1}\tilde{a}$, $b = A^{-1}\tilde{b}$, $\Gamma_i = A^{-1}\tilde{\Gamma}_i$, $\Pi = A^{-1}\tilde{\Pi}$ and $u_t = A^{-1}\epsilon_t$. The variance covariance matrix of u_t can be written as $A^{-1}\Omega(A^{-1})^t$ and is denoted by Σ. Further, Π can be expressed as

$$\Pi = \alpha\beta^t \tag{3}$$

where α is a $k \times r$ matrix including the adjustment coefficients to deviations from the long-run equilibria and β is a $k \times r$ matrix including the restrictions on the cointegrating relations. In this context r is the number of cointegrating vectors among endogenous variables and via equation (3) also the rank of Π.

3.2 Identifying Short-run and Long-run Restrictions

For exact identification of the long-run relationships, r^2 restrictions must be imposed on β. Johansen (1988) and Johansen (1991) investigate systems defined by equation (3) and provide tests for the rank of Π as well as statistically motivated restrictions for exact identification. These restrictions assume that the column vectors of β are orthogonal to each other, in the sense that in the first column vector the first entry is normalized to one, in the second column vector the second entry is normalized to one and so on, while the other $r^2 - r$ restrictions are zero restrictions on the remaining first $r - 1$ entries of each column vector in β. This procedure is meaningful in a statistical sense, but it renders economic interpretation of equation (3) impossible if $r > 1$ (see also Garratt et al. (2006)). Furthermore the restrictions depend on the ordering of endogenous variables in the SVECM, such that different results can be obtained just by changing the rule of sequencing entries in the z_t-vector.

In contrast to this approach, in this thesis overidentifying restrictions are derived with the help of economic theory, and the validity of these restrictions are tested. The corresponding test is a likelihood ratio test, but due to its small sample properties a bootstrapped version is implemented (see section 6.3.6 for the details).

In order to recalculate the structural coefficients of (1) from the reduced form representation (2) additional k^2, so called short-run restrictions, need to be imposed on A and/or Ω (see Garratt et al. (2006)). After this structure is imposed, impulse response analysis can be performed. The most widely used method to implement these short-run restrictions proposed by Sims (1980) requires A to be a lower triangular matrix and Ω to be a diagonal matrix:

$$A = \begin{pmatrix} 1 & 0 & ... & 0 \\ a_{21} & 1 & ... & 0 \\ ... & ... & ... & ... \\ a_{m1} & a_{m2} & ... & 1 \end{pmatrix} \tag{4}$$

$$\Omega = \begin{pmatrix} \omega_{11} & 0 & ... & 0 \\ 0 & \omega_{22} & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \omega_{mm} \end{pmatrix} \tag{5}$$

The described procedure assumes a causal recursive ordering of the variables in z_t. Consequently, also impulse response functions vary subject to the choice of ordering the endogenous variables and one is confronted with similar problems as in the case of statistically motivating the identifying restrictions on the cointegrating vectors.

A similar argument holds for the reduced form representation in equation (2) without structural restrictions imposed on A. In this case Sims (1980) suggests the Choleski decomposition $\Sigma = PP'$ where P is a $k \times k$ lower triangular matrix, to calculate cumulative orthogonalized scaled impulse response functions according to the formula (see Pesaran and Shin (1998)):

$$\psi^o_{z,j}(h) = B_h P e_j \tag{6}$$

where $\psi^o_{z,j}(h)$ refers to the orthogonalized scaled cumulative impulse response of endogenous variables in period $t + h$, to an exogenous shock of the error term in equation j in period t, B_h is a matrix containing the cumulative effects of such a shock according to the infinite moving average representation, and e_j is a $k \times 1$ selection vector with zero in all but the jth entry. Note that due to the presence of the matrix P in equation (6) a causal recursive ordering is imposed on the impulse responses.

In this thesis generalized impulse response functions are used as described in Pesaran and Shin (1998). In contrast to equation (6), they are calculated according to the formula:

$$\psi^g_{z,j}(h) = \frac{B_h \Sigma e_j}{\sqrt{\sigma_{jj}}} \tag{7}$$

where $\psi^g_{z,j}(h)$ refers to the generalized scaled cumulative impulse response of endogenous variables in period $t+h$, to an exogenous shock of the error term in equation j in period t, and σ_{jj} is the variance of the error term in equation j. Note that the matrix P does not show up in this representation, such that the impulse responses do not depend on the ordering of the endogenous variables. Furthermore, in contrast to orthogonalized impulse responses, all endogenous variables are contemporaneously affected by an exogenous shock in a certain period.

To summarize the insights from this section, we are able to circumvent the need to impose a certain ordering of the endogenous variables by relying on economic theory in deriving cointegrating relations and by using generalized impulse response functions instead of the standard approach proposed by Sims (1980).

3.3 Implementation of the SVECM

In the next chapters the SVECM will be implemented and tested according to the following steps, which were also suggested by various modelers (see for example Garratt et al. (2006), Juselius (2007)):

1. First of all we will decide which time series to include as endogenous and exogenous variables. The relevant considerations can be found in Appendix A

2. Theoretically motivated potential long-run relationships between the endogenous variables will be derived and reformulated as statistically observable stochastic long-run restrictions to be imposed on the entries of the cointegrating vectors in the error correction part of the model

3. The variables involved will be inspected graphically and the unit root properties of these variables will be assessed

4. In the next step, unrestricted VAR(ρ) models for $\rho = 1 \ldots 4$ will be estimated in order to obtain the optimal lag-length ρ according to the Akaike Information Criterion (AIC) as well as the Bayes Information Criterion (BIC)

5. Afterwards, the Johansen test on the cointegration rank r will be performed with an underlying unrestricted VAR(ρ) as basis

6. Subsequently, different combinations of the derived potential long-run restrictions will be imposed on the cointegrating vectors and the most suitable combination which additionally fulfills the property that deviations from long-run equilibria exhibit stationary behavior will be chosen for further analysis

7. The plausibility of the restrictions chosen in the previous step will be assessed according to a bootstrapped version of the likelihood ratio test on the validity of overidentifying restrictions

8. The residuals of the resulting model will be tested for heteroscedasticity, deviations from the assumption of normality, autocorrelation and structural breaks. Additionally, generalized impulse response functions with respect to shocks to the small economy will be obtained and the plausibility of their shapes as well as their stability properties will be assessed

9. If the tests show serious deviations from the underlying assumptions, the model will be reformulated

10. If the model passes the various tests, it will be used to investigate the interrelations of the two economies under consideration by means of generalized impulse response functions.

If the model is a good approximation to the data generating process, generalized impulse response analysis should reveal the consequences of German shocks for the Austrian economy as well as the channels by which these shocks transmit. Additionally, one should be able to assess the persistence of these shocks. In the second part of the thesis

11. The obtained model will be used to forecast changes in Austrian inflation, changes in Austrian interest rates, changes in Austrian unemployment and Austrian output growth

12. Afterwards these forecasts will be compared to forecasts from univariate time series procedures, single exponential smoothing algorithms and the Holt-Winters nonseasonal algorithm according to a number of relevant criteria

13. Finally, a forecast combination between the different methods and the SVECM will be performed

If the SVECM contains relevant information that none of the other models incorporates, it will contribute significantly in increasing the predictive power in a combined forecast. This combined procedure could be used as a forecasting tool for the Austrian economy and thereby complement existing models used by economic research institutions.

4 Theoretically Motivated Long-run Restrictions

To motivate potential restrictions on the parameters of the cointegrating vectors, Garratt et al. (2006) use a loose collection of relationships derived on the basis of arbitrage conditions, accounting identities, solvency requirements and assumptions with respect to the production technology in the investigated economy. This procedure leads to five potential restrictions to be imposed on the cointegration space of their model: The Money Market Equilibrium condition (MME), the Fisher Inflation Parity (FIP), the Interest Rate Parity (IRP), the Purchasing Power Parity (PPP), and an Output Gap (OG) relation. However, Garratt et al. (2006) do not provide any microfoundations for their behavioral equations. In contrast, Gaggl et al. (2008) use a single open economy model to derive the MME, the FIP and the IRP, where the PPP has to hold in order for the other three relationships to be consistent. The OG relation is derived in the same way as in Garratt et al. (2006).

The purpose of this chapter is to go one step further and set up a model for two open economies which engage in bilateral trade to motivate the IRP and the FIP. In this setting the PPP relationship follows immediately from the underlying preferences of households. The OG relation is a consequence of the production processes in both economies, following neoclassical production functions with labor augmenting technological progress. There is no MME condition because the relevant variables are not included (see Appendix A) since we shift attention from monetary variables to the labor market. Consequently, a Labor Market Condition (LMC) is required, which relates to the decision of individuals to migrate between the two economies. This condition can be motivated by adapting the Gravity Equation concept (see for example Brücker and Franzmeyer (1997), Huber and Brücker (2003), Feenstra (2004), Faustino and Leitão (2008)), such that a country with low unemployment attracts workers from a country where the unemployment rate is high.

Since the theoretical considerations should help to provide applicable restrictions on the cointegrating vectors, the data availability (see Appendix

A) always has to be kept in mind as a limitation when specifying the model. If the model is able to provide restrictions between data series that are not available, it includes redundant information and should be simplified. For example, there is no need to investigate central banks, or decisions of households with respect to labor market participation, since neither data for high powered money, nor data for voluntary unemployment are to be included in the SVECM.

To summarize, in this section five potential restrictions are derived from a patchwork of different models: OG comes from the properties of the development process in neoclassical growth models with exogenous technological progress, FIP, IRP and PPP result from the first order conditions of dynamically optimizing households, and LMC is a variant of the Gravity Equation.

4.1 Description of the Production Side

The production sides of the two economies are variants of the one described in Garratt et al. (2006) (see also Barro and Sala-i-Martin (2004) or Romer (2001)). Output at home and abroad is produced according to the following constant returns to scale production functions:

$$Y_t = F(K_t, A_t L_t) = A_t L_t F\left(\frac{K_t}{A_t L_t}, 1\right) = A_t L_t f(k_t) \quad (8)$$

$$Y_t^* = F^*(K_t^*, A_t^* L_t^*) = A_t^* L_t^* F^*\left(\frac{K_t^*}{A_t^* L_t^*}, 1\right) = A_t^* L_t^* f^*(k_t^*) \quad (9)$$

where Y_t denotes real output at home, Y_t^* denotes real output in the foreign economy, $F \equiv F^*$ and $f \equiv f^*$ are well behaved production functions, fulfilling the Inada conditions, A_t and A_t^* refer to the technological levels of the two economies and finally k_t and k_t^* are the capital stocks per unit of effective labor. With respect to the overall number of employed workers it is assumed that they represent a fraction of the total population:

$$L_t = \delta N_t \tag{10}$$
$$L_t^* = \delta^* N_t^* \tag{11}$$

where N_t denotes the number of inhabitants in the home country, N_t^* the number of inhabitants in the foreign country, and δ and δ^* comprise a measure for the fraction of total population employed in the steady state. This formulation implies that the natural unemployment rate is equal to $1 - \delta$ in the domestic economy and $1 - \delta^*$ abroad.

Furthermore it is assumed that technology behaves according to:

$$\eta A_t = \theta A_t^* = \bar{A}_t \tag{12}$$

where $\bar{A}_t$ is the technological level in the rest of the world and $\eta > 1$ as well as $\theta > 1$ measure incompletenesses of the diffusion process i.e. technology adoption barriers (see Parente and Prescott (1994)). Equation (12) states that the technological levels of the two countries are determined by the world level of technology. Nevertheless there might be difficulties to implement new ideas in both regions, such that gaps between technological levels of the domestic economy, the foreign economy and the rest of the world can remain. Inserting these expressions into the production functions and dividing domestic by foreign output gives:

$$\frac{y_t}{y_t^*} = \frac{\theta\delta}{\eta\delta^*}\frac{f(k_t)}{f(k_t^*)} \tag{13}$$

where y_t and y_t^* denote per capita output. Equation (13) describes the fact that as long as this ratio is smaller or larger than one, there is an output gap between the two economies, which is determined by the relative size of technology diffusion parameters, the relative size of natural unemployment rates and differences in the capital intensities between the two countries.

4.2 Description of the Consumption Side

In order to get to the FIP, IRP and PPP relations, a dynamic consumer optimization model is set up in discrete time for two open economies with capital mobility restrictions. The underlying structure is that a representative household seeks to maximize its lifetime utility generated by consumption of domestic and foreign goods, subject to a budget constraint, which allows the household to invest its income in domestic capital as well as in domestic and foreign bonds. From this specification it is clear that there is a market in the home economy for the domestic and foreign consumption aggregates, for domestic and foreign bonds, but only for domestic capital. In addition, a cash-in-advance constraint in the spirit of Clower (1967) is implemented, i.e. individuals are allowed to consume from money holdings but not from capital or bonds in the subsequent period. This means that if households want to consume they are forced to convert assets, which pay a rate of return, into money, which does not pay any return but is subject to inflation. This conversion has to take place in period $t-1$, so that in period t individuals own liquid assets, allowing them to buy consumption goods. Therefore the representative household solves the following optimization problem:

$$\max_{C_t, C_t^*} \sum_{t=0}^{\infty} \rho^t U(C_t, C_t^*) \tag{14}$$

subject to

$$\begin{aligned} C_t + P_t^* C_t^* + K_t + B_t + B_t^* + M_t \;&=\; (1+r_t)K_{t-1} + w_t L_t + \frac{1+i_t}{1+\pi_t} B_{t-1} + \\ &\quad + \frac{1+i_t^*}{1+\pi_t^*} B_{t-1}^* + \frac{M_{t-1}}{1+\pi_t} \end{aligned} \tag{15}$$

$$C_t + P_t^* C_t^* \;\leq\; \frac{M_{t-1}}{1+\pi_t} \tag{16}$$

where ρ is the subjective discount rate, C_t denotes consumption of the domestically produced aggregate, which is the numèraire good, C_t^* refers to consumption of the aggregate produced in the foreign country, P_t^* to the price level of foreign goods, K_t is the real capital stock, B_t are real bonds issued by the home government, B_t^* stands for real bonds issued by the foreign government, M_t refers to individual's real money holdings, $(1 + r_t)$ denotes the capital rental rate, which is equal to the real rate of return since we do not allow for depreciation, $(1 + i_t)$ and $(1 + i_t^*)$ describe the domestic and foreign nominal interest rates on bonds respectively, $(1+\pi_t)$ and $(1+\pi_t^*)$ are the domestic and foreign inflation rates, w_t is the real wage rate and L_t refers to labor supply of households. The left hand side of equation (15) comprises total household expenditures and savings in period t, whereas the right hand side refers to total household income in the same period. Note that both countries are members of a currency union and so exchange rates are not included as explanatory variables in the SVECM. Consequently, they do not show up in equation (15). Equation (16) is the cash-in-advance constraint, which ensures that expenditures for consumption in period t are not higher than the period t-real value of nominal liquid assets carried over from period $t - 1$.

In addition, the following assumptions are implemented: First of all, households inelastically supply all available time on the labor market, i.e. they do not value leisure. As a consequence, there is no decision involved with respect to labor market participation. Instead, no matter how low real wages are, it is optimal for individuals to work, hence there is no voluntary unemployment and L_t is exogenously given by time restrictions. This assumption is implemented since we do not have data with respect to voluntary unemployment. Secondly, as individuals are rational, they do not convert more assets into money than absolutely necessary to finance the optimal amount of consumption in period t. Consequently, the cash-in-advance constraint holds with equality. Lastly, individuals are assumed to have Cobb-Douglas preferences over the two available consumption goods, such that the period utility function can be written as

$$U(C_t, C_t^*) = C_t^{\alpha} C_t^{*1-\alpha} \tag{17}$$

where α is the budget share of the consumption good produced at home. With these assumptions implemented, one can solve the dynamic optimization problem either by means of the Bellman Principle or by the method of Lagrange (see for example Stokey et al. (1989) or Sundaram (1996)). The corresponding optimality conditions are derived according to the second approach in Appendix B. After reformulating these conditions, the following relationships, whose logarithmic expressions are estimable versions of the theoretically implied restrictions, can be derived:

$$1 + r_t = \frac{1 + i_t}{1 + \pi_t} \tag{18}$$

$$\frac{1 + i_t}{1 + \pi_t} = \frac{1 + i_t^*}{1 + \pi_t^*} \tag{19}$$

$$\frac{CPI_t}{CPI_t^*} = 1 \tag{20}$$

where CPI_t denotes the consumer price index at home and CPI_t^* the consumer price index abroad. Equation (18) describes the FIP, which states that the real rate of return on capital, i.e. the real interest rate, has to be equal to the deflated nominal interest rate. Equation (19) is the IRP in the absence of an exchange rate, stating that the real interest rates in both economies have to be equal to avoid arbitrage rents. Finally, equation (20) is the PPP in the absence of an exchange rate, which relates the price levels between the domestic and foreign economy in terms of consumer price indices, stating that they have to be equal.

4.3 Description of the Gravity Equation and Labor Migration

The Gravity Equation (see for example Feenstra (2004), Faustino and Leitão (2008)) is used in international trade literature to estimate bilateral trade flows. Basically it states that trade between two economies is positively linked to their size and negatively linked to their distance. Following Faustino and Leitão (2008) it can be written as:

$$F_{ij} = G\frac{Y_i^{\beta_1} Y_j^{\beta_2}}{D_{ij}^{\beta_3}} \tag{21}$$

where F_{ij} denotes the flow of goods from country i to country j, Y_i and Y_j denote the country sizes, usually measured by GDP, D_{ij} is the distance between the two countries, and G is some "gravitational" constant. Expressions β_1, β_2 and β_3 represent parameters to be estimated in the logarithmic expression of equation (21):

$$\log F_{ij} = \log G + \beta_1 \log Y_i + \beta_2 \log Y_j - \beta_3 \log D_{ij} + u$$

where u is the error term assumed to have a mean of zero and variance σ^2. Versions of this equation can be used to characterize migration instead of international trade flows (see Brücker and Franzmeyer (1997), Huber and Brücker (2003), Barro and Sala-i-Martin (2004)). Compared to trade flows there are several other forces that promote migration, the two most important ones being differences in wage income levels and differences in household labor market perspectives between two economies. Additionally, the interpretation of distance is modified in the literature to account for legal impediments, language barriers, personal reluctance to migrate, or simply bureaucratic obstacles as well (see for example Borjas (1995), Borjas (1996)).

In the case considered here, where it is optimal for individuals to supply all their available time on the labor market, independently of the real wage rate, the income differential between the two economies is not an accurate measure to be included in the specific Gravity Equation. Furthermore, as compared to other areas (for example Mexico and the United States), income levels do not deviate substantially between Austria and Germany, so there is no need to consider them as explanatory variables for bilateral migration. Instead, the difference between the two unemployment rates is a more promising determinant. Therefore the Gravity Equation has the following form in our case:

$$M = \beta_4 \left[\frac{[(1-\delta) - (1-\delta^*)]}{D} \right] + u \tag{22}$$

In this specification, M characterizes migration from Austria to Germany, which is positive if the difference of the unemployment rates $(1-\delta)-(1-\delta^*)$ is similarly positive, and negative otherwise. The parameter D is the modified distance parameter, measuring the overall costs of migration as described above, and β_4 is the parameter to be estimated. Note that no constant term is included, since the theoretical considerations, especially the inelastic labor supply of households, do not allow other factors to drive migration. The chosen form of the Gravity Equation ensures that there is migration as long as there is a difference between the unemployment rates. Therefore

$$\frac{1-\delta}{1-\delta^*} = 1 \tag{23}$$

holds in the long-run, stating that home and foreign unemployment rates tend to equalize. Equation (23) can be interpreted as follows: Optimal behavior of individuals ensures that they supply their whole available time on the labor market. In equilibrium there is unemployment in both economies and therefore some agents, who do not find work in the economy with the higher unemployment rate, choose to migrate to the other region, after taking into account the associated costs. This process lasts until the gap between the two unemployment rates, i.e. the fundamental reason for migration, is eventually eliminated. Note that this has an influence on equation (13) in the sense that the ratio $\frac{\delta}{\delta^*}$ disappears and it has to be modified to

$$\frac{y_t}{y_t^*} = \frac{\theta}{\eta} \frac{f(k_t)}{f(k_t^*)} \tag{24}$$

which will be used in the next subsection to describe the logarithmic version of the output gap relation.

4.4 Implementation of the Restrictions

The theoretically derived equations (18), (19), (20), (23) and (24) have to be matched with the data in Appendix A, and so logarithmic versions are obtained as:

$$\begin{aligned}
\log(1+r_t) &= \log(1+i_t) - \log(1+\pi_t) && (25)\\
\log(1+i_t) - \log(1+\pi_t) &= \log(1+i_t^*) - \log(1+\pi_t^*) && (26)\\
\log(CPI_t) &= \log(CPI_t^*) && (27)\\
\log(y_t) - \log(y_t^*) &= \log(\theta f(k)) - \log(\eta f(k^*)) && (28)\\
\log(1-\delta) &= \log(1-\delta^*) && (29)
\end{aligned}$$

which are deterministic conditions, holding in the theoretical model. The empirically observable time series are subject to various shocks, but forces ensure that the economy fulfills the described restrictions in the long-run. However, during the adjustment process, they need not be fulfilled with equality. Instead, so called “long-run errors” (Garratt et al. (2006)) describe deviations from these relations in the short-run. As a consequence (25), (26), (27), (28) and (29) are augmented by an error term, i.e. reformulated in a stochastic way, to represent cointegrating equations, which can be estimated. Recalling that the vector z_t contains the following elements (see Appendix A): $(z_t)^t = (DPAT, PD, RAT, RGER, UAT, UGER, YAT, YGER)$ these cointegrating equations read:

$$\begin{aligned}
RAT_t - DPAT_t &= \beta_{1,0} + \xi_{1,t+1} && (30)\\
RAT_t - RGER_t &= \beta_{2,0} + \xi_{2,t+1} && (31)\\
PD_t &= \beta_{3,0} + \xi_{3,t+1} && (32)
\end{aligned}$$

$$
\begin{aligned}
YAT_t - YGER_t &= \beta_{4,0} + \xi_{4,t+1} && (33)\\
UAT_t - UGER_t &= \beta_{5,0} + \xi_{5,t+1} && (34)
\end{aligned}
$$

where $\beta_{i,0}$ represents the constant and $\xi_{i,t+1}$ the error term, i.e. the "long-run error" of the respective restriction. The first equation is the stochastic version of the FIP, and consequently $\beta_{1,0}$ represents an estimate for the real interest rate. The second equation refers to the stochastic version of the IRP, such that the estimated value of $\beta_{2,0}$ should be zero. The third relation is the stochastic version of the PPP, so the estimate of $\beta_{3,0}$ should be zero as well. The next equation describes the stochastic OG relation, with $\beta_{4,0}$ being an estimate for $\log(\theta f(k_t)) - \log(\eta f(k_t^*))$, the natural output gap between the two economies, and the last equation is the stochastic counterpart of the LMC, stating that the unemployment rates of the two economies should be equal in the long-run, which implies $\beta_{5,0} = 0$. Note that the "long-run errors" $\xi_{i,t+1}$ have to be stationary, otherwise the restriction cannot be imposed as an estimable cointegrating equation (see Juselius (2007)). Putting all these things together the following version of equation (2)

$$
\Delta z_t = a + bt + \alpha\beta^t z_{t-1} + \sum_{i=1}^{\rho_1 - 1} \Gamma_i \Delta z_{t-i} + \Psi_0 \Delta x_t + u_t \qquad (35)
$$

where exogenous variables are only allowed to affect endogenous variables contemporaneously as in Garratt et al. (2006), the vector x_t contains the oil price, so $x_t = (POIL)$, and the matrix β^t has the following form:

$$
\beta^t = \begin{pmatrix}
-1 & 0 & 1 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 1 & -1 & 0 & 0 & 0 & 0\\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0\\
0 & 0 & 0 & 0 & 0 & 0 & 1 & -1\\
0 & 0 & 0 & 0 & 1 & -1 & 0 & 0
\end{pmatrix} \qquad (36)
$$

can be obtained. Again recalling the z_t-vector, the first row of this matrix represents the FIP, the second row the IRP, the third row refers to the PPP, the fourth row to the OG relation, and the last row defines the restrictions implied by the LMC. After establishing the general form of the model, the next tasks are to find out the appropriate lag-length and to test whether such a specification is reasonable. Before the respective analyses are carried out, the properties of the variables in the z_t-vector are investigated in section 5.

5 Properties of the Variables

In this section, the properties of the variables used in the estimation procedure are assessed. Graphical inspection should reveal whether one has to be aware of outliers or structural breaks, and should help to identify the unit root properties of the various series. In addition, some commonly used unit root tests, the augmented Dickey-Fuller test (ADF-test), the Phillips-Perron test (PP-test) and the Kwiatkowski-Phillips-Schmidt and Shin test (KPSS-test) are carried out to investigate those unit root properties in more detail. The associated calculations were performed using the Eviews software package (Eviews 6 (2007)). Note that as endogenous variables we use logarithmic indices, which are normalized to one in the base year. Therefore negative values of the variables in levels will show up.

5.1 Prices

Figure 1 shows the Austrian price level, and its first and second differences. In the original series there were two outliers in the Quarters 1984:1 and 1990:1, which resulted from increases in consumption taxes. To adjust for these outliers the associated growth rates of the prices were replaced by the four year averages of the preceding corresponding quarters. Since the price levels were calculated as the logarithm of the price index with the first quarter of the year 2000 as base year, PAT has a value of zero in that quarter. The second picture of figure 1 shows the first differences of the logarithmic price level, i.e. the inflation rate. One can easily see that during the 1980s the inflation rate declined, which was due to the disinflationary policy of the Austrian Central Bank at that time. A similar effect is present in figure 2, which shows the German price level, German inflation and the first differences of German inflation. In contrast to Austria, inflation rose again in Germany during the early 1990s, due to the boost in demand resulting from unification.

The two graphics related to Austrian and German prices indicate that the logarithmic price levels are integrated of order two, i.e. they would have to be differenced twice in order to obtain a stationary series. Intuitively, the disinflationary policy of many central banks during the 1980s could explain

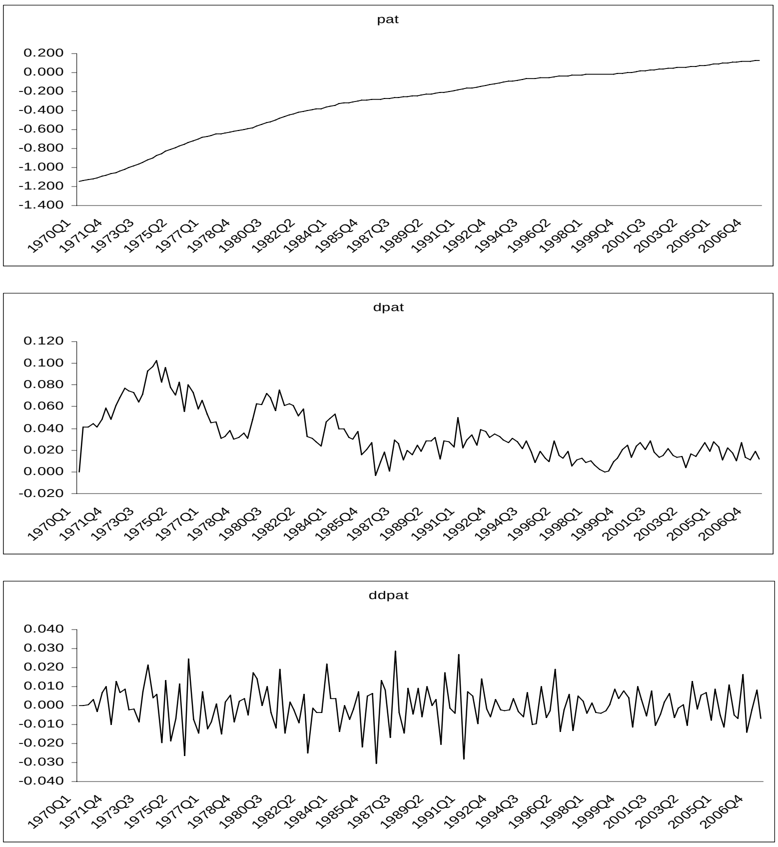

Figure 1: Austrian Price Level, Inflation and First Differences of Inflation

that there was a shift in the mean of inflation (the differenced logarithmic price levels) during this period. This would provide a theoretical explanation for the price *level* being I(2). In the Austrian case the ADF-test, as well as the KPSS-test confirm this suspicion, whereas in the German case all tests suggest to treat the logarithmic price levels as I(1) (see Appendix C). However, there are some arguments that nevertheless suggest to treat German prices as I(2). First of all, when forecasting is the central purpose

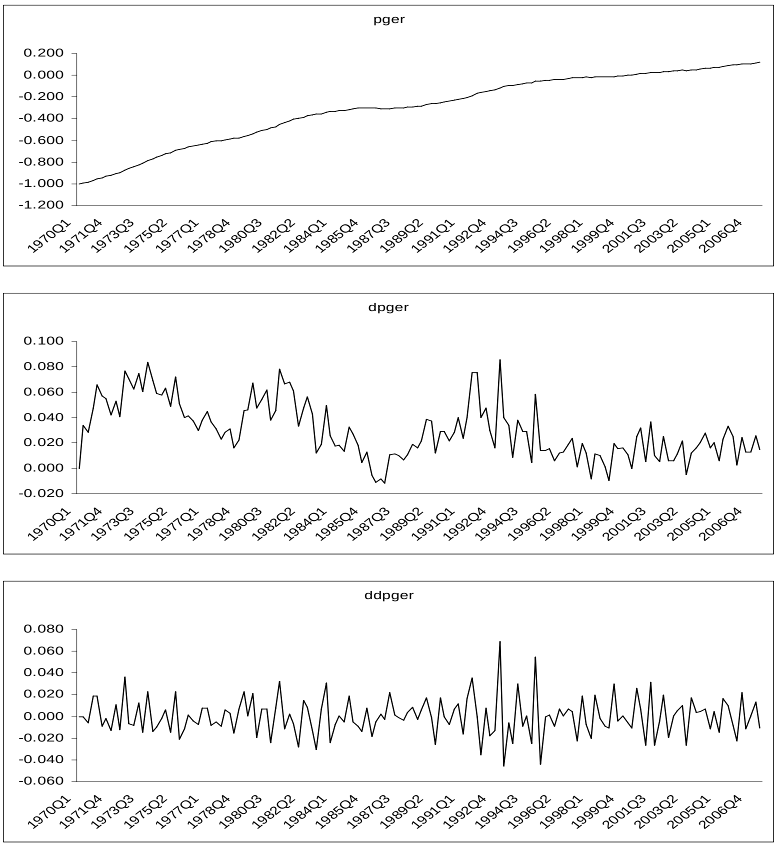

Figure 2: German Price Level, Inflation and First Differences of Inflation

of the model, the mistake to treat an I(1)-variable as I(2) has much less serious consequences than the mistake to treat an I(2)-variable as I(1). The former case of misspecification is associated with a loss of information but the model is fit to stationary data and forecasts are robust with respect to structural breaks (see Hendry (1997), see also Clements and Hendry (2001)). In the latter case of misspecification the model is fit to nonstationary data and could produce spurious outcomes. Secondly, as Garratt et al. (2006)

point out, the Fisher Inflation Parity requires inflation and interest rates to have the same order of integration. If one treats interest rates as I(1), as suggested in section 5.2, then the logarithmic price levels would have to be I(2) according to this argument. These points, together with the implications of visual inspection, justify treating Austrian and German price levels as I(2) and therefore both inflation rates as I(1).

The next variable included in the SVECM is the price differential between Austria and Germany calculated as $PAT - PGER$. The diagram of the variable in levels reveals that during the 1970s and 1980s Austrian prices steadily increased in relation to the German price level. After German unification the pattern changed until the mid-1990s. Since then the relative prices appeared more or less constant.

The first differences of the price differential seem to exhibit a stationary behavior. In addition, all three tests unambiguously lead to the conclusion that the price differential is I(1), and it is treated as such in the remaining analysis.

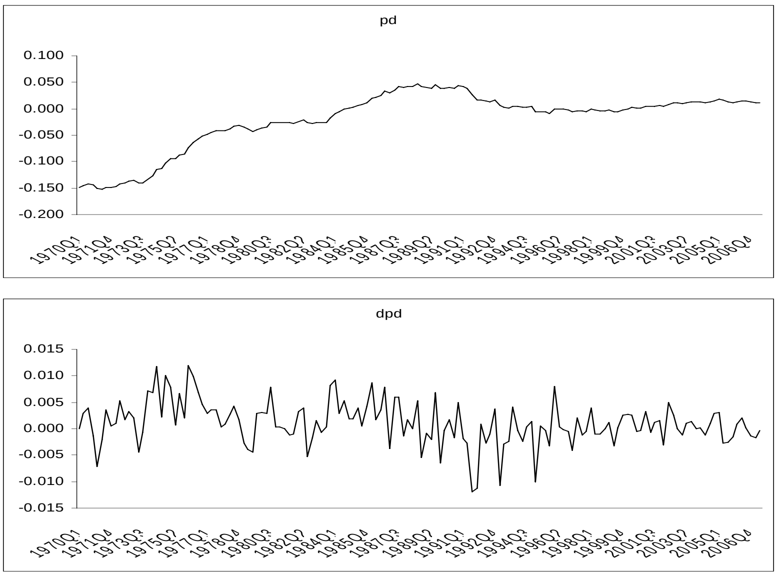

Figure 3: Austro-German Price Differential and its First Differences

The oil prices and their first differences are described in figure 4, where the impacts of the two oil crises in 1973 and 1979 can be identified. Both events led to sustained increases in oil prices. Afterwards the prices kept roughly constant or fell to a small extent, until the next hike occurred due to the Gulf War in 1990. Beginning in 2004, oil prices steadily increased again until the end of the sample period in the second quarter of 2007.

Looking at the first differences, one would expect that the variance of oil prices increased after the second oil crisis. Nevertheless, all three tests conclude that the first differences of the variable are stationary at the five percent significance level and therefore oil prices are treated as I(1) too.

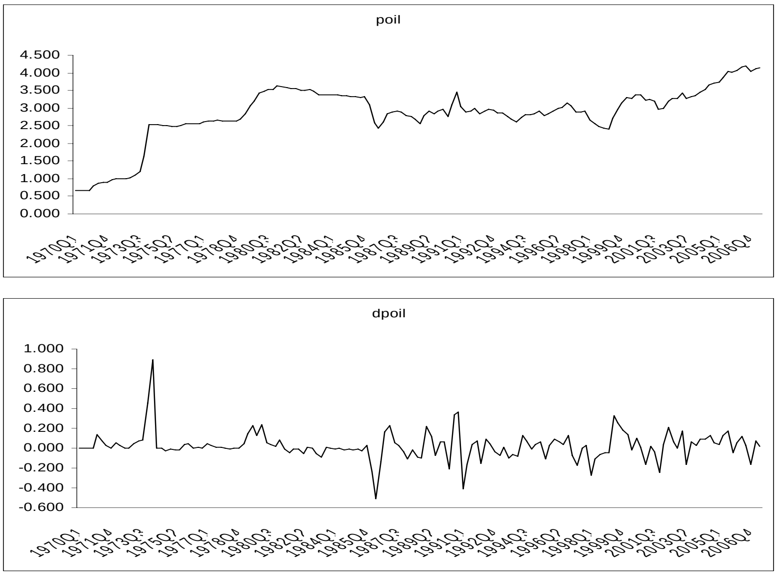

Figure 4: Oil Price and its First Differences

5.2 Interest Rates

When considering the behavior of the interest rates, the first fact worth mentioning is that the Austrian interest rate was lower than the German rate in the aftermath of the first oil crisis. This could be due to the fact that the Austrian Central Bank did not concentrate that much on inflation at that time but also tried to stabilize output growth. In the rest of the sample the behavior of both interest rates is similar: During the 1980s and in the early 1990s they were quite high due to the aforementioned disinflationary policies of central banks, but they decreased considerably afterwards.

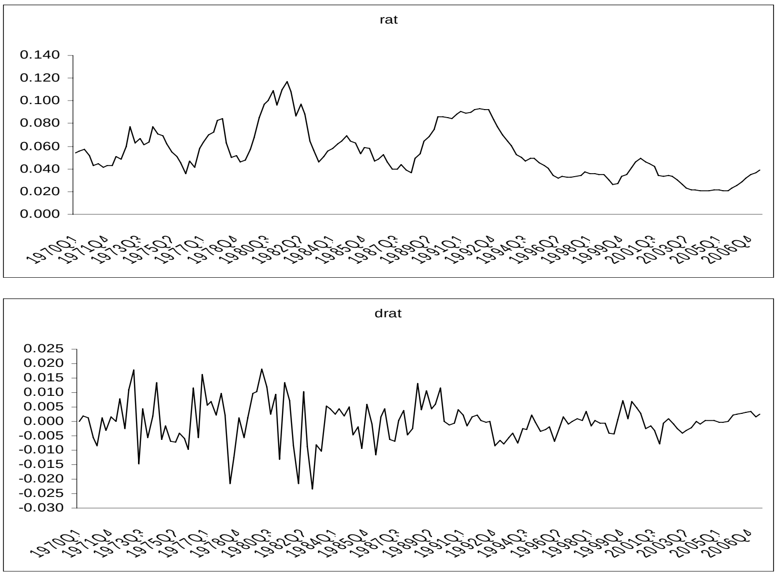

Figure 5: Austrian Interest Rate and its First Differences

With respect to the unit root properties, all three tests conclude that Austrian interest rates are I(1) at the five percent significance level. In the case of German interest rates the PP-test and the KPSS-test also indicate this but the ADF-test suggests treating German interest rates as I(0). The same arguments can be advanced as in the previous section in favor of assuming a higher order of integration in case of doubt. In addition, implementation of the uncovered interest rate parity requires Austrian and German interest rates to have the same order of integration. Therefore both interest rates are treated as I(1) in the remaining analysis.

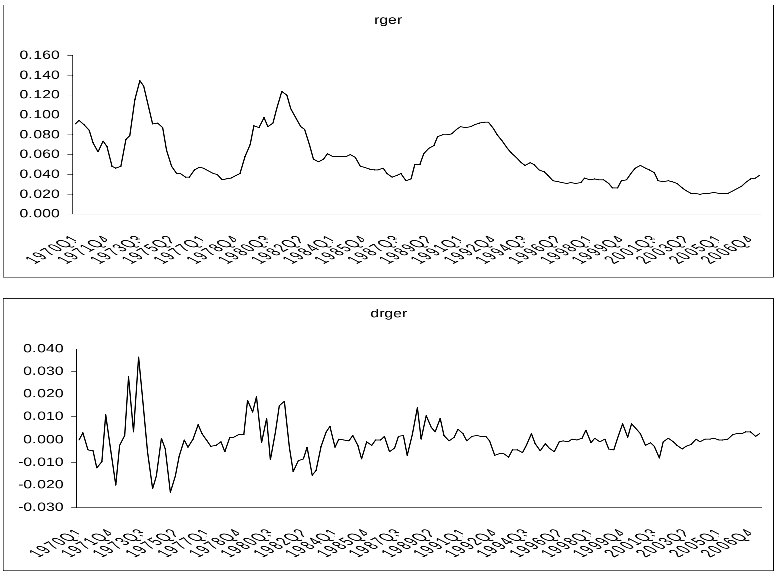

Figure 6: German Interest Rates and its First Differences

5.3 Unemployment Rates

The unemployment rates were comparatively low in both economies during the 1970s. After the first oil crisis they increased considerably, and in the early 1980s they again rose to a large extent. Since then, unemployment rates seem to tend slightly upwards. The first differences indicate that unemployment rates were quite volatile during the early 1970s, but that this volatility decreased considerably over time.

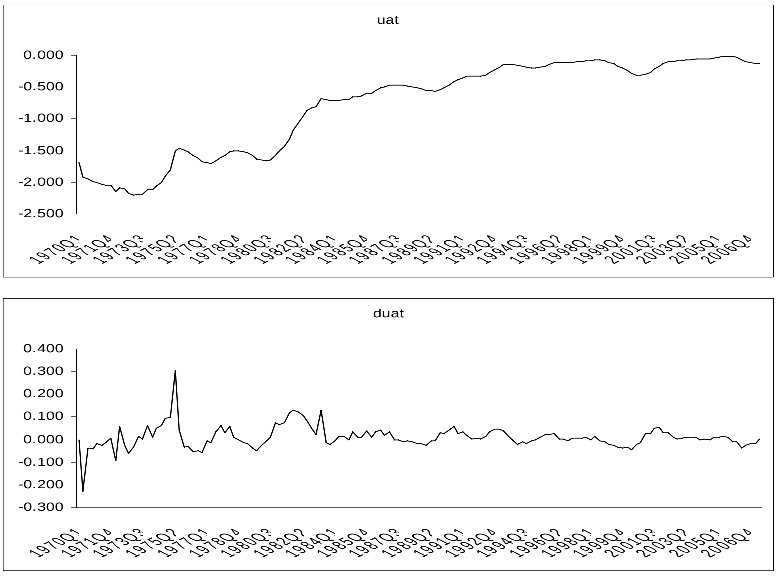

Figure 7: Austrian Unemployment and its First Differences

The PP-test and the KPSS-test both suggest treating Austrian and German unemployment rates as I(1). The ADF-test identifies the Austrian unemployment rate as I(1) but the German unemployment rate as I(0). There is more evidence in favor of unemployment rates being stationary in first differences and so they are treated as I(1) in the remaining analysis.

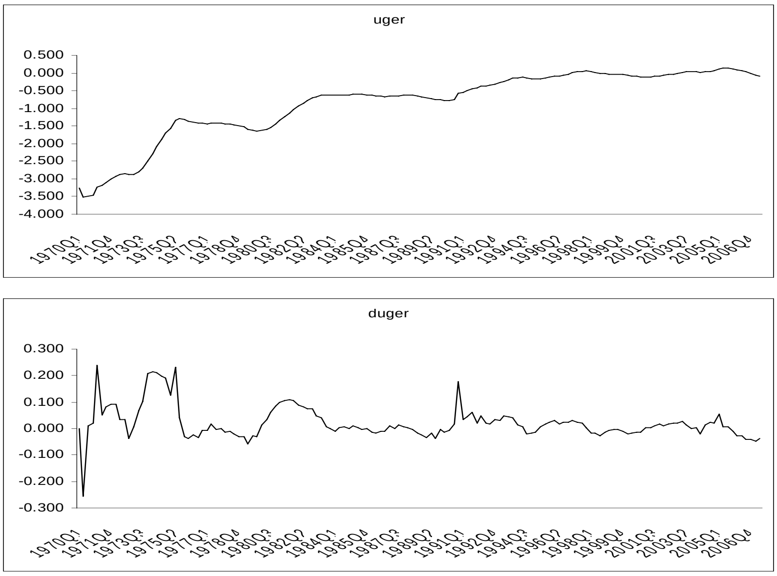

Figure 8: German Unemployment and its First Differences

5.4 Output

The next two graphics display Austrian and German output levels and their first differences. In both countries they appear to be difference-stationary. In the case of German output all three tests confirm this suspicion, whereas for Austria the ADF-test and the PP-test do not. Since the KPSS-test identifies Austrian Output as I(1) and it does not make much sense to treat Output levels as stationary, they are included in the SVECM as I(1)-variables.

Again it is worth mentioning that the two oil crises had considerable influence on the data series under consideration. It seems as if these shocks had a larger impact on the German economy as compared to Austria. This could be due to the fact that interest rates were lower in Austria after the oil price shocks and consequently the Austrian Central Bank did not concentrate that much on inflation but tried to stabilize output growth.

Furthermore, in both countries the slowdowns at the beginning of the 1990s and after the bursting of the "New Economy" bubble are clearly visible.

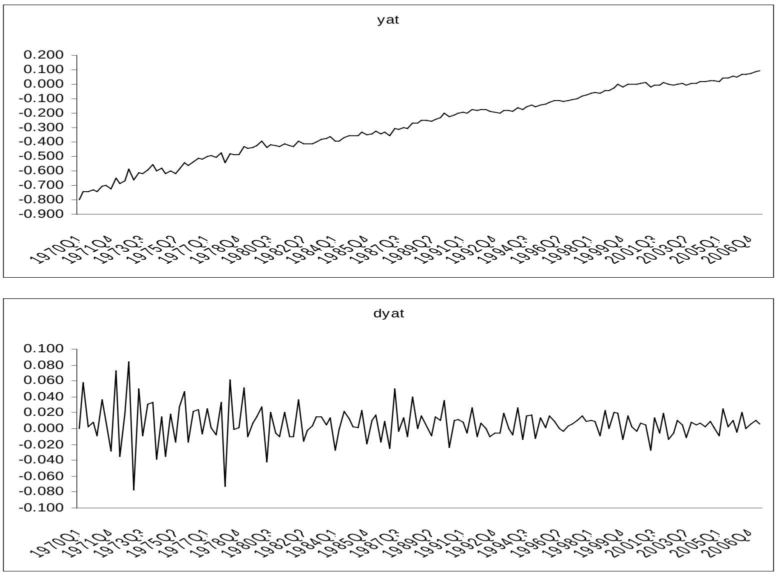

Figure 9: Austrian Output and its First Differences

The latter seemed to be more serious in Germany, which conforms with the views commonly expressed by commentators during this period. In looking at the first differences, one would suspect that output volatility declined in both economies during the time span under consideration but unit-root tests do not confirm this.

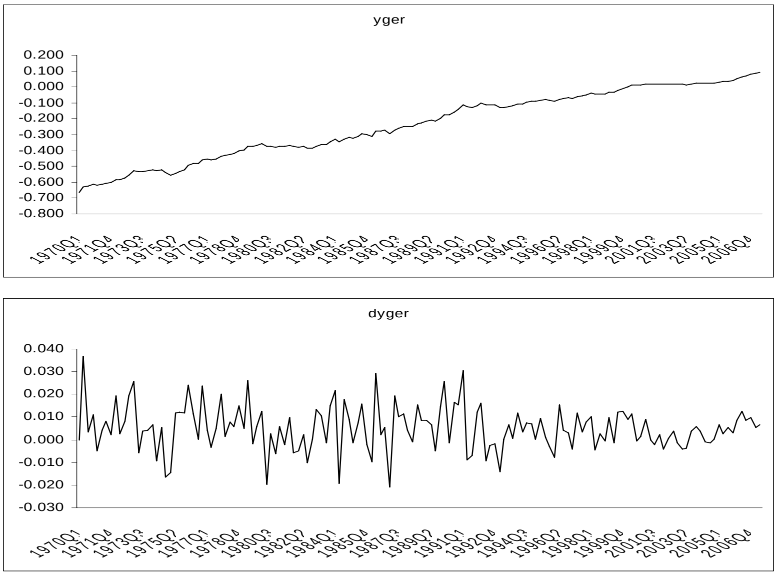

Figure 10: German Output and its First Differences

6 Estimating the Structural Vector Error Correction Model

In this section the econometric implementation of the model will be carried out. First of all the optimal number of time lags is assessed according to the Akaike Information Criterion (AIC) and the Bayes Information Criterion (BIC), afterwards the associated number of cointegrating vectors among the endogenous variables is tested for. With these outcomes in mind, models are estimated with all possible combinations of theoretically implied restrictions imposed on the cointegrating vectors. The results are used to identify the model which is closest to the data generating process. Subsequently, a number of tests are applied to identify misspecifications, which have to be removed and to find out whether there is scope for improving the model in various other ways.

6.1 Lag Selection

In the first step, VAR(ρ) models were estimated in levels for $\rho = 1...4$ and compared to each other according to AIC and BIC. Since there are eight endogenous variables in the SVECM and only 146 observations are available for estimation, lag orders higher than 4 would clearly lead to models that could not be estimated in a meaningful way. The resulting values of AIC and BIC are displayed in table 1, where three asterisks indicate smallest numbers in the respective column.

LAGS	AIC		BIC	
1	-49.4882		-48.0301	***
2	-50.3602		-47.5936	
3	-50.3207		-46.2336	
4	-50.9030	***	-45.4833	

Table 1: Model Selection Criteria

Not surprisingly, BIC favors a specification with one lag only, whereas AIC favors the specification with four lags. While BIC is a consistent model selection criterion for the in sample fit, meaning that it is able to find the model closest to the data generating process if the number of observations tends to infinity, AIC is designed to select the model with the best forecasting properties (see Lutkepohl (2005)). Since the purpose of this analysis is to perform impulse response analysis and to forecast certain time series, AIC is more appropriate than BIC. For this reason, a lag-length of four is chosen in the subsequent analysis. The specification with four lags in levels corresponds to one with three lags in first differences, so the SVECM will include variables from lag order $t-1$ up to lag order $t-3$. Specification tests performed later confirm that a lag-length of four in levels is a good choice.

6.2 Properties of the Cointegrating Relations

With the results of section 6.1 in mind, the trace test was carried out to find the number of cointegrating relations between endogenous variables (see Johansen (1995), Juselius (2007), see also Eviews 6 (2007) User's Guide). In the underlying case the test regression has four lags in levels and hence three lags in first differences. The corresponding scenario is marked with three asterisks in table 2. Recalling the potential restrictions on the cointegrating relations from section 4

$$
\begin{aligned}
RAT_t - DPAT_t &= \beta_{1,0} + \xi_{1,t+1} \\
RAT_t - RGER_t &= \beta_{2,0} + \xi_{2,t+1} \\
PD_t &= \beta_{3,0} + \xi_{3,t+1} \\
YAT_t - YGER_t &= \beta_{4,0} + \xi_{4,t+1} \\
UAT_t - UGER_t &= \beta_{5,0} + \xi_{5,t+1}
\end{aligned}
$$

it is clear that economic theory only allows for intercepts and not for trends. Therefore the trace test indicates the presence of two cointegrating relations between endogenous variables.

Lags		intercept	intercept and trend
1		6	5
2		3	3
3	***	2	3
4		3	3

Table 2: Trace Test on the Number of Cointegrating Relations

Altogether the theoretical discussion revealed the possibility of five cointegrating relations among endogenous variables. However, the trace test indicates that only two of them are present in the data. Therefore the question arises which of the potential relationships are the "true" ones. This question can be reformulated to ask which combination of the possible cointegrating relations leads to a model that fits closest to the data generating process. From this point of view the natural way to proceed is to estimate different models with all possible combinations of the five potential long-run restrictions imposed on the two cointegrating vectors and to assess the resulting specifications according to AIC and BIC. Since all models under consideration have the same degrees of freedom, AIC and BIC only reflect differences in the likelihood. Consequently, the model with the lowest AIC also exhibits the lowest BIC and can be regarded as the best approximation to the data generating process. The corresponding values of the two model selection criteria are shown in table 3 for all possible combinations of the theoretically implied restrictions imposed on the cointegrating vectors.

	PPP + LMC	OG + PPP	OG + LMC	IRP + PPP	IRP + OG
AIC BIC	-50.49 -45.57	-50.42 -45.49	-50.37 -45.45	-50.52 -45.59	-50.45 -45.53
	IRP + LMC	FIP + PPP	FIP + OG	FIP + IRP	FIP + LMC
AIC BIC	-50.55 -45.62	-50.53 -45.61	-50.51 -45.59	-50.59 -45.66	-50.57 -45.65

Table 3: AIC and BIC for Different Combinations of the Available Restrictions

The model which appears to be the best one on first sight includes the FIP and the IRP conditions. Due to the fact that since 1998 interest rates of Austria and Germany are coupled, the long-run errors in IRP are zero afterwards. For the cointegrating equations to be estimated appropriately, another important property of the resulting model would be that the "long-run errors" of the finally implemented cointegrating relations exhibit a stationary behavior. As this is not the case for the IRP condition, we decided to look for other model restrictions which fulfill this requirement.

The second best model chosen by AIC and BIC includes the FIP and the LMC. In the model including FIP and LMC the long-run errors exhibit a stationary behavior, which can be seen in figure 11. Furthermore, a Dickey-Fuller test was performed on these "long-run errors", which rejected the null hypothesis of unit roots in both cases at the five percent significance level. Taking both, the values of model selection criteria as well as the unit root properties of the resulting "long-run errors" into account, leads to the conclusion that a combination of FIP and LMC is the most appropriate choice[1].

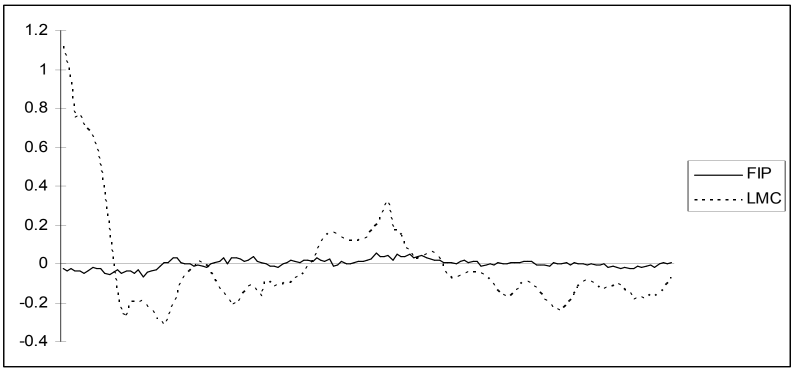

Figure 11: Long-run Equilibrium Errors for FIP and LMC

In addition to the two criteria mentioned above, the validity of the imposed restrictions is tested in section 6.3.6 by means of a bootstrapped likelihood ratio test suggested by Garratt et al. (2006). This test is not able to reject the restrictions implied by the FIP and the LMC at the five percent significance level. Therefore also from this point of view the model is deemed to be appropriate. With all information gathered thus far, the specific model has the following form in our case and is estimated in Eviews 6 (2007):

$$\Delta z_t = a + \alpha\beta^t z_{t-1} + \sum_{i=1}^{3} \Gamma_i \Delta z_{t-i} + \Psi_0 \Delta x_t + u_t \tag{37}$$

with

$$\beta^t = \begin{pmatrix} -1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \end{pmatrix} \tag{38}$$

[1]Due to the shrinkage principle (see for example Diebold (2007)) it could nevertheless be a good choice to include the IRP condition instead of the LMC, if the model is used for forecasting only. Here we follow the procedure outlined in the main text which is consistent with the theoretical literature on cointegration (see for example Juselius (2007)).

containing the FIP in the first row and the LMC in the second.

The parameter estimates and associated t-values are displayed in Appendix D. Residual tests carried out in section 6.3 are able to reject the null hypothesis of homoscedasticity in some of the series so standard errors and t-values are biased and have to be interpreted cautiously.

Most of the parameters have reasonable signs according to an economic interpretation: All three lags of Austrian inflation have a positive impact on Austrian interest rates, suggesting that central banks react to increases in inflation by tightening monetary policy and hence increasing interest rates. Furthermore, the inverse relationship between inflation and unemployment implied by the Phillips curve can be observed. In addition, German interest rates have a positive impact on German unemployment, reflecting the fact that high interest rates tend to hamper investment and the creation of new jobs. Conversely, higher unemployment rates are associated with lower interest rates in both economies, which would imply that the target of the central banks was not only to keep inflation low they also cared for stabilizing output growth and hence unemployment in the short-run. Additionally, it is worth mentioning that higher interest rates seem to have a negative effect on inflation in both economies, as one would expect from economic theory.

6.3 Model Fit and Specification Tests

In this section the model is assessed according to the adjusted R^2 and whether specification tests report serious deviations from the underlying assumptions of a VEC-model. In table 4, adjusted R^2 is reported for each of the endogenous variables. Additionally, the p-values of the Jarque-Bera test on normality of the residuals and those for the White test on heteroscedasticity are provided. In the former case, the null hypothesis is that the residuals under consideration are normally distributed, in the latter case the null hypothesis is homoscedasticity.

	D(DPAT)	D(PD)	D(RAT)	D(RGER)
adjusted R^2	0.5384	0.1255	0.4193	0.3047
Jarque-Bera	0.0960	0.2259	0.3679	0.0000
White	0.0798	0.2434	0.0416	0.0008
	D(UAT)	D(UGER)	D(YAT)	D(YGER)
adjusted R^2	0.6090	0.7682	0.4383	0.0740
Jarque-Bera	0.0000	0.0000	0.8313	0.0255
White	0.0022	0.0474	0.0187	0.1722

Table 4: Adjusted R-squared, Jarque-Bera Test and White Test for the Resulting Model

6.3.1 Adjusted R^2 and Model Fit

As compared to similar models, which allow at most for two lags of endogenous variables and use monetary aggregates instead of unemployment rates (Gaggl et al. (2008), Garratt et al. (2006)) the fit of the SVECM measured by the adjusted R^2 is quite good. Especially the adjusted R^2 for changes in Austrian inflation, changes in Austrian interest rates, changes in Austrian unemployment and Austrian output growth, which are the main series of interest in the impulse response analysis and the forecasting procedure later on, exhibit quite large values between 0.4 and 0.61. In contrast, the model does not perform very well with respect to changes in the price differential and foreign output growth. Since these two variables do not play such an important role in impulse response analysis and forecasting later on, this is of minor importance.

One source for the poorer fit of other models could emerge from aggregating different data series, coming from individual countries, into one series of the hypothetical foreign economy. As mentioned in the introduction, such an approach collects the measurement errors and it tends to smooth the data series for the foreign economy since shocks are averaged out.

6.3.2 White Test on Heteroscedasticity

To get an overall impression regarding the behavior of the residuals, they are plotted in Appendix E.1 together with lines at plus/minus two standard deviations. Despite the presence of some outliers, especially during time periods that coincide with oil crises, there do not seem to be obvious problems with the data. Nevertheless, there is some indication of heteroscedasticity in the residuals, i.e. the variance of some series decreased over time.

Whether these effects are significant depends on the results of the White test. It rejects homoscedasticity with respect to interest rates, unemployment rates and Austrian output. If heteroscedasticity is present, standard errors and t-values are biased and should be interpreted with care. Another problem could arise if confidence intervals for impulse response functions relied on asymptotic standard errors, since they would be biased. Nevertheless, the parameter estimates are still unbiased and consistent, so there is no need to respecify the model in this case.

6.3.3 Jarque-Bera Test on Normality

The Jarque-Bera test rejects normality of the residuals for the two unemployment series, the German interest rates and German output. Authors address such problems different weights (see Juselius (2007), Garratt et al. (2006)) where the latter accepts deviations of the residuals from normality. Since changes in the specification did not help in solving the problem but seemed to have negative impacts on other parts of the model, it was decided to proceed with the current formulation. As deviations from normality of the residuals indicate that there are influences on the series which are not yet included in the model, there may be scope for finding these influences and therefore finding more accurate endogenous variables in future research.

6.3.4 Portmanteau Test on Autocorrelation

A serious misspecification would arise if the residuals were correlated. Since lagged dependent variables show up as regressors on the right hand side,

LAG	D(DPAT)	D(PD)	D(RAT)	D(RGER)
1	0.6040	0.9670	0.9550	0.9330
2	0.8650	0.9420	0.9470	0.9400
3	0.6780	0.9720	0.9880	0.5700
4	0.2460	0.8650	0.8780	0.6430
5	0.3370	0.7300	0.3150	0.7600
6	0.4470	0.8300	0.2840	0.4930
7	0.5420	0.6340	0.3540	0.5650
8	0.6320	0.5570	0.4440	0.5240
9	0.6770	0.6390	0.5230	0.4880
10	0.7330	0.6210	0.4750	0.5810
11	0.7440	0.6510	0.5530	0.6690
12	0.8050	0.1840	0.5570	0.7370
LAG	D(UAT)	D(UGER)	D(YAT)	D(YGER)
1	0.5330	0.9320	0.8880	0.9240
2	0.8230	0.6270	0.9370	0.8820
3	0.8930	0.5140	0.3100	0.9610
4	0.8770	0.2050	0.4440	0.5780
5	0.0550	0.2690	0.2070	0.6880
6	0.0830	0.3790	0.2370	0.7800
7	0.1250	0.3140	0.3200	0.8610
8	0.1760	0.3440	0.2070	0.6210
9	0.2440	0.3210	0.2760	0.6360
10	0.2930	0.3870	0.3560	0.7240
11	0.3270	0.2550	0.3600	0.7440
12	0.1300	0.2390	0.3520	0.5920

Table 5: P-values of the Portmanteau Test on Autocorrelation among Residuals

parameter estimates would be biased and inconsistent in this case. Consequently, the model would have to be reformulated or allowed to include higher lag orders. Since we used AIC as the relevant model selection criterion, it is quite unlikely that autocorrelation among residuals is left. However, since the literature often suggests the use of tests for autocorrelation (see for example Lutkepohl (2005), Juselius (2007)), we additionally computed the Portmanteau test up to a lag-order of twelve. Table 5 contains the corresponding p-values, where the null hypothesis is that the residuals are serially uncorrelated up to the respective lag. The table reveals that, on the five percent significance level, the null hypothesis cannot be rejected for all endogenous variables and all lag-orders. Consequently, there is no need to respecify the model from this point of view.

6.3.5 CUSUM Test on Parameter Stability

Regarding the stability of parameters the CUSUM test is performed (see for example Johnston and DiNardo (1997) and the results are displayed in Appendix E.2. There are no significant deviations from the null hypothesis that parameter estimates are constant over the whole sample period at the five percent level. This result is very important since it does not indicate the presence of a regime change, i.e. a structural break in the data series. In addition, the CUSUMSQ test was performed, which is able to detect deviations from the assumption of homoscedasticity in the error terms. Since homoscedasticity was already rejected by the White test in some cases, and the CUSUMSQ tests only confirm the rejections, the results are not shown here for the sake of saving space[2].

6.3.6 Likelihood Ratio Test on the Validity of Overidentifying Restrictions

Where r cointegrating relations are present, r^2 restrictions are needed to exactly identify the parameters of these relations. In the case considered so far, this means that four restrictions would suffice. However, economic theory provides eight restrictions, so the system is overidentified. It is possible to assess the validity of overidentifying restrictions by testing the null hypothesis that the overidentified model is the "true" model against the alternative hypothesis that a VEC-model with two unrestricted cointegrating vectors

[2]These results are available from the author upon request.

is the “true” model. This can be done by a standard likelihood ratio test. However, Garratt et al. (2006) point out that the critical values of this test are biased for small sample sizes so they advocate the use of bootstrapped critical values. We follow a similar approach where the bootstrapping procedure is nonparametric, and can be described by the following steps (see for example Johnston and DiNardo (1997), Lutkepohl (2005)):

1. Estimate the model and store the fitted values as initial estimates
2. Randomly draw residuals with replacement from the residuals of the model obtained in the previous step
3. Calculate the mean of the randomly drawn residuals (which should be close to zero) and subtract it from them to get new residuals
4. Add the new residuals to the initial estimates
5. Estimate the model subject to the overidentifying restrictions and store the value of the log-likelihood ($logl$)
6. Estimate the model subject to the exactly identifying restrictions and store the value of the log-likelihood ($logl$)
7. Calculate the test statistic as $2(logl(ei) - logl(oi))$, where ei and oi denote the exactly identified and overidentified model respectively, and store this test statistic
8. Repeat these steps a number of times and obtain the upper critical value (since it is a one sided test) from the stored test statistics

The resulting bootstrapped distribution of the test statistic is shown in figure 12 for 2000 replications of the described algorithm. The density function of the bootstrapped critical values was obtained with the help of a Gaussian kernel estimate under the default smoothing bandwidth in the software package R (R Development Core Team (2007)).

The upper 5 percent critical value of this distribution is 52.27, whereas the test statistic obtained by comparing the original overidentified model with the exactly identified one exhibits a value of 37.64. Therefore the validity of the theoretically implied overidentifying restrictions cannot be rejected and hence there is no need to lift them.

This represents a first central result because the presence of the FIP in Austria and the LMC between Austria and Germany cannot be rejected. Consequently, the labor markets of the two countries seem to be closely related and allowing for labor migration when specifying the restrictions on the cointegrating vectors is a good choice.

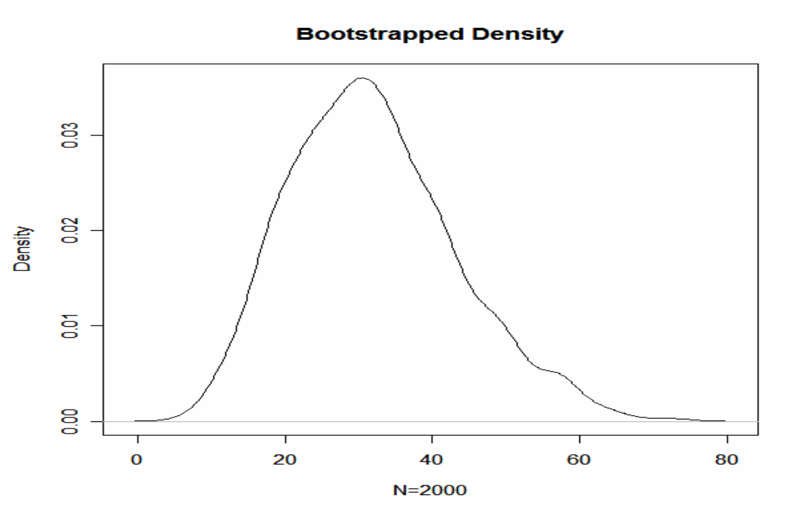

Figure 12: Density-Function of 2000 Bootstrapped Critical Values for the Likelihood Ratio Test on the Validity of Overidentifying Restrictions

To summarize, specification tests with respect to normality and homoscedasticity of the error terms suggest that there might be scope for finding other factors that influence the endogenous variables in this model. Since the SVECM is already very large, including more time series as endogenous and exogenous variables as well as increasing the lag-length will render meaningful estimation of the parameters impossible. However, it could be a good choice to replace some of the included series by others and to investigate whether this leads to an improvement in the model fit. This is suggested for future research. As there is no evidence for the presence of autocorrelation among the residuals or for instability of the estimated parameters, the model is acceptable. Furthermore the test on the validity of overidentifying restrictions was not able to reject the null hypothesis so the decision was to keep the specified form of the SVECM for impulse response analysis and forecasting.

7 Generalized Impulse Response Analysis

Since the model performed well with respect to criteria assessing its fit, with respect to model specification tests and with respect to tests on the validity of overidentifying restrictions imposed on the cointegration space, it will be used to study the impacts of different shocks to domestic and foreign variables in the next two sections.

7.1 Effects of Domestic Shocks on Austrian Variables

First of all the estimated model is used to investigate responses of Austrian inflation, Austrian interest rates, Austrian unemployment and Austrian output to shocks in each of these variables themselves. These results can be used to assess whether the implications of the model are reasonable at all, but they also have an intrinsic value, since they expose domestic adjustment processes to exogenous shocks.

The method used for computing these impulse response functions is described in section 3.2. It is called generalized impulse response analysis, is due to Pesaran and Shin (1998) (see also Koop et al. (1996)) and does not rely on an arbitrary orthogonalization of shocks, i.e. the order of endogenous variables does not matter. Since Eviews 6 (2007) does not compute asymptotic standard errors for the point estimates of impulse response functions in VEC-models, a bootstrapping procedure was used to obtain 95 percent confidence intervals. Implementing this procedure required the following calculations, quite similar to those in section 6.3.6:

1. Estimate the model and store the fitted values as initial estimates

2. Randomly draw residuals with replacement from the residuals of the model obtained in the previous step

3. Calculate the mean of the randomly drawn residuals (which should be close to zero) and subtract it from them to get new residuals

4. Add the new residuals to the initial estimates

5. Reestimate the model and obtain generalized impulse response functions

6. Repeat these steps a number of times and obtain the upper and lower critical values from the stored generalized impulse response functions

The first innovation to be considered in figure 13 is a one standard deviation shock to Austrian inflation (DPAT). The generalized impulse response functions over a time span of 40 quarters are displayed as solid lines, whereas the corresponding lower and upper bounds of the bootstrapped 95 percent confidence intervals are displayed as dashed lines. Note that the number of iterations in the bootstrapping procedure was set to 2000.

As can be seen, the model exhibits stable properties, i.e. generalized impulse response functions do not tend to plus/minus infinity. In addition, the responses are plausible and have a clear economic interpretation: Output and unemployment do not react significantly but inflation itself stays slightly higher than in the baseline scenario for some quarters, leading to a reaction of the Central Bank, which increases interest rates. This increase is significant in the short-run for about seven quarters. Due to these adjustments, inflation is dampened again and does not react significantly in the long-run.

Next a positive, one standard deviation shock to the Austrian interest rate is considered and its impact on the other variables is assessed. Figure 14 reveals the dynamics created by this shock. The interest rate itself stays significantly higher than in the baseline scenario for about eight quarters and output stays significantly lower for about 25 quarters. Prices and unemployment do not react significantly, although point estimates suggest that inflation keeps slightly lower for about six quarters. Afterwards inflation increases, which could be interpreted as an effect due to the FIP: Since the real interest rate is constant in the steady state and the nominal interest rate increases, inflation has to adjust such that the FIP holds in the long-run. According to the point estimates, output decreases and unemployment increases for the whole time range of 40 quarters. This behavior has a standard economic interpretation, since increases in interest rates are considered to slow down economic growth in the short-run, which in turn raises unemployment.

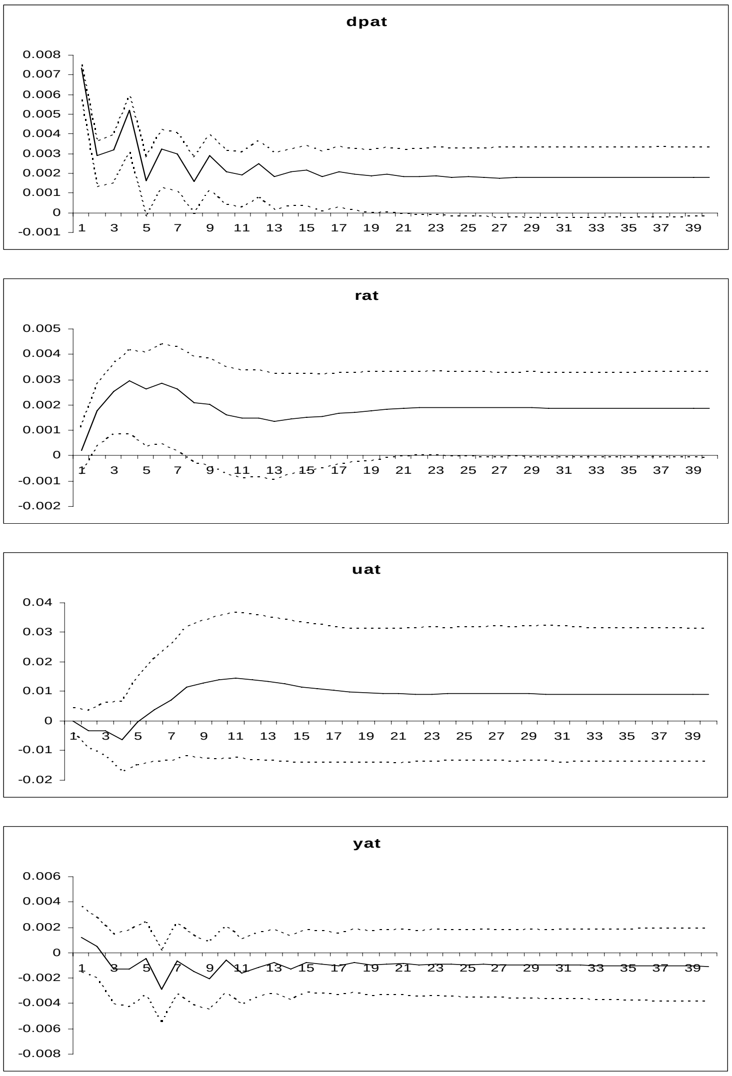

Figure 13: Generalized Impulse Responses to One Standard Deviation Shock to Austrian Inflation

The next innovation to be investigated is one to Austrian unemployment whose effects are shown in figure 15. In response to this shock unemployment

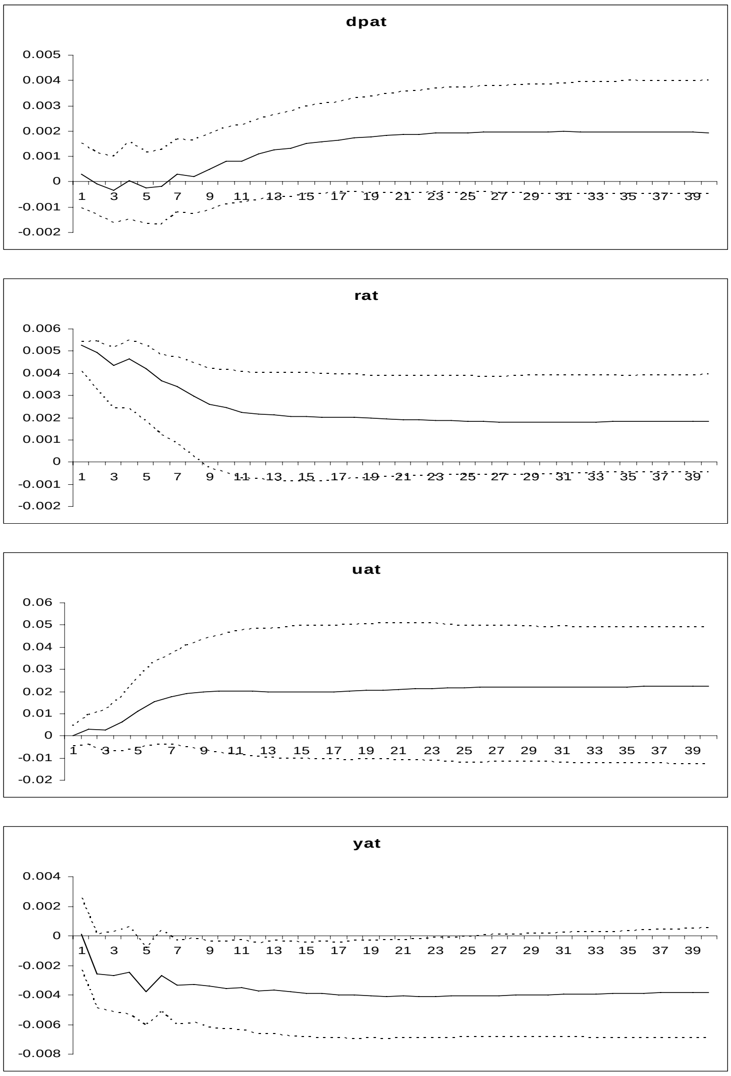

Figure 14: Generalized Impulse Responses to a One Standard Deviation Shock to the Austrian Interest Rate

remains significantly higher than in the baseline scenario. This finding relies on the results of the unit root tests, which suggested treating unemployment rates in both economies as I(1) and has an interesting economic interpretation, referred to as the phenomenon of hysteresis (see for example Blanchard (1991), Heijdra and van der Ploeg (2002)). This phenomenon describes situations where unemployment is very persistent, such that positive shocks to the unemployment rate have long-lasting effects. In particular, European economies are considered to suffer from this problem. Inflation does not react significantly, although according to the point estimate there is a slight tendency for it to decrease in the long-run. Therefore the central bank has scope for acting against the increase in unemployment by decreasing interest rates. According to the figure it does so in the short-run, such that output is negatively effected only for 1 quarter and does not react significantly in the long-run.

Finally, the impacts of a shock to Austrian output are shown in figure 16. This shock has the effect that output stays significantly higher for about 25 quarters. As a consequence unemployment decreases and stays significantly lower for six quarters. However, in the long-run there is no significant effect of the positive output shock on unemployment. In order to prevent the economy from overheating and to suppress inflationary tendencies, the central bank increases the interest rate significantly for a time period of 11 quarters. Because of this behavior, inflation does not react significantly. Furthermore, it is worth mentioning that the response of output itself does not indicate the presence of a multiplier effect, i.e. output does not increase by more than the initial shock in the short-run. The data rather supports the hypothesis that deviations of actual output from potential output are very short lived. Besides the efforts of the central bank to prevent the economy from overheating, another possible explanation for the absence of a multiplier effect in Austria could be that the economy exhibits a high degree of openness, such that additional income is largely spent on imported goods (see Blanchard (2003)).

To summarize, the main findings of this section are that, firstly the labor market in Austria suffers from hysteresis, i.e. temporary shocks have long-lasting impacts; secondly, there is no multiplier effect with respect to output shocks, meaning that deviations from the long-run trend are short lived; and

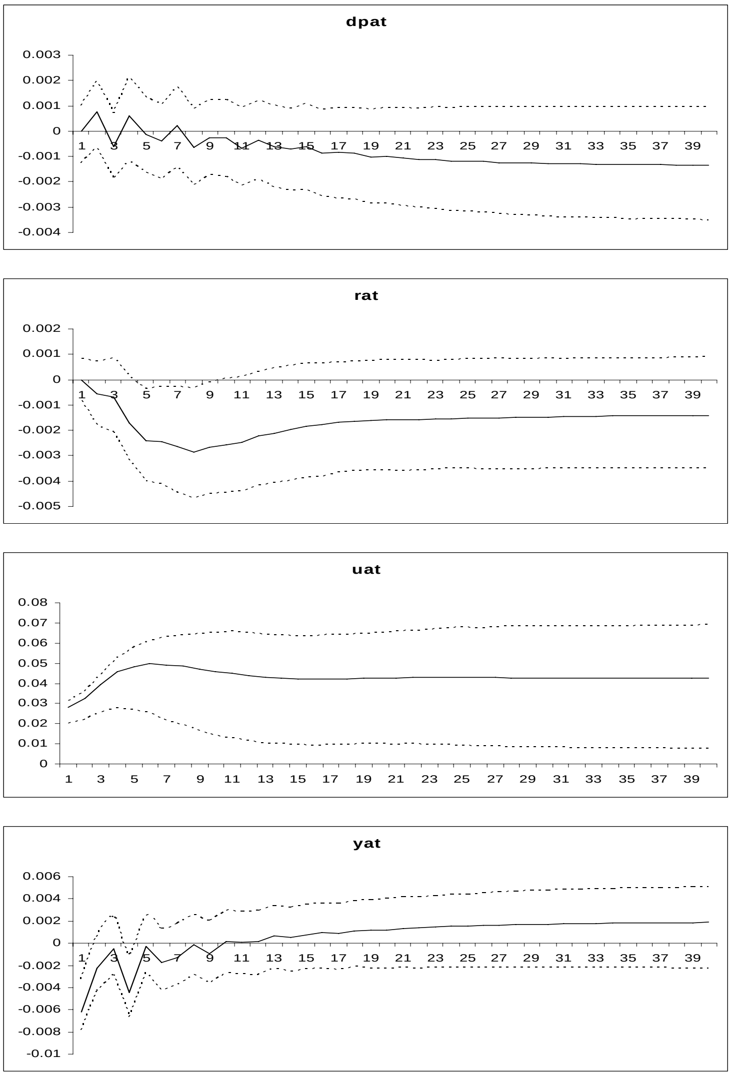

Figure 15: Generalized Impulse Responses to a One Standard Deviation Shock to Austrian Unemployment

thirdly, central banks did not only address inflation during the investigated time period but also output stabilization. All in all these analyses show that

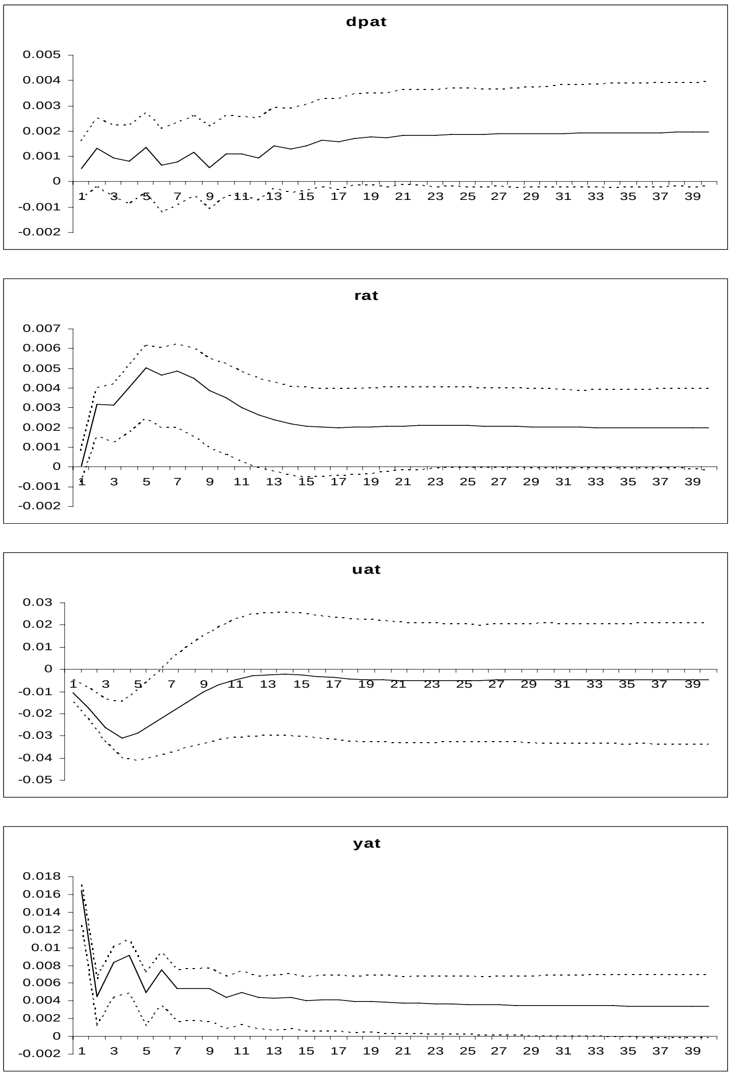

Figure 16: Generalized Impulse Responses to a One Standard Deviation Shock to Austrian Output

the model is able to create plausible responses of endogenous variables to different shocks in the domestic economy. From this point of view one could expect to gain valuable insights into the transmission mechanisms from the German to the Austrian economy by shocking foreign variables and using the same method as before to track the responses of domestic variables.

7.2 Effects of Foreign Shocks on Austrian Variables

In this section the SVECM is used for analyzing the extent to which shocks to German variables influence Austrian inflation, Austrian interest rates, Austrian unemployment and Austrian output growth. For the sake of comparability, shocks to inflation rates and interest rates as well as their respective responses are standardized to represent one percentage point innovations. In contrast, shocks to unemployment and output as well as their responses, are measured in percent deviations from the baseline scenario.

At first, a one percentage point shock to the German interest rate is considered and its effects are depicted in figure 17. This shock does not have significant effects on Austrian output and inflation, but in the short-run the Austrian interest rate increases significantly, which could be due to the IRP, although this relation is not modeled explicitly for reasons explained in section 6.2. Austrian unemployment does not react significantly in the short run, but starts to rise after about four quarters. On the one hand this is caused by lagged effects of the increased domestic interest rate, on the other hand the LMC ensures that rising unemployment in Germany leads to higher unemployment in Austria as well, since some of the newly unemployed seek jobs in Austria. On average Austrian unemployment increases by 6.65 percent in this scenario. It is interesting to see that these effects are long-lasting which again supports the theory of hysteresis.

The next scenario to be investigated is a one percent shock to German unemployment with the results shown in figure 18. The effects of this shock again have straightforward interpretations. As unemployment in Germany increases, demand for foreign goods decreases, which lowers Austrian exports and hence Austrian output. This in turn leads to increased Austrian unemployment. Furthermore, Germans who become unemployed will move to Austria, which further increases unemployment there. One can see that

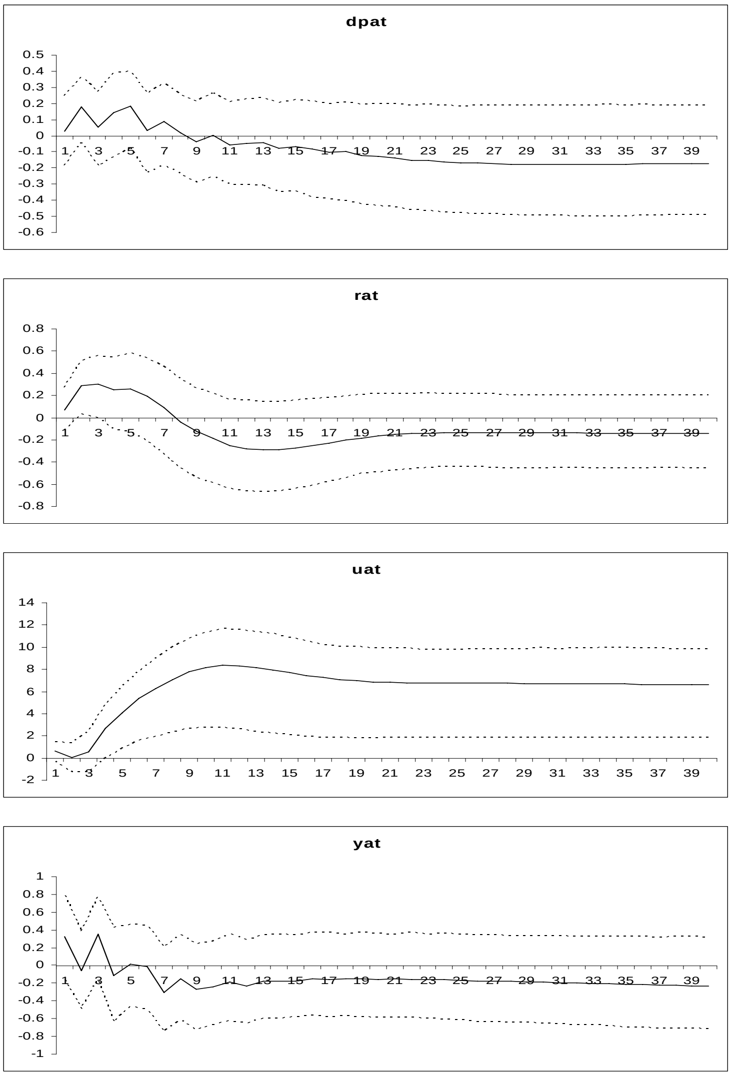

Figure 17: Generalized Impulse Responses to a One Percentage Point Shock to German Interest Rates

the average increase in Austrian unemployment is higher in percentage terms than the increase in Germany - a one percent increase in German unemploy-

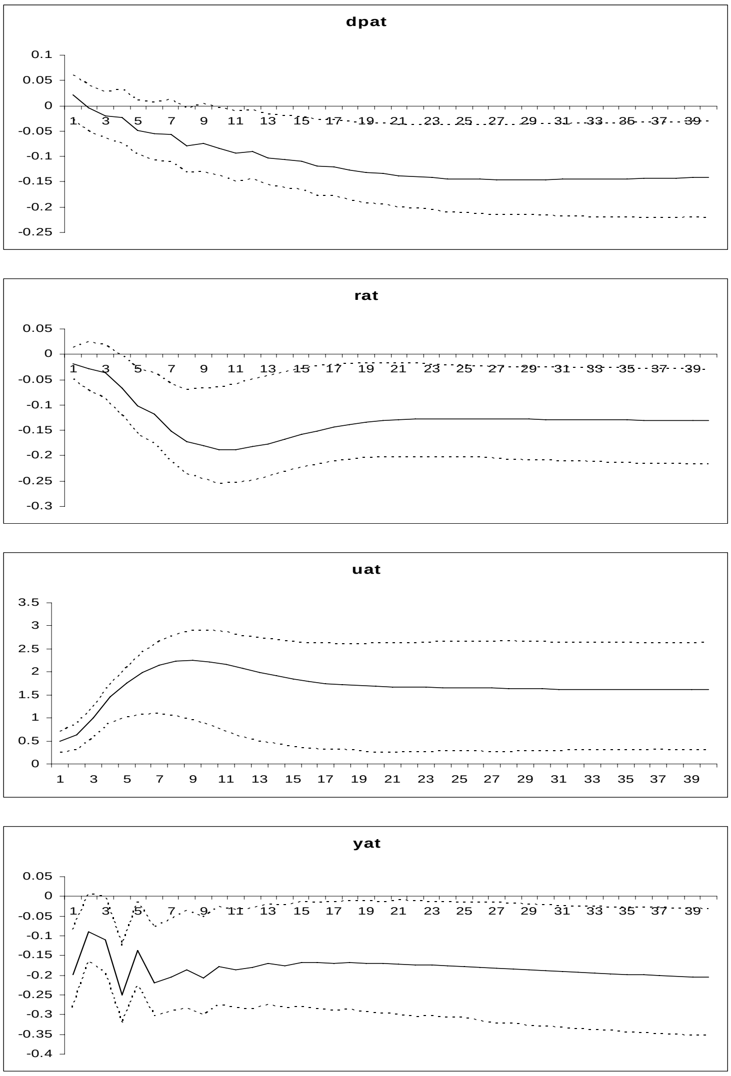

Figure 18: Generalized Impulse Responses to a One Percent Shock to German Unemployment

ment leads to an increase in Austrian unemployment of about 1.6 percent in the long-run. This effect can be explained by the relative sizes of the labor forces in both countries. Since the absolute number of unemployed in Germany is very large compared to those in Austria, an inflow of some of the newly unemployed Germans has serious effects on Austrian unemployment in percentage terms. As another consequence of the aforementioned dynamics, inflationary pressure declines, leaving latitude for the central bank to decrease interest rates. All in all, inflation drops on average by 0.15 percentage points in the long-run. In the short-run the central bank therefore decreases the interest rate, in this case by about 0.18 percentage points, but in the long-run the FIP prevents the interest rate from decreasing too much. As a consequence, the interest rate decreases by the same amount as inflation in the long-run.

In the last scenario, a positive one percent shock to German output occurs. Figure 19 reveals that the positive significant spillovers to Austrian output only last for a very short time period. Due to the temporary boom in Germany, demand for Austrian goods rises such that output in Austria stays significantly higher for seven quarters, and unemployment stays significantly lower for five quarters. The interest rate increases significantly for about ten quarters, which in turn prevents the inflation rate from increasing significantly.

To summarize the most important insights gained in this section, shocks to German interest rates and unemployment have quite large influences on Austrian unemployment. This is due to the labor mobility in the model: The Austrian labor market comes under pressure from two distinct sides in the event of a German economic slowdown. Firstly, Austrian exports to Germany drop and secondly, unemployed Germans migrate to Austria. Both phenomena seriously increase Austrian unemployment. In addition to these dynamics, the properties of the labor markets mean that exogenous shocks lead to long lasting effects, which is commonly referred to as the phenomenon of hysteresis. Together these facts explain why the Austrian labor market is affected to this extent. In contrast to shocks affecting the German interest rate and unemployment, positive shocks to German output have only transient effects on Austrian variables, which is partly due to the absence of multiplier effects, as mentioned above. However, in the short-run,

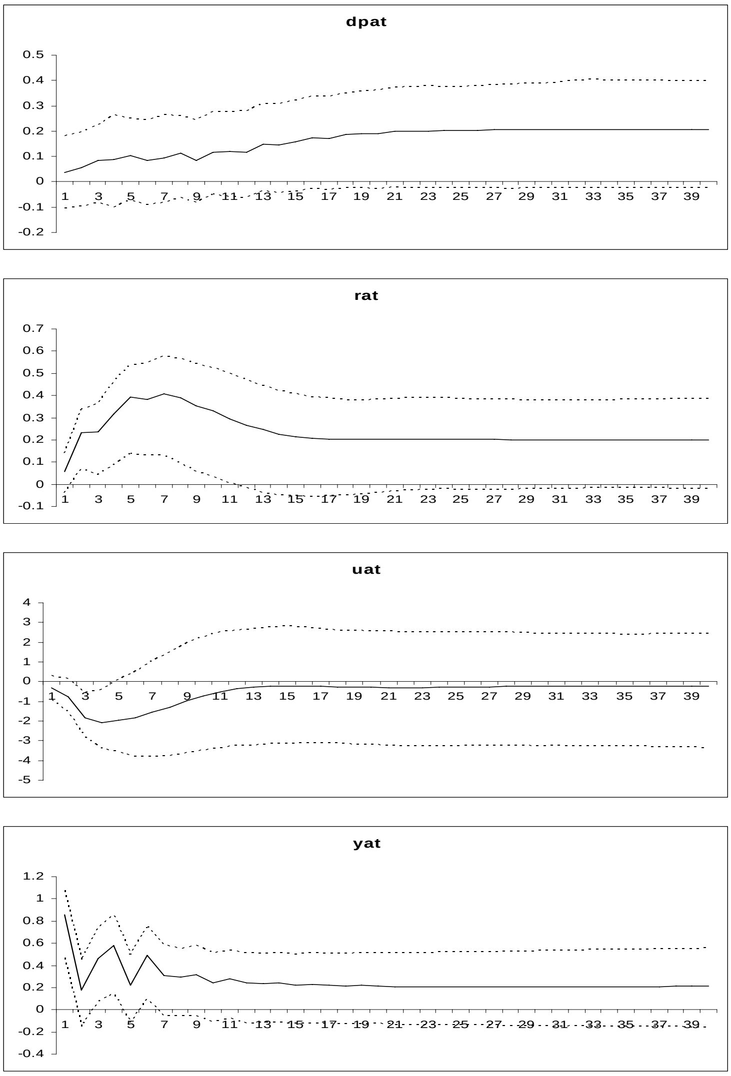

Figure 19: Generalized Impulse Responses to a One Percent Shock to German Output

the Austrian interest rate increases significantly and unemployment decreases significantly, which is reasonable according to standard economic arguments.

7.3 Effects of Domestic Shocks on German Variables

The model also allows for investigating the effects on the German economy of shocks felt by Austrian variables. Since the German economy is far larger than the Austrian economy, this case is less interesting. To save space, only the most important issues will be stated here[3]. Again, shocks to inflation rates and interest rates and their responses were standardized to represent one percentage point innovations, whereas shocks to unemployment and output and their responses were measured in percent deviations from the baseline scenario. Since the vector of endogenous variables did not include German inflation, the responses to Austrian shocks can only be traced for interest rates, unemployment and output.

If Austrian inflation is shocked, German interest rates, German unemployment and German output do not react significantly. The same holds true for shocks to Austrian interest rates. Shocks to Austrian unemployment do not have significant effects on German interest rates or German output, but an increase in Austrian unemployment is likely to increase German unemployment as well, although not to the same extent as the corresponding German shock increases Austrian unemployment. The effect of Austrian unemployment on German unemployment is mainly due to the LMC which states that some newly unemployed Austrians will try to find work in Germany.

The most interesting case, depicted in figure 20, is the response of German interest rates, German unemployment and German output to a temporarily boost in Austrian output. It can be seen that German variables do not react as much to a shock of Austrian output as in the reverse case but in the short-run German interest rates rise significantly, German unemployment decreases significantly and German output increases significantly. Again, these responses can be explained by standard economic arguments but there is one important difference between the response of German output to a positive Austrian output shock and the response of Austrian output to a positive German output shock: In the former case the presence of a multiplier

[3]The other calculations are available from the author upon request.

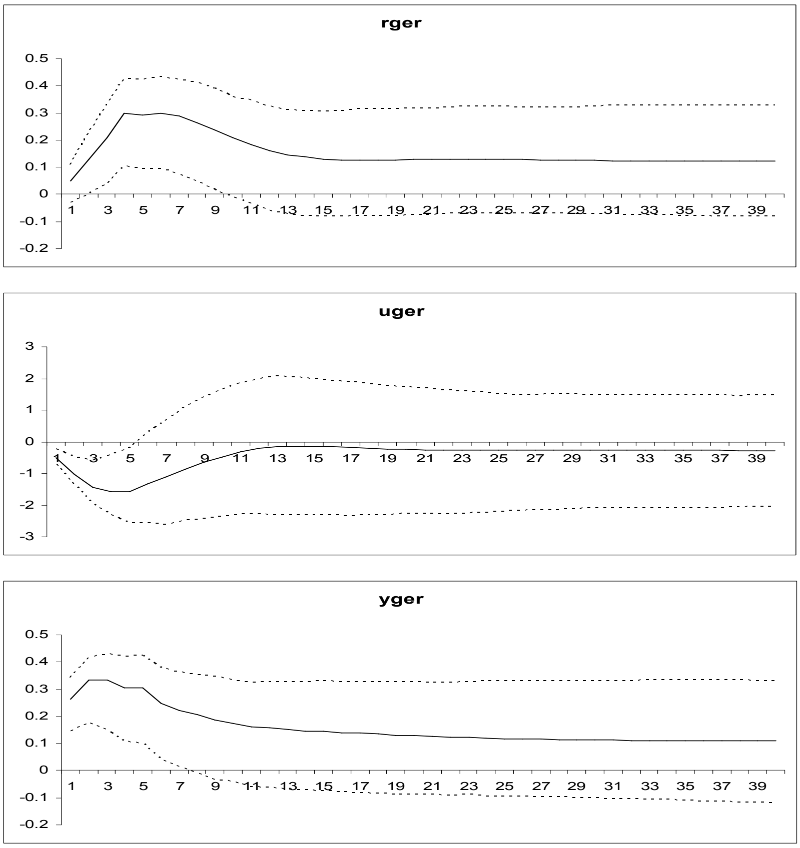

Figure 20: Generalized Impulse Responses of German Variables to a One Percent Shock to Austrian Output

effect is clearly indicated by the third picture in figure 20. German output reacts to an Austrian shock immediately, yet the dynamics are reinforced in the subsequent quarters. This could be explained by the fact that in Germany imports are a lower percentage of GDP than in Austria and thus the degree of openness is lower for the German economy. Consequently, additional income is largely spent on domestic goods and the standard multiplier effect sets in (see for example Blanchard (2003)).

To summarize, shocks that hit Austrian variables barely have any significant effects on the German economy, with some exceptions: Output shocks are able to significantly affect German variables at least in the short-run and due to the LMC, labor market shocks tend to transmit to Germany as well. However, these effects are comparatively small.

8 Forecasting Austrian Economic Performance

8.1 Forecasts Using the Estimated SVECM

In this section the SVECM is used to forecast changes in inflation (DDPAT), changes in the interest rates (DRAT), changes in unemployment (DUAT) and absolute values of output growth in Austria (DYAT) (for general issues related to forecasting techniques see for example Chatfield (2000) and Diebold (2007)). These variables were selected because outcomes can easily be compared to those of univariate forecasting techniques for stationary time series. If one is interested in forecasts for inflation, interest rates, unemployment and output in levels, the forecast growth rates can be used to recalculate indices and forecasts for the series in original units with the help of appropriate back-transformations (see Appendix A).

To perform the forecasts, the SVECM is transformed into a model object in Eviews 6 (2007). Afterwards the model is solved numerically in a deterministic dynamic manner, using 5000 iterations and the Gauss-Seidel algorithm (see Eviews 6 (2007) User's Guide). The forecast evaluation period starts in the first quarter of the year 2000 and ends in the second quarter of 2007. In the beginning, the model is estimated using information until the fourth quarter of 1999. Forecasts for the first quarter of 2000 are computed with this model. In the next step, the model is estimated using information up to the first quarter of 2000 and forecasts are obtained for the second quarter of 2000. Analogously, one step ahead forecasts are then obtained for each quarter in the forecast evaluation period.

Figure 21 reveals that the model predicts changes in inflation quite well, whereas output growth is overestimated between 2001 and 2003 and consequently unemployment growth is underestimated during this period. The reason is that the model may not accurately cover some of the factors that explained the recession between 2001 and 2003. Similar results are reported for the forecasting models of the Austrian Central Bank (OeNB), the Institute of Advanced Studies (IHS) and the Austrian Institute of Economic

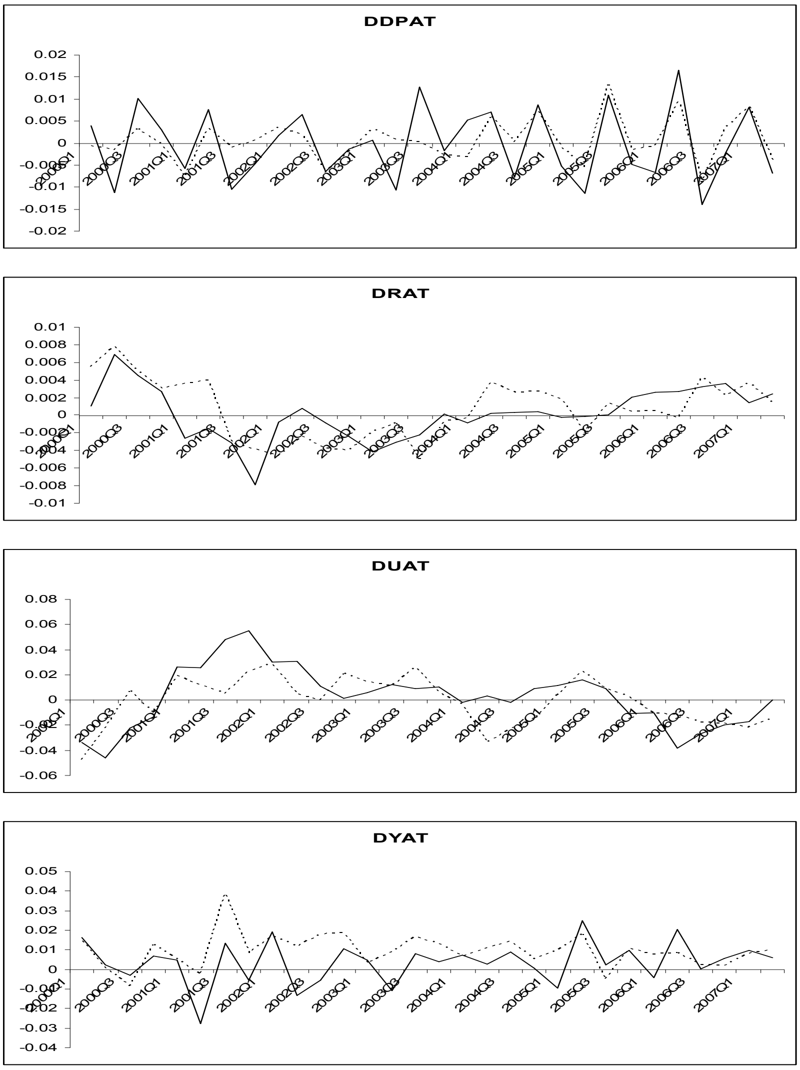

Figure 21: One Step Ahead Forecasts of the SVECM (Dashed Line) and Actual Values (Solid Line)

Research (WIFO) in Ragacs and Schneider (2007). In general, the SVECM seems to perform better at the end of the forecast horizon, during the phase of economic recovery.

The question arises whether the SVECM is able to compete with other models regarding the predictive power. If this is the case and none of the other considered forecasting models encompasses the SVECM, it can contribute to a combined forecast, which has higher predictive power than each of the individual forecasts. In the next sections standard forecasting techniques are used to obtain one step ahead predictions over the same time horizon as for the SVECM. Afterwards the results of the various forecasts will be compared with the help of several criteria assessing the predictive power of forecasting techniques.

8.2 Forecasts Using Univariate ARMA Models

Univariate time series models are widely used in forecasting, since they are barely outperformed by multivariate models. Similar to Garratt et al. (2006) various ARMA-models (see Brockwell and Davis (1996) for a general description of this model class) are estimated for DDPAT, DRAT, DUAT and DYAT over the whole sample period. The highest lag order to be allowed for is four in the autoregressive and in the moving average part. Hence there are 25 possible combinations of autoregressive and moving average terms, excluding subset models. These 25 models are compared to each other via the AIC and the best model is chosen for forecasting purposes. In the case of DDPAT, an ARMA(3,4) performed best, in the case of DRAT and DUAT an ARMA(4,4) had the lowest AIC, and for DYAT an ARMA(4,3) had the best fit. In the next step the sample was again split into an estimation period, ranging from the first quarter of 1970 to the fourth quarter of 1999, and a forecasting evaluation period, ranging from the first quarter of 2000 to the second quarter of 2007. Afterwards the same one step ahead forecasts where made as in the case of the SVECM using the most suitable ARMA model mentioned above.

Figure 22 indicates that the chosen univariate time series models perform quite well in predicting patterns of the various series under consideration, although peaks and troughs for changes in inflation are underestimated. In the

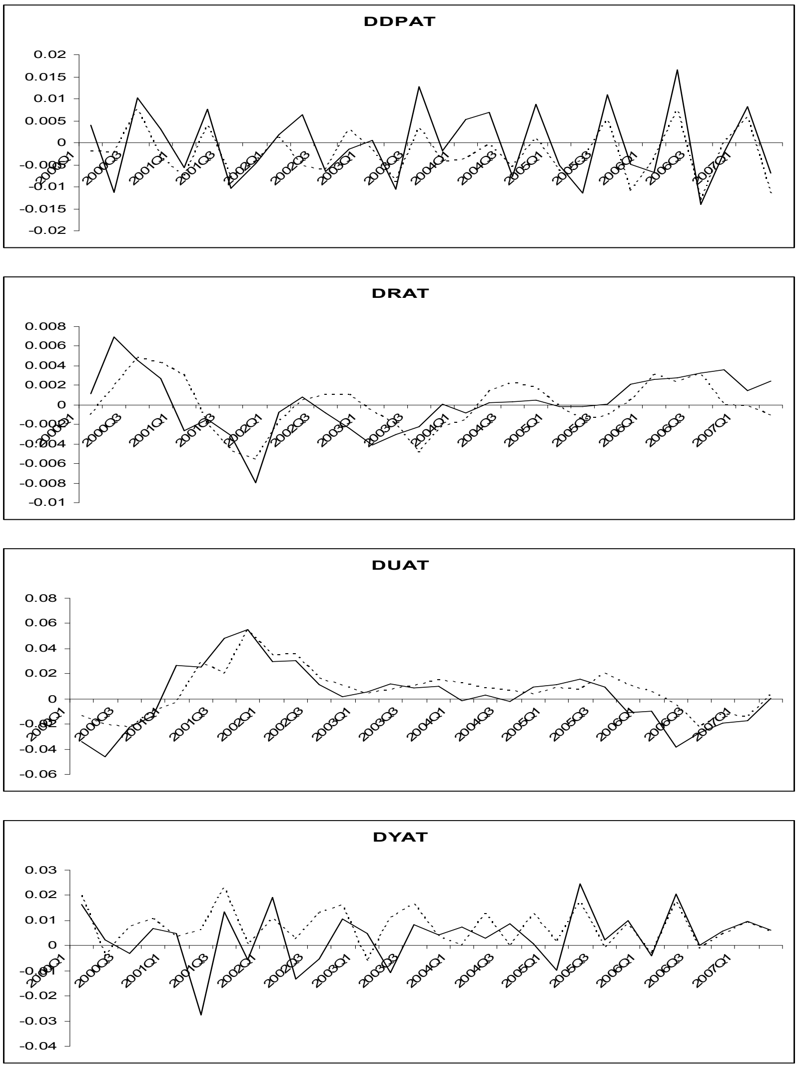

Figure 22: One Step Ahead Forecasts of the Appropriate ARMA Models (Dashed Line) and Actual Values (Solid Line)

case of changes in the interest rates and changes in unemployment the series of one step ahead forecasts seem to lag behind real developments. With respect to output growth, the same problem as in the SVECM-forecast arises, i.e. the economic slowdown at the beginning of this century is underestimated.

8.3 Forecasts Using Holt-Winters Nonseasonal Algorithm

The Holt-Winters nonseasonal algorithm (see for example Brockwell and Davis (1996), Chatfield (2000)) is an ad-hoc procedure which is based on estimates of local levels and local trends, which are smoothed versions of past local levels and local trends. The procedure often leads to quite accurate forecasts, especially if the investigated series exhibits seasonal behavior and the algorithm is augmented with a local seasonal component. Since this is not the case in the present setting, one cannot expect to get very good forecasts. Nevertheless, it may be possible that some dynamics are revealed by this and none of the other procedures. Again one step ahead forecasts where obtained for the forecast evaluation period between the first quarter of 2000 and the second quarter of 2007.

As is obvious from figure 23, the algorithm performs poorly in forecasting changes in inflation and output growth. In contrast, changes in interest rates and unemployment rates are predicted quite accurately, and the forecasts are comparable to those of the SVECM and those of univariate ARMA models. Whether the Holt-Winters forecasts are able to improve the overall performance via a combined forecast is assessed in section 8.6.

8.4 Forecasts Using Single Exponential Smoothing

In this section, Single Exponential Smoothing (see Brockwell and Davis (1996)) is applied to calculate the respective one step ahead forecasts for the forecast evaluation period. The procedure is quite simple and is meant to produce benchmark forecasts, which more sophisticated models should be able to outperform. The results are shown in figure 24.

Again the algorithm fails to give accurate forecasts for changes in infla-

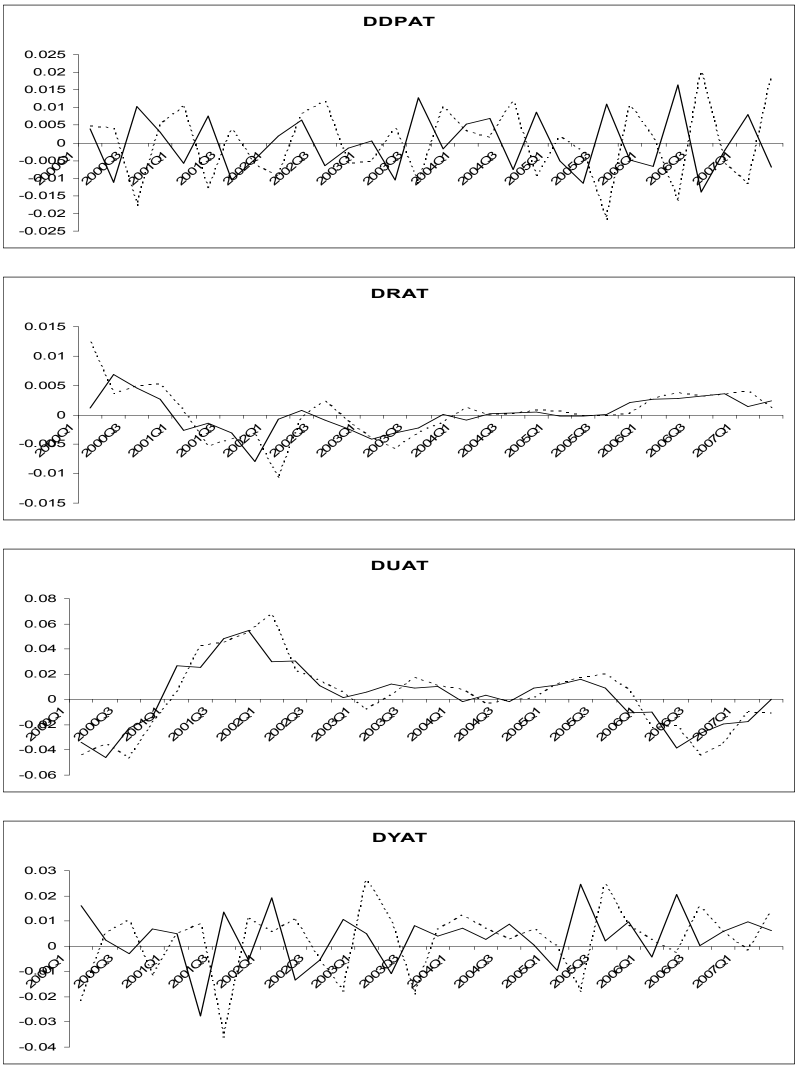

Figure 23: One Step Ahead Forecasts of the Holt-Winters Nonseasonal Algorithm (Dashed Line) and Actual Values (Solid Line)

tion. Regarding changes in interest rates and unemployment, the forecast series look like a smoothed, delayed version of actual values, which is due to

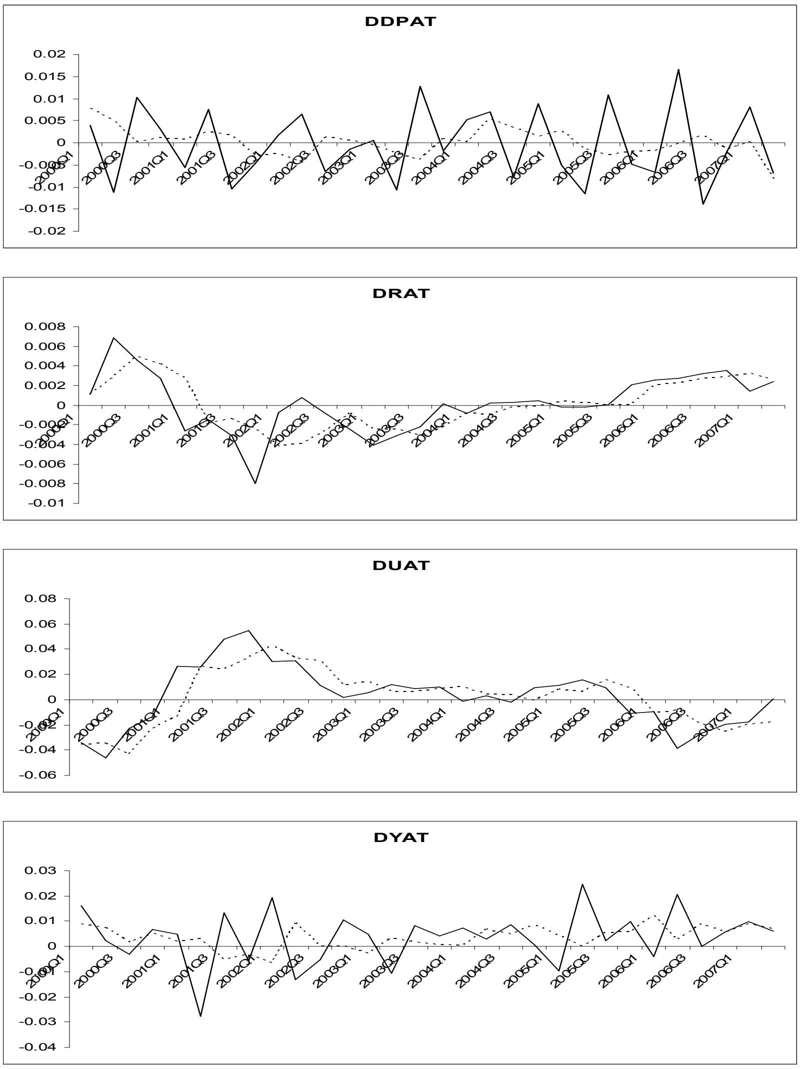

Figure 24: One Step Ahead Forecasts of Single Exponential Smoothing (Dashed Line) and Actual Values (Solid Line)

the properties of the algorithm.

8.5 Evaluating the Predictive Accuracy of the Different Procedures

To compare the forecasts obtained via the different procedures in sections 8.1-8.4 they have to be assessed according to their predictive accuracy. There are several indicators used for comparing the forecasting performance of different models (see for example Chatfield (2000), see also Ragacs and Schneider (2007)). The criteria used here are the root mean squared error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the Theil coefficient (THEIL) and the sign test (SIGN). The first one is calculated according to the formula:

$$RMSE = \sqrt{\frac{1}{P}\sum_{t=1}^{P}\left(y_t - \hat{y}_t\right)^2} \tag{39}$$

where P is the number of periods in the forecast evaluation period, y_t is the realized value of the variable to be forecast, and $\hat{y}_t$ is the value of the forecast obtained with the model. Critics argue that the RMSE is very sensitive to large forecast errors, whereas small errors are given less weight, i.e. a model that predicts very well over long forecasting horizons and fails badly in one period could be ranked below a model that regularly produces forecast errors. Therefore another criterion is also frequently used, the mean absolute error (MAE):

$$MAE = \frac{1}{P}\sum_{t=1}^{P}\left|y_t - \hat{y}_t\right|. \tag{40}$$

Since the errors are not squared in this procedure, less weight is given to large deviations of forecasts from actual values. To get a measure for predictive accuracy that does not depend on the scaling of variables, the above expression can be modified to the mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{P}\sum_{t=1}^{P}\left|\frac{y_t - \hat{y}_t}{y_t}\right|. \tag{41}$$

This measure allows direct comparisons between the predictive power of different models in percentage terms. Another criterion often used is called the Theil coefficient or Theil's U:

$$THEIL = \frac{\sqrt{\frac{1}{P}\sum_{t=1}^{P}\left(y_t - \hat{y}_t\right)^2}}{\sqrt{\frac{1}{P}\sum_{t=1}^{P}\left(y_t - y_{t-1}\right)^2}}. \tag{42}$$

This criterion relates the RMSE of the model under consideration to those of a certain naive forecast. In this version the naive forecast for period $t + 1$ is just the actual value of the corresponding variable in period t. If the investigated model had a high predictive power, this ratio will be small, otherwise it will be close to 1.

All criteria considered so far evaluated deviations of forecasts from actual values. However, it may be interesting to know whether a model is able to predict the correct sign of future variables, i.e. whether an upswing or a downturn is likely. For this purpose the proportion of correctly predicted signs is calculated as the success rate:

$$SIGN = \frac{a + d}{a + b + c + d} \tag{43}$$

where a stands for the number of correctly predicted negative signs, d for the number of correctly predicted positive signs, and $b + c$ is the number of all incorrectly predicted signs. Table 6 shows these criteria for all four forecasting techniques.

With respect to changes in inflation, the chosen ARMA model exhibits the lowest values of RMSE, MAE and THEIL. The SVECM on the other hand is the best model according to SIGN, i.e. best at forecasting upswings and downturns. The Holt-Winters algorithm performs poorly and exhibits a value of 1.23 in THEIL, which means that it is worse than the naive forecast. Single Exponential Smoothing performs surprisingly well, but on average only 50 percent of the predicted signs were correct, which is the same as the expected number of randomly predicted correct signs.

DDPAT	RMSE	MAE	MAPE	THEIL	SIGN
SVECM	0.0058	0.0047	0.8642	0.4053	0.7667
ARMA	0.0055	0.0045	0.9070	0.3810	0.7333
HW	0.0173	0.0142	2.4371	1.2283	0.3000
SES	0.0088	0.0073	1.0552	0.6234	0.5000
DRAT	RMSE	MAE	MAPE	THEIL	SIGN
SVECM	0.0027	0.0023	4.6384	1.0483	0.8000
ARMA	0.0023	0.0018	3.4316	0.9134	0.7333
HW	0.0033	0.0021	2.4104	1.0717	0.7333
SES	0.0022	0.0015	1.9797	0.8811	0.7333
DUAT	RMSE	MAE	MAPE	THEIL	SIGN
SVECM	0.0183	0.0142	3.1519	1.2640	0.8000
ARMA	0.0135	0.0097	1.3733	0.8979	0.8333
HW	0.0134	0.0106	2.0186	0.9195	0.8333
SES	0.0144	0.0108	2.6988	0.9989	0.8000
DYAT	RMSE	MAE	MAPE	THEIL	SIGN
SVECM	0.0119	0.0089	2.0711	0.6755	0.7667
ARMA	0.0107	0.0078	2.0726	0.6037	0.6000
HW	0.0206	0.0094	4.2262	1.1036	0.5333
SES	0.0124	0.0094	4.2262	0.7024	0.6333

Table 6: Criteria for Assessing the Predictive Accuracy

Regarding the interest rate, Single Exponential Smoothing is the best algorithm according to RMSE, MAE, MAPE and THEIL, but the SVECM is better in predicting whether changes in the interest rate are positive or negative. With respect to THEIL, all models exhibit values between 0.88 and 1.08, which indicates that forecasting changes in the interest rate is very difficult and more sophisticated models do not necessarily lead to better results than naive ones do.

In the case of changes in unemployment, the SVECM performs poorly and exhibits a value of 1.26 in THEIL. With respect to MAE, MAPE and THEIL, the ARMA model performs best, but according to the RMSE the Holt-Winters algorithm has a slightly lower value. Single Exponential Smoothing does not lead to good forecasts in this case.

Finally, the SVECM and the ARMA model perform best in forecasting output growth. The ARMA model is slightly better according to RMSE, MAE and THEIL, whereas the SVECM is able to predict upswings and downturns more accurately.

To summarize, ARMA models performed very well with respect to all variables considered here. The SVECM leads to good forecasts with respect to changes in inflation and output growth and is the model which performs best in predicting signs of changes, i.e. upswings and downturns in all series except Austrian unemployment. The Holt-Winters algorithm does not perform very well on average, but with respect to changes in unemployment it is the best model according to the RMSE. Single Exponential Smoothing leads to surprisingly accurate forecasts in some cases and with respect to changes in interest rates it is the best model according to all criteria except SIGN.

To evaluate the overall performance of all four models, we rank them in the following way: The model with highest predictive power according to the relevant criterion is given three points, the model with the second highest predictive power is given two points and so on. If two models cannot be distinguished by a certain criterion they are given the same number of points. Afterwards the points are summed for each model and each criterion separately over the four variables to be forecast. The model with the highest score is ranked as the "best" model according to the criterion under consideration.

OVERALL	RMSE	MAE	MAPE	THEIL	SIGN
SVECM	5	4	9	4	10
ARMA	10	11	8	11	8
HW	3	4	5	3	5
SES	6	6	6	6	6

Table 7: Scores of the Different Models Regarding their Predictive Accuracy

Table 7 contains the scores of each model with respect to the relevant criterion. Altogether ARMA models are ranked as "best" models according to RMSE, MAE and THEIL, whereas the SVECM is chosen by MAPE and SIGN. Consequently, it can be expected that ARMA predicts specific values most accurately, whereas the SVECM better identifies upswings and downturns.

8.6 Forecast Encompassing

Following Diebold (2007), forecast encompassing tests can be used to assess whether all relevant information is already contained in a subset of the available forecasts. To perform this test, the following OLS-regression is implemented:

$$y_{t+P} = \beta_1 \hat{y}^{arma}_{t+P} + \beta_2 \hat{y}^{vec}_{t+P} + \beta_3 \hat{y}^{hw}_{t+P} + \beta_4 \hat{y}^{ses}_{t+P} + \epsilon_{t+P}. \tag{44}$$

The dependent variable y_{t+P} contains the realizations of the variable under consideration in period $t+P$, the explanatory variables $\hat{y}^{arma}_{t+P}$, $\hat{y}^{vec}_{t+P}$, $\hat{y}^{hw}_{t+P}$ and $\hat{y}^{ses}_{t+P}$ contain the forecast series according to the model mentioned in the superscript, and ϵ_{t+P} is the error term. As long as none of the coefficients β_i are significantly different from zero, all models contain relevant information. If there are significant and insignificant parameters, the forecasting procedures with significant parameter estimates already incorporate all relevant information and therefore they encompass the other models whose coefficients are insignificant. Parameter estimates of models which perform well according to their predictive accuracy should be high as compared to less accurate models. Altogether the sum of parameter estimates on equation (44) should be close to one.

DDPAT	COEFFICIENT	P-VALUE
ARMA	0.7727	0.0100
VEC	0.7620	0.0155
HW	0.1051	0.5925
SES	-0.1953	0.5340
DRAT	COEFFICIENT	P-VALUE
ARMA	0.3565	0.0763
VEC	0.1925	0.2373
HW	0.1040	0.4245
SES	0.2415	0.3685
DUAT	COEFFICIENT	P-VALUE
ARMA	0.4081	0.1070
VEC	0.1802	0.2372
HW	0.5353	0.0133
SES	-0.1599	0.5259
DYAT	COEFFICIENT	P-VALUE
ARMA	0.3179	0.3154
VEC	0.2347	0.3364
HW	-0.0706	0.6694
SES	-0.2219	0.5554

Table 8: Forecast Encompassing Regressions

Table 8 reveals that with respect to changes in inflation, ARMA and SVECM together incorporate all relevant information, and so it is likely that Holt-Winters and Single Exponential Smoothing algorithms will not contribute to more accurate forecasts. Consequently, the SVECM and the corresponding ARMA model are used in a forecast combination. In the case of changes in the interest rate, none of the models is able to outperform the others at the 5 percent significance level. However, at the 10 percent significance level all the relevant information would be incorporated in the ARMA model. Therefore we chose to include all four procedures to perform the combined forecast. The Holt-Winters algorithm is able to outperform all other algorithms with respect to changes in unemployment, so the "combined forecast" includes only one procedure in this case. Finally, none of the models contains all relevant information when it comes to forecasting output growth, so all procedures are included in the combined framework. Note that the sum of all parameter estimates is not close to one in case of DYAT due to the fact that none of the models contains all the relevant information.

8.7 Forecast Combination

The next step is to compute optimal weights for the procedures that are considered as useful in a combined forecast. Therefore the sample is split into three parts[4]. The first part refers to the estimation sample, ranging from the first quarter in 1970 to the fourth quarter in 1999. This part is used to estimate the coefficients of the models as in section 8.6. The second part is a training sample, which is used to compute the optimal weights for forecast combination. This training sample ranges from the first quarter of 2000 to the fourth quarter of 2005. Finally, the third part is the new evaluation sample, which is used to assess the predictive accuracy of the combined forecast and ranges from the first quarter of 2006 to the second quarter of 2007.

If there is no significant parameter in the forecast encompassing regression, all models are contained as regressors to estimate the following equation:

[4] A combined forecast for the whole forecast evaluation period is available from the author upon request. Note however, that a comparison between the combined forecast for the whole evaluation period and the individual forecasts is not accurate, since the evaluation period is also used to assess the corresponding weights. This leads to an unfair advantage for the combined forecast.

$$y_{t+P} = \beta_0 + \beta_1 \hat{y}^{arma}_{t+P} + \beta_2 \hat{y}^{vec}_{t+P} + \beta_3 \hat{y}^{hw}_{t+P} + \beta_4 \hat{y}^{ses}_{t+P} + \epsilon_{t+P}. \qquad (45)$$

Otherwise only models which had a significant parameter estimate in the encompassing regression are included in the right hand side. Note that in contrast to the forecast encompassing regression there is a constant term in equation (45). This solves problems relating to the combination of biased forecasts, since the constant is able to eliminate the average bias (see Diebold (2007)). The coefficients of the estimated OLS-regression are displayed in table 15 in Appendix F and are used as weights in summing up the corresponding one step ahead forecasted series to an aggregate combined forecast. This combined forecast is shown in figure 25 for the new evaluation sample.

According to this figure, the combined forecast seems to perform well in predicting changes in inflation and changes in unemployment. In contrast, changes in the interest rate are underestimated, as it is the case with per capita output growth. To assess whether the combined forecast performs better than the individual forecasts, the proposed criteria for evaluating the predictive power are computed for the new evaluation sample. Table 9 shows the results of this exercise, where COMB refers to the combined forecast.

Comparing the values in table 9 reveals that with respect to changes in inflation the combined forecast is better than the four individual procedures according to all criteria but MAPE. This means that the ARMA(3,4) model was able to explain other important aspects in the underlying data series than the SVECM. Therefore forecast combination clearly improves the predictive performance and is highly recommended in this case.

With respect to changes in the interest rate, the combined forecast is able to outperform the SVECM and the corresponding ARMA model according to all criteria. Surprisingly, in the new evaluation sample, HW and SES are able to forecast changes in the interest rate very well and the combined forecast does not lead to substantial improvements. Nevertheless, it is able to compete with these models, so that forecast combination can be recommended in this

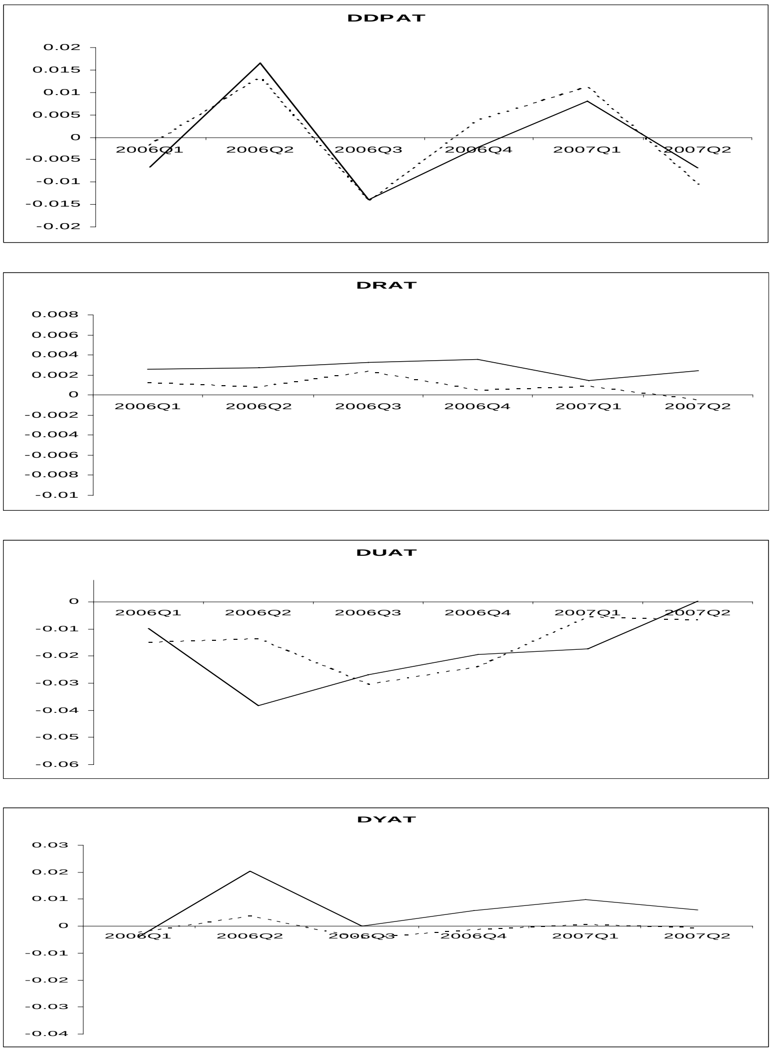

Figure 25: Combined Forecast According to the Estimated Weights (Dashed Line) and Actual Values (Solid Line)

case as well. In contrast to changes in inflation, all four models were used to construct the combined aggregate in this case. Hence, all models contained

DDPAT	RMSE	MAE	MAPE	THEIL	SIGN
COMB	0.0038	0.0034	0.7065	0.2114	0.8333
SVECM	0.0050	0.0045	0.7775	0.2801	0.8333
ARMA	0.0046	0.0037	0.5130	0.2535	0.8333
HW	0.0237	0.0207	2.2282	1.3198	0.1667
SES	0.0101	0.0079	0.7315	0.5627	0.6667
DRAT	RMSE	MAE	MAPE	THEIL	SIGN
COMB	0.0013	0.0011	0.3957	1.2559	1.0000
SVECM	0.0020	0.0018	0.7766	1.9446	0.8333
ARMA	0.0021	0.0016	0.6377	2.1291	0.6667
HW	0.0013	0.0009	0.4716	1.2449	1.0000
SES	0.0009	0.0007	0.3455	0.8647	1.0000
DUAT	RMSE	MAE	MAPE	THEIL	SIGN
COMB	0.0119	0.0098	3.8773	0.7981	0.8333
SVECM	0.0133	0.0096	7.1291	0.8972	1.0000
ARMA	0.0157	0.0111	1.6726	1.0569	0.8333
HW	0.0142	0.0138	5.9733	0.9569	0.8333
SES	0.0147	0.0105	8.4485	0.9881	0.8333
DYAT	RMSE	MAE	MAPE	THEIL	SIGN
COMB	0.0069	0.0058	5.6183	0.5142	0.8333
SVECM	0.0073	0.0059	4.1746	0.5439	0.8333
ARMA	0.0732	0.0012	2.3692	0.1072	0.8333
HW	0.0129	0.0107	26.6409	0.9624	0.5000
SES	0.0105	0.0075	15.0980	0.7832	0.8333

Table 9: Predictive Accuracy of the Combined Forecasts

relevant information which was not encompassed by other models.

The "combined" forecast regarding changes in unemployment only uses the result of the Holt-Winters nonseasonal algorithm as information. It is not surprising that this “combined” forecast has the lowest RMSE value, since the OLS-regression is designed to minimize this criterion throughout the training sample. Regarding the other criteria, the combined forecast is able to compete successfully with the individual forecasts. It is worth mentioning that the “combined” forecast is less appropriate than the SVECM according to MAE and the SIGN-criterion and it is less appropriate than ARMA models according to MAPE.

Regarding forecasts of output growth rates, the combined procedure is again selected as the most appropriate model by RMSE and SIGN. It also exhibits desirable values in MAE, MAPE and THEIL. Therefore a combination of all four models seems to be a good choice. However, ARMA models perform better according to MAE, MAPE and THEIL.

A similar procedure as in case of individual forecasts is used to assess the overall predictive power of the five models. In particular, the model which performs best is given 4 points, the second best model is given 3 points and so on. Again, models which perform equally well are given the same number of points. The resulting scores are depicted in table 10.

OVERALL	RMSE	MAE	MAPE	THEIL	SIGN
COMB	15	12	11	13	15
SVECM	9	8	5	8	13
ARMA	3	9	13	7	11
HW	6	3	4	5	7
SES	9	8	7	7	12

Table 10: Scores of the Models for Predictive Accuracy in the New Evaluation Period

This table reveals that the combined forecast is able to outperform all individual forecasts according to all criteria but one. Only in case of MAPE do corresponding ARMA models perform better than the combined forecast.

To summarize, combining the various forecasts according to the weights resulting from estimation of equation (45) is a good choice. In the case of all four variables this leads to accurate forecasts and sometimes even to substantial improvements in the forecasting performance as compared to individual models. In addition, the overall predictive power of the combined forecast is very high, which can be seen in table 10. It is worth mentioning that with respect to three of the four variables the SVECM-forecast contains useful information and therefore contributes to improving the overall predictive power.

An interesting exercise would be to compare the performance of the SVECM or the combined forecast to the performance of the large-scale models used by IHS, OeNB and WIFO. However, there are two major problems in doing so. First of all, only the model of the OeNB is used to forecast quarterly figures and is thus comparable to the model outlined in this thesis (see Fenz and Spitzer (2004)). Secondly, when the forecasts of IHS, OeNB and WIFO were performed, they only had access to rough estimates of the underlying data series during the most recent time points in the estimation period. These data series were subject to revisions later on, so that the data used in this thesis is more reliable. Therefore a comparison of the models could be misleading.

9 Conclusions

In this thesis the framework of a Structural Vector Error Correction Model (SVECM) was used to study interrelationships and transmission mechanisms of shocks between Austria and Germany. In the first step, theoretically motivated potential relations between the variables were derived using a dynamic open economy model. Due to the available data series, the results of utility maximization by individuals, considerations with respect to the production side of the model, and considerations regarding migration decisions, we chose the Fisher Inflation Parity, the Interest Rate Parity, the Purchasing Power Parity, the Output Gap relation and the Labor Market Condition to represent possible restrictions to be imposed on the parameters of the cointegrating vectors.

In the next steps, the optimal lag-length and the associated number of cointegrating vectors among endogenous variables were assessed. It turned out that two cointegrating relations are supported by the data, which contrasted to the fact that five potential relations were suggested by economic theory. According to model selection criteria and the desired properties of the residuals from estimation of cointegrating equations, the Fisher Inflation Parity and the Labor Market Condition were chosen for the final specification. Tests on the validity of these theoretical long-run relationships did not go against this choice. Consequently, these two equations were implemented, the resulting model was estimated and several specification tests were performed. Since the results of these tests were satisfactory, the model was used to study the effects and the transmission channels to Austrian variables of shocks to the German economy.

The results were in line with standard economic findings and allowed a straightforward interpretation. The main finding was that reactions of the Austrian interest rate and Austrian output exhibit a transient behavior in response to shocks hitting the German economy, whereas responses of Austrian unemployment rates were long-lasting. This phenomenon is commonly referred to as hysteresis. Another important result was the absence of a multiplier effect in the Austrian economy. This could be firstly because deviations from the long-run trend are very short lived in Austria and therefore variables tend to return to their steady state equilibrium growth rates rather quickly, and secondly that Austria represents an open economy, so that additional income is also spent on foreign goods, which reduces the multiplier effect according to standard economic theory (see for example Blanchard (2003)).

Shocks to the Austrian economy and their effects on Germany were also considered. As expected, most of these shocks did not have significant influence on the German economy. A noteworthy exception were shocks to Austrian output. However, in terms of their magnitude, these Austrian output shocks had less severe effects on the German economy than in the converse case. An interesting point was that for Germany the multiplier effect is supported by the data. This could be due to the fact that Germany is less open as compared to Austria and therefore output shocks have a higher effect on domestic consumption.

In the last section, the forecasting properties of the estimated SVECM were investigated. It turned out that it was able to outperform some of the simpler procedures and at least to compete with univariate time series models. The model significantly contributed in improving forecasts with respect to changes in inflation, changes in the interest rate and output growth in a combined procedure.

These combined forecasts constitute an optimal framework to further improve the predictive power of macroeconometric models nowadays in use. For instance, the results of the SVECM could be combined with results coming from large-scale models, DSGE-models or judgments of experts regarding future economic development. Institutions engaged in economic forecasting are recommended to apply the procedure described.

Similar models like the one used in this thesis could be implemented for example to analyze Canada and the United States, Mexico and the United States or Portugal and Spain. It could be useful to compare these models and the one described here with respect to the robustness of results as well as with respect to differences in the underlying transmission channels. Doing so would reveal weaknesses of some models and it could prove useful to find out more about other explanatory variables to be included in the vector z_t. For instance, the exchange rate could play an important role in determining trade flows between some of the aforementioned regions. In the case of a model for Mexico, foreign direct investment from the United States could be a more promising variable than unemployment in the United States, since there is no incentive for United States citizens to work in Mexico, where wages are far lower. Altogether these considerations indicate that there is scope for applying similar models in future research.

A Data

The decision which time series to include as endogenous and exogenous variables involves the crucial tradeoff between working with a small model, where parameters can be estimated meaningfully but with the risk of a serious omitted variable bias, and the use of a large model, where the number of observations may be too small to estimate all parameters accurately. Therefore only variables with high explanatory power should be included. Consequently, we use one exogenous and eight endogenous variables, which are described below.

The data series were made available by the Austrian Institute of Economic Research (WIFO) and were originally obtained from the OECD Economic Outlook and Main Economic Indicators databases. Since there were problems with respect to structural changes in the available series of Austrian Gross Domestic Product, the relevant data of the International Financial Statistics database from the International Monetary Fund was used to construct growth rates of the appropriate variable for each quarter in the sample period. Afterwards the series was reconstructed in levels using the obtained growth rates together with the value of Austrian Gross Domestic Product in the first quarter of 1970 according to the original OECD database. In the estimation procedure and the associated tests, the following variables with the respective transformations were used:

- PD: Price Differential between Austria and Germany calculated as $PAT - PGER$ (see below)
- PAT: log of the Austrian Consumer Price Index (base: first quarter of 2000)
- PGER: log of the German Consumer Price Index (base: first quarter of 2000)
- POIL: log of the crude import price of oil in US Dollar
- RAT: Austrian interest rates constructed as $log(1 + i)$, where i is the nominal interest rate divided by 100

- RGER: German interest rates constructed as $log(1 + i)$, where i is the nominal interest rate divided by 100

- UAT: log of the Austrian unemployment rate index (base: first quarter of 2000)

- UGER: log of the German unemployment rate index (base: first quarter of 2000)

- YAT: log of the Austrian per capita gross domestic product index (base: first quarter of 2000)

- YGER: log of the German per capita Gross Domestic Product index (base: first quarter of 2000)

All variables were observed on a quarterly basis starting with the first quarter of 1970 and ending with the second quarter of 2007. Seasonal adjustment was carried out for all price variables and for unemployment rates using the Tramo-Seats procedure implemented in Eviews 6 (2007). To calculate per capita variables, Austrian and German population sizes, observed on a yearly basis, were interpolated to obtain quarterly variables. This was done using the method described by Boot et al. (1967)), which is implemented in Ecotrim.

In addition, the Austrian Consumer Price Index had to be adjusted for outliers in the first quarter of 1984 and in the first quarter of 1990 due to increases in the rates of consumption taxes. The quarterly inflation rate obtained was replaced by the average of the inflation rate in that quarter during the preceding four years.

B Derivation of the Restrictions

B.1 Fisher Inflation Parity and Interest Rate Parity

The Lagrangian for the representative household's optimization problem can be expressed as:

$$
\begin{aligned}
L \;=\; & \sum_{t=0}^{\infty} \rho^t \{ C_t^{\alpha} C_t^{*1-\alpha} + \lambda_t [(1+r_t)K_{t-1} + w_t L_t + \frac{(1+i_t)}{(1+\pi_t)} B_{t-1} + \\
& + \frac{(1+i_t^*)}{(1+\pi_t^*)} B_{t-1}^* + \frac{M_{t-1}}{1+\pi_t} - C_t - P_t^* C_t^* - B_t - B_t^* - K_t - M_t] \\
& + \mu_t [\frac{M_{t-1}}{1+\pi_t} - C_t - P_t^* C_t^*] \} \qquad (46)
\end{aligned}
$$

where λ_t is the Lagrange multiplier for the budget constraint and μ_t represents the Lagrange multiplier for the cash-in-advance constraint. Three necessary first order conditions for an optimum can be obtained by taking the derivative of the Lagrangian with respect to the control variables C_t, C_t^* and M_t and equalizing these derivatives to zero. Other three necessary first order conditions can be obtained by taking the derivative of the Lagrangian with respect to the state variables K_t, B_t and B_t^* and setting them to zero as well. Altogether this leads to six first order conditions reading:

$$\frac{\partial L}{\partial C_t} \stackrel{!}{=} 0 \;\Rightarrow\; \rho^t [\alpha C_t^{\alpha-1} C_t^{*1-\alpha} - \lambda_t - \mu_t] = 0 \qquad (47)$$

$$\frac{\partial L}{\partial C_t^*} \stackrel{!}{=} 0 \;\Rightarrow\; \rho^t [C_t^{\alpha}(1-\alpha) C_t^{*(-\alpha)} - \lambda_t P_t^* - \mu_t P_t^*] = 0 \qquad (48)$$

$$\frac{\partial L}{\partial M_t} \stackrel{!}{=} 0 \;\Rightarrow\; \rho^{t+1} \left[\frac{\lambda_{t+1}}{1+\pi_{t+1}} + \frac{\mu_{t+1}}{1+\pi_{t+1}} \right] - \rho^t \lambda_t = 0 \qquad (49)$$

$$\frac{\partial L}{\partial K_t} \stackrel{!}{=} 0 \;\Rightarrow\; \rho^{t+1} \lambda_{t+1} (1 + r_{t+1}) - \rho^t \lambda_t = 0 \qquad (50)$$

$$\frac{\partial L}{\partial B_t} \stackrel{!}{=} 0 \;\Rightarrow\; \rho^{t+1} \lambda_{t+1} \frac{(1+i_{t+1})}{(1+\pi_{t+1})} - \rho^t \lambda_t = 0 \qquad (51)$$

$$\frac{\partial L}{\partial B_t^*} \stackrel{!}{=} 0 \quad \Rightarrow \quad \rho^{t+1}\lambda_{t+1}\frac{(1+i_{t+1}^*)}{(1+\pi_{t+1}^*)} - \rho^t\lambda_t = 0 \tag{52}$$

Equations (50) and (51) together lead to:

$$(1+r_t) = \frac{1+i_t}{1+\pi_t} \tag{53}$$

which is the Fisher Inflation Parity (FIP) and equations (51) and (52) together lead to:

$$\frac{1+i_t}{1+\pi_t} = \frac{1+i_t^*}{1+\pi_t^*} \tag{54}$$

which is the Interest Rate Parity (IRP) in the absence of an exchange rate.

B.2 Purchasing Power Parity

The first order conditions for consumption lead to:

$$C_t = \frac{\alpha}{1-\alpha}P_t^* C_t^* \tag{55}$$

Plugging the related expressions for C_t and C_t^* into the budget constraint and using the following definitions:

$$\begin{aligned} S_t &= S_t(r_t, i_t, i_t^*, \pi_t, \pi_t^*) \\ &= B_t + B_t^* + M_t + K_t \end{aligned} \tag{56}$$

$$\begin{aligned} I_t &= I_t(r_t, i_t, i_t^*, \pi_t, \pi_t^*) \\ &= w_t L_t + (1+r_t)K_{t-1} + \frac{M_{t-1}}{1+\pi_t} + (1+i_t)\frac{B_{t-1}}{1+\pi_t} + (1+i_t^*)\frac{B_{t-1}^*}{1+\pi_t^*} \end{aligned} \tag{57}$$

where S_t denotes a household's savings and I_t denotes the household's income, yields the familiar results for demand:

$$C_t = \alpha(I_t - S_t) \tag{58}$$

$$C_t^* = (1-\alpha)\frac{I_t - S_t}{P_t^*} \tag{59}$$

which are consequences of the assumed Cobb-Douglas utility functions. These equations imply that a fraction α of the household's income net of savings is spent on the domestic aggregate, whereas a fraction $1-\alpha$ is spent on the foreign aggregate. Since preferences in both economies are identical, similar expressions hold for demand in the foreign economy. As a consequence, the consumer price index in both countries is a weighted average of the price levels for the goods produced at home and abroad, with α and $1-\alpha$ representing the weights. Therefore

$$CPI_t = CPI_t^* = \alpha + (1-\alpha)P_t^*$$

holds, where CPI_t and CPI_t^* denote the consumer price indices in the domestic and foreign economy, and consequently

$$\frac{CPI_t}{CPI_t^*} = 1 \tag{60}$$

has to fulfilled. This equation is the PPP in the absence of an exchange rate.

C Unit Root Tests

In this section the outputs of the unit root tests are described. Table 11 contains the critical values of the Kwiatkowski-Phillips-Schmidt and Shin test, and table 12 the associated test statistics. Table 13 displays the p-values of the augmented Dickey-Fuller test, and table 14 those of the Phillips-Perron test. The null hypothesis of the ADF-test and the PP-test is equivalent to the assumption that the respective series is nonstationary, whereas the null hypothesis of the KPSS-test is equivalent to the assumption that the series under consideration is stationary (see for example Pfaff (2006)).

In the case of price levels, the price differential, oil prices, unemployment and output levels, the correct specification of the test regression is the one including a trend, whereas in the case of interest rates the trend has to be omitted. Three asterisks indicate that the null hypothesis is rejected at the one percent significance level, two asterisks that it is rejected at the five percent significance level and one asterisk indicates that it is rejected at the ten percent significance level.

const α-level	critical value	const+trend α-level	critical value
0.01	0.7390	0.01	0.2160
0.05	0.4630	0.05	0.1460
0.10	0.3470	0.10	0.1190

Table 11: Critical Values of the Kwiatkowski-Phillips-Schmidt-Shin Test

Kwiatkowski-Phillips-Schmidt-Shin Test

const			const+trend		
UAT	0.6305	**	UAT	0.3054	***
UGER	1.2484	***	UGER	0.2798	***
PD	0.9298	***	PD	0.3186	***
PAT	1.3810	***	PAT	0.3464	***
POIL	0.7568	***	POIL	0.2057	**
PGER	1.4151	***	PGER	0.3158	***
RAT	0.6305	**	RAT	0.1802	**
RGER	0.7022	**	RGER	0.0731	
YAT	1.4625	***	YAT	0.2235	***
YGER	1.4628	***	YGER	0.2289	***
DUAT	0.0442		DUAT	0.0942	
DUGER	0.4061	*	DUGER	0.0424	
DPD	0.6012	**	DPD	0.1168	
DPAT	1.0504	***	DPAT	0.1301	*
DPOIL	0.1884		DPOIL	0.1319	*
DPGER	0.8434	***	DPGER	0.0767	
DRAT	0.0442		DRAT	0.0333	
DRGER	0.0314		DRGER	0.0297	
DYAT	0.5107	**	DYAT	0.1020	
DYGER	0.2080		DYGER	0.0384	
DDUAT	0.0761		DDUAT	0.0549	
DDUGER	0.1609		DDUGER	0.0708	
DDPD	0.0889		DDPD	0.0884	
DDPAT	0.1718		DDPAT	0.1529	**
DDPOIL	0.0252		DDPOIL	0.0254	
DDPGER	0.1194		DDPGER	0.1146	
DDRAT	0.0761		DDRAT	0.0694	
DDRGER	0.0734		DDRGER	0.0653	
DDYAT	0.1619		DDYAT	0.0863	
DDYGER	0.0636		DDYGER	0.0301	

Table 12: Kwiatkowski-Phillips-Schmidt-Shin Test

Augmented Dickey-Fuller Test

const			const+trend		
UAT	0.1923		UAT	0.8290	
UGER	0.2549		UGER	0.0178	**
PD	0.0555	*	PD	0.8884	
PAT	0.0002	***	PAT	0.0257	**
POIL	0.1215		POIL	0.2541	
PGER	0.0310	**	PGER	0.2514	
RAT	0.1923		RAT	0.2264	
RGER	0.0237	**	RGER	0.0271	**
YAT	0.0589	*	YAT	0.0178	**
YGER	0.4154		YGER	0.2866	
DUAT	0.0000	***	DUAT	0.0000	***
DUGER	0.0037	***	DUGER	0.0112	**
DPD	0.0000	***	DPD	0.0000	***
DPAT	0.4650		DPAT	0.1169	
DPOI	0.0000	***	DPOIL	0.0000	***
DPGER	0.1162		DPGER	0.0455	**
DRAT	0.0000	***	DRAT	0.0000	***
DRGER	0.0000	***	DRGER	0.0000	***
DYAT	0.0000	***	DYAT	0.0000	***
DYGER	0.0000	***	DYGER	0.0000	***
DDUAT	0.0000	***	DDUAT	0.0000	***
DDUGER	0.0000	***	DDUGER	0.0000	***
DDPD	0.0000	***	DDPD	0.0000	***
DDPAT	0.0000	***	DDPAT	0.0000	***
DDPOIL	0.0000	***	DDPOIL	0.0000	***
DDPGER	0.0000	***	DDPGER	0.0000	***
DDRAT	0.0000	***	DDRAT	0.0000	***
DDRGER	0.0000	***	DDRGER	0.0000	***
DDYAT	0.0000	***	DDYAT	0.0000	***
DDYGER	0.0000	***	DDYGER	0.0000	***

Table 13: Augmented Dickey-Fuller Test

Phillips-Perron Test

const			const+trend		
UAT	0.1506		UAT	0.8545	
UGER	0.0487	**	UGER	0.6716	
PD	0.0571	*	PD	0.8727	
PAT	0.0000	***	PAT	0.5547	
POIL	0.1722		POIL	0.3884	
PGER	0.0002	***	PGER	0.6529	
RAT	0.1506		RAT	0.1748	
RGER	0.0780	*	RGER	0.1055	
YAT	0.0589	*	YAT	0.0178	**
YGER	0.4215		YGER	0.2226	
DUAT	0.0000	***	DUAT	0.0000	***
DUGER	0.0000	***	DUGER	0.0000	***
DPD	0.0000	***	DPD	0.0000	***
DPAT	0.0658	*	DPAT	0.0011	***
DPOIL	0.0000	***	DPOIL	0.0000	***
DPGER	0.0000	***	DPGER	0.0000	***
DRAT	0.0000	***	DRAT	0.0000	***
DRGER	0.0000	***	DRGER	0.0000	***
DYAT	0.0000	***	DYAT	0.0000	***
DYGER	0.0000	***	DYGER	0.0000	***
DDUAT	0.0000	***	DDUAT	0.0000	***
DDUGER	0.0000	***	DDUGER	0.0000	***
DDPD	0.0000	***	DDPD	0.0001	***
DDPAT	0.0000	***	DDPAT	0.0000	***
DDPOIL	0.0000	***	DDPOIL	0.0001	***
DDPGER	0.0000	***	DDPGER	0.0000	***
DDRAT	0.0000	***	DDRAT	0.0000	***
DDRGER	0.0000	***	DDRGER	0.0001	***
DDYAT	0.0000	***	DDYAT	0.0001	***
DDYGER	0.0000	***	DDYGER	0.0000	***

Table 14: Phillips-Perron Test

D Estimation Output

Appendix D includes the coefficient estimates and t-values of the VEC(3)-model finally used. This specification exhibits two cointegrating relations, the first one is restricted to represent the FIP and the second one to represent the LMC. Parameters which are significant at the five percent level are in bold. Note that due to the presence of heteroscedasticity, standard errors are biased and so the t-values have to be interpreted cautiously.

	CE1	CE2						
DPAT(-1)	-1	0						
PD(-1)	0	0						
RAT(-1)	1	0						
RGER(-1)	0	0						
UAT(-1)	0	1						
UGER(-1)	0	-1						
YAT(-1)	0	0						
YGER(-1)	0	0						
C	-0.020	-0.027						
EC	D(DPAT)	D(PD)	D(RAT)	D(RGER)	D(UAT)	D(UGER)	D(YAT)	D(YGER)
CE1	-0.056	**-0.077**	-0.020	-0.032	**0.577**	**0.369**	**-0.254**	-0.059
	-1.240	-3.304	-0.617	-0.816	3.341	2.275	-2.507	-1.049
CE2	0.003	-0.001	**-0.005**	0.003	-0.010	0.011	**0.017**	**0.008**
	1.032	-0.506	-2.292	1.220	-0.857	1.071	2.570	2.182
D(DPAT(-1))	**-0.423**	-0.003	**0.156**	0.137	-0.449	-0.347	0.004	0.033
	-4.153	-0.065	2.134	1.531	-1.152	-0.949	0.018	0.261
D(DPAT(-2))	-0.069	0.017	**0.184**	0.060	**-0.723**	-0.167	-0.227	0.064
	-0.655	0.303	2.426	0.652	-1.790	-0.440	-0.960	0.484
D(DPAT(-3))	**0.397**	**0.073**	**0.189**	0.038	**-1.039**	0.078	-0.217	-0.019
	5.422	1.926	3.600	0.597	-3.712	0.298	-1.321	-0.211
D(PD(-1))	**-0.815**	0.051	0.004	**-0.358**	**2.073**	**2.153**	-0.658	-0.129
	-3.927	0.478	0.029	-1.971	2.612	2.889	-1.414	-0.497
D(PD(-2))	-0.206	0.050	0.050	0.191	1.370	0.738	0.154	0.064
	-0.902	0.422	0.305	0.958	1.572	0.902	0.301	0.224
D(PD(-3))	-0.196	0.021	0.000	-0.041	-0.066	-0.216	0.035	0.283
	-0.870	0.182	0.001	-0.207	-0.076	-0.267	0.069	1.011
D(RAT(-1))	-0.011	0.001	-0.072	0.078	0.196	-0.520	-0.263	0.015
	-0.090	0.021	-0.805	0.713	0.412	-1.163	-0.943	0.094
D(RAT(-2))	-0.100	0.027	-0.024	0.103	-0.426	-0.605	-0.262	0.029
	-0.830	0.436	-0.275	0.969	-0.923	-1.396	-0.968	0.193
D(RAT(-3))	0.033	**0.134**	**0.152**	0.116	0.075	-0.207	-0.095	0.004
	0.295	2.301	1.893	1.187	0.176	-0.515	-0.377	0.030
D(RGER(-1))	0.018	-0.042	**0.152**	**0.216**	-0.362	**0.873**	-0.179	0.159
	0.169	-0.769	1.997	2.324	-0.892	2.291	-0.751	1.199
D(RGER(-2))	-0.032	0.000	-0.001	-0.107	**1.090**	**1.320**	0.278	-0.122
	-0.282	-0.006	-0.017	-1.071	2.503	3.229	1.090	-0.856
D(RGER(-3))	-0.069	-0.038	-0.123	-0.136	**1.926**	**1.316**	-0.055	-0.057
	-0.562	-0.601	-1.394	-1.260	4.099	2.984	-0.201	-0.369
D(UAT(-1))	**0.051**	0.011	0.015	0.016	0.113	-0.014	-0.014	-0.012
	2.079	0.830	0.869	0.759	1.208	-0.164	-0.252	-0.399
D(UAT(-2))	**-0.044**	-0.001	-0.012	0.015	0.068	-0.108	**0.116**	0.021
	-1.831	-0.101	-0.677	0.732	0.740	-1.254	2.139	0.686
D(UAT(-3))	0.028	**0.027**	**-0.045**	-0.027	-0.084	-0.060	-0.017	**0.061**
	1.184	2.268	-2.722	-1.325	-0.943	-0.724	-0.332	2.098
D(UGER(-1))	-0.012	0.005	0.012	**-0.038**	0.012	**0.412**	-0.024	-0.003
	-0.524	0.399	0.759	-1.963	0.141	5.194	-0.493	-0.114
D(UGER(-2))	0.013	0.006	-0.006	-0.012	**0.157**	**0.417**	-0.017	-0.037
	0.585	0.510	-0.386	-0.616	1.848	5.250	-0.351	-1.345
D(UGER(-3))	-0.025	**-0.022**	-0.006	0.000	**0.292**	0.128	-0.063	-0.033
	-1.107	-1.897	-0.338	0.020	3.362	1.566	-1.241	-1.170
D(YAT(-1))	0.076	0.029	**0.187**	0.018	-0.190	-0.122	**-0.748**	0.111
	1.574	1.138	5.357	0.433	-1.027	-0.703	-6.881	1.831
D(YAT(-2))	0.045	0.029	**0.117**	0.026	-0.311	0.107	-0.181	0.115
	0.728	0.909	2.670	0.492	-1.330	0.487	-1.319	1.501
D(YAT(-3))	0.002	0.032	0.044	0.048	-0.212	0.214	0.121	0.039
	0.035	1.300	1.272	1.144	-1.157	1.247	1.124	0.649
D(YGER(-1))	0.012	-0.026	0.020	**0.133**	-0.317	**-0.752**	0.000	**-0.229**
	0.145	-0.612	0.329	1.834	-1.005	-2.535	0.001	-2.221
D(YGER(-2))	0.074	0.008	0.025	0.084	**-0.919**	**-1.067**	0.040	-0.137
	0.908	0.199	0.431	1.171	-2.933	-3.630	0.220	-1.338
D(YGER(-3))	0.073	0.026	0.045	0.007	-0.071	0.149	0.136	0.024
	0.934	0.632	0.811	0.108	-0.240	0.533	0.781	0.252
C	-0.001	0.000	**-0.002**	0.000	**0.009**	0.005	**0.011**	**0.006**
	-0.635	0.495	-2.141	-0.368	1.832	1.157	4.025	3.795
DPOIL	**0.022**	-0.001	0.002	-0.002	**-0.034**	**0.052**	0.005	-0.006
	4.395	-0.460	0.670	-0.433	-1.744	2.840	0.471	-0.971

Figure 26: Estimation Output

E Properties of the Residuals

E.1 Residual Plots

In figure 27 the residuals of the eight endogenous variables included are plotted together with bounds at plus/minus two standard deviations. One can expect that on average five percent of the residuals lie outside these bands.

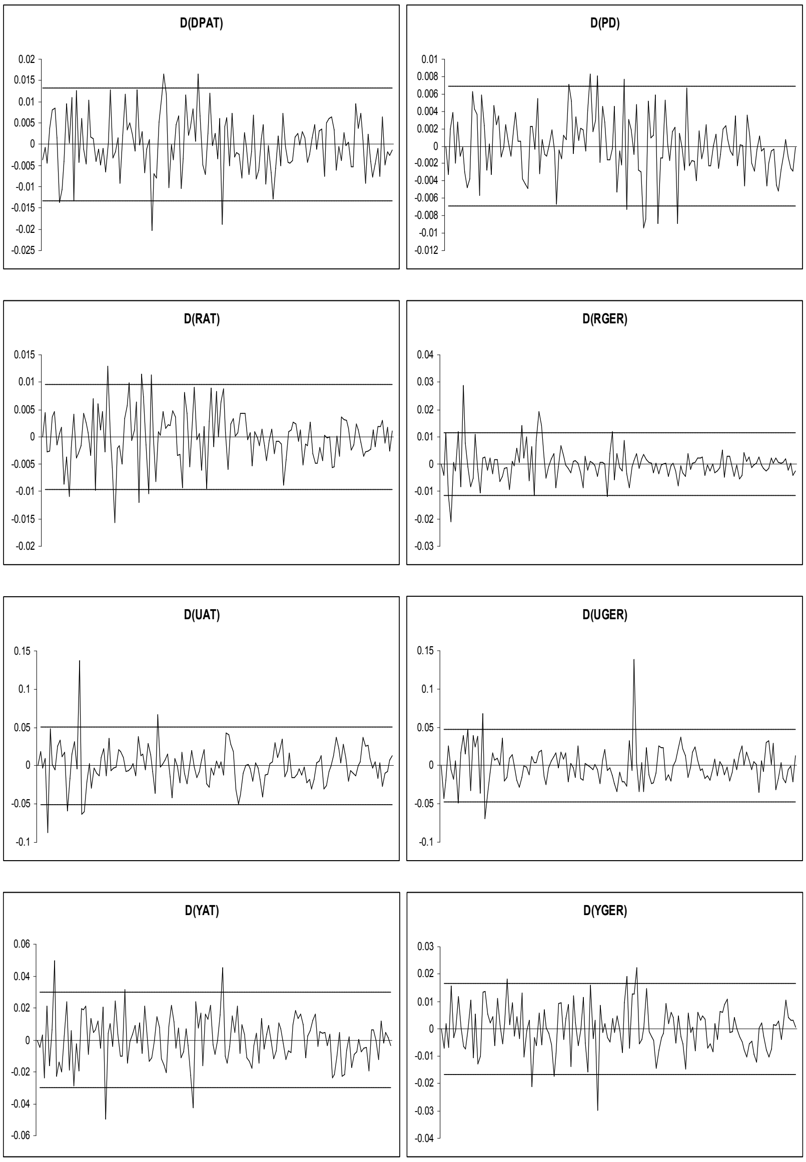

Figure 27: Residuals of the Eight Equations

E.2 CUSUM Test on Parameter Stability

In this section the results of the CUSUM test on stability of the estimated parameters are displayed. In figure 28 the top diagram on the left refers to the equation for D(DPAT), the next one to the right to the equation for D(PD), the left diagram in the second row refers to equation D(DPAT), the right diagram to the equation for D(RGER), the left diagram in the third row refers to the equation for D(UAT), the right diagram to the equation for D(UGER), the left diagram in the last row refers to the equation for D(YAT) and the left diagram to the equation for D(YGER). As can be seen, the test statistic never reaches values in the area of significance, although with respect to German interest rates in the early 1980s it comes very close.

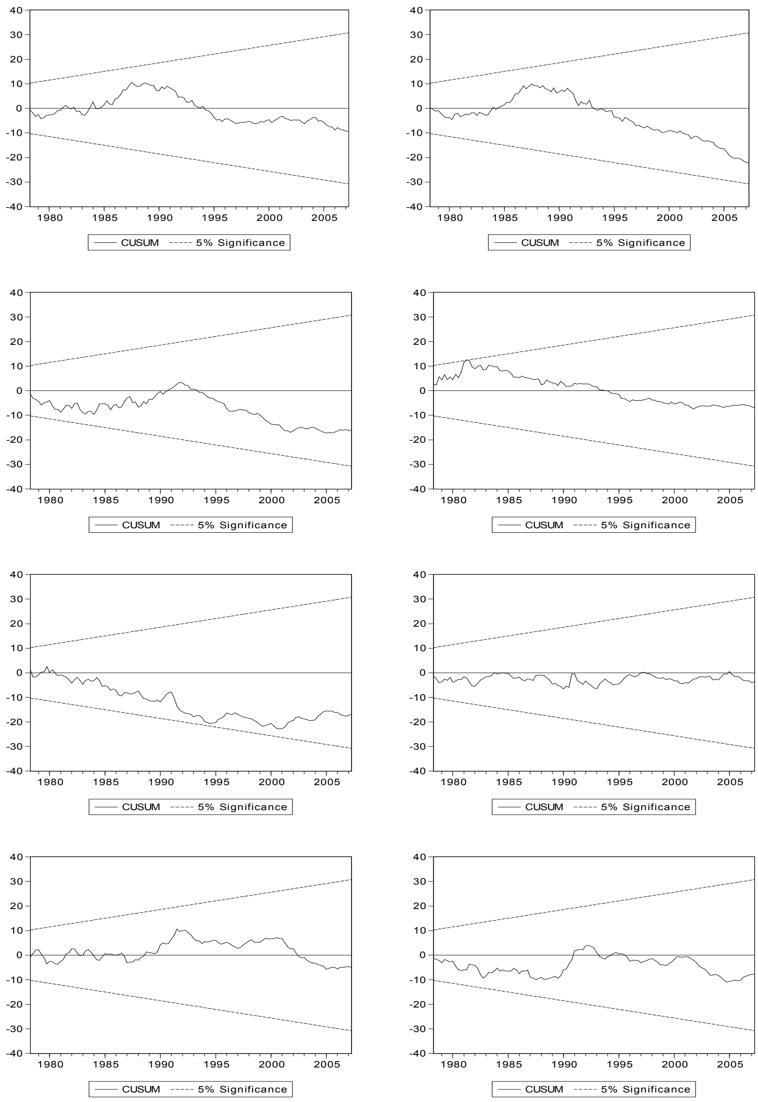

Figure 28: CUSUM Test

F Assessing the Weights for Forecast Combination

Table 15 displays the results of an OLS-estimation of equation 45. Note that the coefficients do not have to sum up to unity.

DDPAT	COEFFICIENT	P-VALUE
C	0.0018	0.1701
ARMA	0.8918	0.0038
VEC	0.4958	0.1072
DRAT	COEFFICIENT	P-VALUE
C	-0.0004	0.3885
ARMA	0.4247	0.0868
VEC	0.2937	0.1482
HW	0.1086	0.4481
SES	-0.0571	0.8700
DUAT	COEFFICIENT	P-VALUE
C	0.0016	0.5111
HW	0.7300	0.0000
DYAT	COEFFICIENT	P-VALUE
C	0.0006	0.9268
ARMA	0.0628	0.8977
VEC	0.2880	0.4910
HW	-0.1569	0.6257
SES	-0.3690	0.5317

Table 15: Weights of the Combined Forecast

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Zusammenfassung

In dieser Arbeit werden mittels eines Strukturellen Multivariaten Fehlerkorrekturmodells die Beziehungen zwischen den zwei stark integrierten asymmetrischen Volkswirtschaften Österreich und Deutschland untersucht. Im ersten Teil werden, auf Basis des dynamisch optimalen Verhaltens von Haushalten in beiden Wirtschaftsräumen, der steady state Eigenschaften von Neoklassischen Wachstumsmodellen und einer Gravitätsgleichung für Arbeitsmigration, langfristige Gleichgewichtsbeziehungen hergeleitet. Diese Relationen zwischen endogenen Variablen dienen als Restriktionen des Kointegrationsraumes. Im Gegensatz zu dieser theoretisch motivierten Herangehensweise, sind die kurzfristigen Anpassungen unrestringiert und werden rein statistisch über den vektorautoregressiven Teil des Modells geschätzt. Nach dem Modellselektionsprozess und einer Reihe an Spezifikationstests wird das resultierende Strukturelle Multivariate Fehlerkorrekturmodell dazu verwendet, die Auswirkungen von Schocks, welche die große Volkswirtschaft treffen, auf die kleine Volkswirtschaft und die damit verbundenen Transmissionskanäle zu untersuchen. Dies geschieht mittels einer verallgemeinerten Impulsantwortanalyse. Im zweiten Teil der Arbeit werden verschiedene Kriterien, die die Prognosegüte von ökonometrischen Modellen beschreiben, herangezogen, um die Vorhersagequalität des Strukturellen Multivariaten Fehlerkorrekturmodells in Bezug auf die Veränderungen der Inflationsrate, die Veränderungen des Zinssatzes, die Veränderungen der Arbeitslosigkeit und die Wachstumsraten des Bruttoinlandsprodukts in der kleinen Volkswirtschaft zu bewerten. Schließlich wird eine kombinierte Prognose aus den Vorhersagen des Strukturellen Multivariaten Fehlerkorrekturmodells, geeigneten ARMA Modellen, Holt-Winters Prozeduren und einfachen exponentiellen Glättungen konstruiert. Diese kombinierte Prognose hat eine bessere Vorhersagequalität als die individuellen Prognosen und könnte in zukünftigen Arbeiten um die Vorhersagen von großen makroökonometrischen Modellen, dynamisch stochastischen allgemeinen Gleichgewichtsmodellen oder den Vorhersagen von Experten erweitert werden.

Abstract

The framework of a Structural Vector Error Correction Model (SVECM) is used to study interrelations between the two closely related asymmetric economic areas Austria and Germany. In the first part of this thesis, theoretical long-run relations are derived via the dynamic optimizing behavior of households in both open economies, via the steady state properties of neoclassical growth models, and via a gravity equation characterizing labor migration. These relations define plausible equilibrium relationships between endogenous variables which can be implemented as restrictions on the elements of the cointegrating vectors. In contrast to this theoretically motivated approach, short-run adjustments are estimated without theoretical guidance according to the vector autoregressive part of the model. After the model selection process and a number of specification tests, the resulting SVECM is used to study shocks and their transmission channels from the large to the small economy with the help of generalized impulse response functions. In the second part of this thesis, different criteria for evaluating predictive accuracy are used to assess whether the model obtained is useful in forecasting changes in inflation, changes in the interest rate, changes in unemployment as well as output growth levels in the small economy. Finally, forecast combinations are performed between the SVECM, appropriately chosen ARMA models, the Holt-Winters algorithm and Single Exponential Smoothing methods. These combined forecasts are able to outperform all individual forecasts and could be extended to include the results of large-scale models, Dynamic Stochastic General Equilibrium models and the judgment of experts in future work.

JEL-Classification: C32, C53, F41

Keywords: Structural Vector Error Correction Model; Open Economies; Economic Integration; Generalized Impulse Response Analysis; Forecasting

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