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Forecasting Global Flows*

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Abstract

The theory suggests that investment activities and monetary policy influence the development of the global business cycle. The oil price and other raw material prices also play a key role in the economic development and there is a co-movement among oil consumption and global output. Therefore, the aim of this study is to explain the development of this set of variables by ARs, small-scale VARs and ECMs. The lag length and the rank of the time series models have been determined using information criteria. Then one-step ahead forecasts have been generated. It was found, that the ARs generate the best forecasts at the beginning of the forecasting horizon. However, when the forecasting horizon increases the VARs outperform the ARs. Comparing the forecasting performance of the ECMs, it was found that the forecasting ability of the ECMs in first differences outperform the level based ECMs when the forecasting horizon increases.

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1 Introduction

The external sector of an open economy like Austria is closely linked to the development of global flows of goods and capital. Hence, the idea of the following empirical analysis is to make the forecasting of the external sector of one country simpler. A top-down approach has been developed, which means, that first the global demand is subject to forecast. Then it depends on the competitiveness of the individual country how successful the external sector performs. In this study the world has been treated as a closed economy with its own business cycle. The theory suggests that investment activities and monetary policy influence the development of the business cycle. The oil price and other raw material prices also play a key role in the economic development and there is a co-movement among oil consumption and global output.

This set of variables has been explained by ARs and small-scale VARs and ECMs. Assuming independency it was found, that each variable sufficiently could be explained by its past development. If one also considers the interrelation of the variables, the appropriate data generation processes (DGPs) to use are unrestricted VARs in first or second differences or ECMs in levels and first differences. (Clements & Hendry 2001) showed that some models offer greater protection against unforeseen structural breaks than other. In particular, models in first and second differences might robustify forecasts against breaks. When estimating such models, the determination of the lag length and the rank has been based on information criteria (IC). Here the findings of (Inoue & Kilian 2006) have been applied.

When comparing the forecasting performance by the root mean square percentage error (RMSPE) of the different DGP-types, it was found that at the beginning of the forecasting horizon the ARs in second differences, with fixed and re-estimated coefficients, generate the best results. However, when the forecasting horizon increases the VAR in first differences, with re-estimated coefficients, starts to outperform the ARs in second differences. For the whole time span 2004 to 2006, on average, the VAR in first differences, with re-estimated coefficients, generates the smallest RMSPE in particular because this model is able to forecast the turning point of the aggregate world interest rate at the beginning of the forecasting horizon correctly. Comparing the forecasting performance of the ECMs, it was found that the forecasting ability of the ECM in first differences, with re-estimated coefficients, outperforms the other ECMs when the forecasting horizon increases.

The study starts with a brief description of the problem and the data. In the subsequent sections the set of variables have been estimated with different types of DGPs, from which forecasts have been generated. The last section gives a description of the forecasting performance of the DGPs under consideration.

2 Background

The driving forces for long-term economic growth emerge from the supply side of an economy. In long-term growth models there exists equilibrium across input, output and prices. In a simplified set up (Equation 1) there are only two inputs, physical capital (K) and labour (L) and the level of technology (A). Y is the flow of output.

$$Y = F(K, AL) \tag{1}$$

The mainstream models (Whitley 1994) for short-term economic forecasting are based on the income - expenditure approach, with the level of output and employment principally determined by the level of demand. The demand side of these models can be set out in a very stylised way as shown in Equations 2 to 7.

$$\begin{aligned}
Y &= C + I + \Delta S + X - M && (2)\\
C &= c(Y - HP) && (3)\\
I &= i(Y, r) && (4)\\
\Delta S &= s(Y) && (5)\\
X &= x(Y^*, \frac{ep^*}{p}) && (6)\\
M &= m(Y, \frac{ep^*}{p}) && (7)
\end{aligned}$$

where Y is real income, C is real consumption, HP is credit restrictions, G is real government consumption, I is real investment, r is the real interest rate, and ΔS are real stock changes. In aggregate demand, investments of companies and households (see Equations 4 to 5) are the prime movers in economic fluctuations, being by far the most cyclical and the most volatile element of domestic demand. Credits from banks and other private sources provide the financing for this process. Equations 6 to 7 explain the foreign sector of an economy. Real exports (X) and imports (M) are explained by the domestic and foreign income (Y, Y^*) and by competitiveness (ep/p^*), where e is the exchange rate measured as the foreign price of domestic currency, p is the domestic price level, and p^* the foreign price level.

The equations above reflect a macroeconomic model where a single country has only one trading partner. However, in reality, a single country performs trade with a number of countries. The trade pattern may vary across partner-countries, which implies an individual treatment of trade flows in the external sector of the model.

Greater integration of economic activity and the desire to take interdependencies between economies into account have increased the interest in multi-country models. The links between economies in multi-country models are through trade, prices, interest rates and exchange rates, and through flows of factors of production. Multi-country models have to ensure consistency between single-country outcomes and world aggregates, which are the sum of these individual components. In the case of exchange rates, there is the need to ensure plausible behaviour of cross-rates.

Figure 1 shows the high level of integradeness of the Austrian foreign sector with the rest of the world. A close link exists between the global and the Austrian trade of goods. Regarding the cross border capital flows the level of integration has been increasing over time. When forecasting the Austrian foreign sector, it would be sufficient, to model the relation of Austria with the rest of the world.

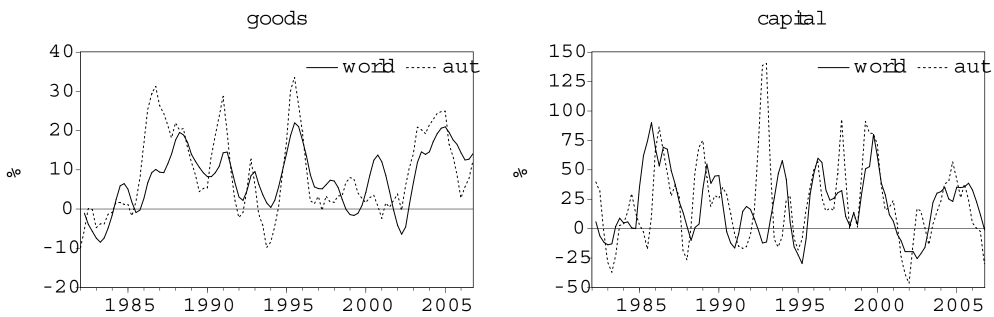


Figure 1: Growth of cross-border flows, world vs. Austria

The purpose of this study is to make the forecasting of world trade simpler. A top-down approach has been developed, such that first the global demand is subject to forecast. The world is treated as a closed economy with its own business cycle. It depends on the competitiveness of the individual countries how successful their external sectors perform.

A forecast on global flows, published on a regular basis, could contribute to a better evaluation of future developments that bear an influence on the external sector of a country. As a leading or coincident indicator of the international business cycle, it reduces the number of equations in the external sector of country specific macroeconomic models. This implies a reduction of uncertainties and errors in forecasting the economic development of one country.

3 Determinants of global growth

Economies are high dimensional, dynamic, non-linear, and evolving over time as technology, production, and financial possibilities alter, social behaviour fluctuates, and institutional and legal changes affect the environment with which the agents interact. The ongoing globalisation process can be thought of as a process of integration of goods and capital markets across the world in which barriers to international trade and foreign investment are reduced. As economies become more open to international markets, the transmission and propagation of economic fluctuations through external links has gained increased importance. Hence, open economies are strongly exposed to fluctuations in the global business cycle (Gable & Prasad 1998). The cyclical dynamics of international flows therefore have implications in a number of different dimensions, including macroeconomic development, short-run policy making and international politics.

The theory suggests that investment activities and monetary policy strongly influence the development of the business cycle. The oil price and other raw material prices also play a key role in the economic development and there exists a co-movement among oil consumption and global output.

3.1 International goods market

International flows of goods are considered as the major factors for sustainable development, as open economies have experienced faster productivity growth (Edwards 1997) than others. Openness in the goods market implies the opportunity of consumers and firms to choose between domestic and foreign goods. Cross-border trade contributes to growth in one country, because it stimulates technological progress and increases human capital. In order to keep competitiveness, countries have to specialize, which leads to increased cross-border trade flows. Hence, integration is the reason why the growth cycles of cross-border trade flows are so closely linked.

The decades following the World War II were characterised by an unprecedented movement towards openness of the global economy. Global and regional trade reforms were complemented by continuing technological advance, which has lowered the costs of transportation and communication between countries. Trade barriers in the EEC, the EFTA and between the United States and Canada were partially or completely removed. Furthermore, a structural change in the world trade development occurred with the switch from fixed to flexible exchange rate regimes. From 1960 onwards, the average import and export shares in output indicate that increases in cross-border flows were fairly widespread.

3.2 International capital market

As financial markets become more and more closely integrated, investors benefit from the opportunity to choose between domestic and foreign financial assets. The mobility of capital increases and the cross-border capital flows are directed to the economies with the best growth prospects. A strong inflow of capital stimulates investment and as a consequence activities in the domestic and foreign sector of this economy increase. Several studies have investigated the impact of capital flows on investment and growth. The composition of capital flows matters since their impact on world trade varies across different types of flows. Foreign direct investment (FDI) flows (Mody & Murshid 2002) are associated with a significant increase in domestic investment. However, this effect has become less pronounced, since the nature of FDI transactions has changed over time.[1] The impact of the cross-border portfolio investments flows (FPI) on economic growth is comparatively modest. There are plausible reasons for this observed difference. FDI are typically associated with new projects, whereas portfolio flows are associated with the objective of sourcing lower cost funds and/or of diversifying risk, and hence, are more

[1]Mergers and acquisitions - as distinct from the traditional FDI - have become more prominent, implying that a greater share of the foreign capital is being used to purchase assets rather than finance new investments.

often used to finance ongoing projects. Since the beginning of the 1990s the relationship between FDI-flows and world trade is weakening. However, a strongly increasing share of FPI-flows in the long-term capital is offsetting this development.

3.3 International commodity prices, excluding oil

A key characteristic of the development of commodity prices is their cyclical behaviour, as prices tend to increase when the demand is above its natural level and to decrease when demand is low. These cyclical movements in prices have important implications for many developing countries that depend on commodity exports, as booms and slumps in prices can induce wide fluctuations in earnings from commodity exports. (Cashin, McDermott & Scott 1999) examined the properties of the price cycles of 36 different commodities, and point out four important features of commodity price booms and slumps. First, there is an asymmetry in commodity price cycles, as the duration of slumps exceeds the duration of booms by nearly a year. Second, the magnitude of price falls in a slump is slightly larger than the magnitude of price rebounds in a subsequent boom period, while the rate of price changes is typically faster in booms than in slumps. Thirdly, there is little evidence of a consistent shape in the cycles of commodity prices. Finally, for all commodities the probability of an impeding end of the slump cannot be predicted from the duration of the time already spent in the slump. This finding — that the past duration of slumps is irrelevant for predicting their turning point — also holds for the boom periods of most commodity prices.

3.4 Interest rates

Monetary aggregates tend to move in the same direction as the aggregate economic activity. This co-movement accounts for the passive response of the money supply to changes in the level of activity that are not directly related to monetary policy. In some countries, this endogenous feedback is interrupted by interventions of the monetary policy authorities. However, most changes in monetary policy reflect macroeconomic conditions, since the monetary authorities are committed to macroeconomic stabilisation. Economists closely connected with policy tend to view the monetary authority as capable of controlling nominal short-term interest rates and thereby of strongly influencing the level of aggregate activity. Many authors have addressed the measurement of the effects of monetary policy by means of the VAR methodology, e.g. (Sims 1992) or (Bernanke, Gertler & Watson 1997).

3.5 Oil price

A large body of researchers, e.g. (Hamilton 2003), has found that energy supply disruptions have a significant impact on economic activity. In this context, one can clearly identify military conflicts in the Middle East that have significantly disrupted world petroleum supplies. An exogenous decrease in the supply of energy pushes up prices and reduces economic output directly by lowering the productivity and indirectly — to the extent that lower wages include movements in the labour supply scheme — by inducing changes in business mark-ups, or capacity utilisation rates. Hence, a clear negative relation between energy prices and aggregate measures of output and employment has been reported. This obviously implies that a linear regression explaining output by lagged oil prices must exhibit instability over time. Some researchers have attributed this to the fact that the true relation between the price of oil and economic growth is non-linear. If the magnitude of supply disruptions is used as an instrument for oil price changes, the predictions of a linear regression become very similar to those of the non-linear specifications. The use of oil prices themselves as an exogenous instrument or disturbance factor is certainly called into question.

Given that part of the oil price/macroeconomy relationship appears to be driven by unanticipated supply-side shocks, it remains a distinct possibility that the military conflicts themselves, rather than the specific changes in oil prices, lead economies. The wars may cause anxiety about future availability and prices of energy or have other destabilizing effects whose consequences for consumer spending or monetary policy might even be more important than the actual movements in oil prices. Notwithstanding, it is obvious that in history armed conflicts have proven highly disruptive to the world economy.

3.6 Oil market

There is a co-movement of the demand for oil and the business cycle of the global economy. The recent upturn in economic power of Asian countries (China and India) is responsible for the strong oil demand today. It offsets the slowing oil demand that is observable in many industrialized countries. Hence, the global demand for crude oil increases steadily. From 1995 to 2005, the demand for oil increased by an average annual rate of 1.7 percent and if the world economy is in a normal mode, the demand for oil might increase by additional 1.5 million barrels per day (mb/d) every year, which corresponds to an average yearly growth rate of 1.9 percent (Banks 2002).

The oil market has changed in the last three decades. During the 1970s the oil production could easily be raised by an extra million of barrels per day by more drilling and/or a more intensive application of various attainable technological improvements. Today the quantity of discovered oil is on a falling trend (Banks 2002). Since 1981, much less oil has been found than consumed, with this deficit steadily increasing.[2] The profitability gains due to technological advances do not offset the deterioration in geological prospects. Global proven reserves in the low-cost, easily accessible category are overwhelmingly located in the Middle East, where major investors might have the intention to leave a large fraction of reserves stay in the ground, unless buyers in the oil-importing countries are willing to pay sensible prices for their extraction (Teitelbaum 1995). Oil still provides 40 percent of traded energy, which means that, in the not-too-distant future, some traumatic economic and political decisions may be necessary.

4 Data

The empirical analysis is based on the variables world trade ($wdexm$), foreign capital flows ($wdfcf$), world commodity prices ($wdpri$), short-term interest rates ($wdirst$), the oil price ($brent$) and the world production of crude oil ($wdpro$).

The time series of world exports ($wdexm$) is regularly published by the International Monetary Fund, International Financial Statistics (IFS). It is reported in billion USD at current prices. The time series has a monthly frequency and its observations start in January 1960. The time series on global capital flows ($wdfcf$), reported in billion USD, is a world aggregate of individual cross-border flows of portfolio investment and direct investment. The source is the IFS. The data entries of the aggregate time series start in January 1960. As the original time series has a quarterly frequency it has

[2]According to M. King Huberts 'mid-point depletion rule', production will begin to decline in a given oil producing region, when approximately half the oil discovered and likely to be discovered has been produced. World discovery peaked in 1964, which suggests that a the peak in global production will be reached around the year 2010 (Deffeyes 2001).

been converted to an index with monthly frequency.

The time series on world commodity prices (*wdpri*) is an index that consists of prices for food, beverages, agricultural raw materials and metals. The index does not include the prices for fossil fuels. The source is the IFS. The time series has a monthly frequency. Its observations start in February 1980. The world interest rate series (*wdirst*) is a weighted average of short-term interest rates of the major trading blocks, namely the USA, Japan and the Euro zone. The data source for all variables is the IFS. The time series has a monthly frequency. Its observations start in January 1980. Since the Euro zone has been established in 1999, the German short-term interest rates were taken for the preceding years.

The price of oil (*brent*) is reported in USD per barrel, the monthly data is an average of the daily prices. The basket of oil prices consists of light qualities. Datastream provides their daily quotations. The observations start in January 1960. The world production of crude oil (*wdpro*) is reported in 1000 barrels per day. The time series is being published by the US Department of Energy (DOE), and has a monthly frequency. The observations start in January 1973.

In data analysis the sample size matters as economic relationships vary over time. The first common data entry of the set of observations starts in January 1981 and the latest commonly available data point is December 2006. This time horizon is referred to as the full sample size (FS). The subsequent empirical analysis will be based on sub-samples. One starts in January 1982 and ends in December 2003 (SS1); the other starts in January 1985 and ends in December 2006 (SS2).

Figure 2 presents a set of graphs showing how the variables in levels and logarithms evolve over time. Some features can be readily spotted from the plots. The individual time series have either an upward or a downward sloping trend with drift. The time series *wdexm*, *wdfcf* and *wdpro* have the typical shape of a macroeconomic time series as they are increasing over time. Also the time series on prices (*wdpri* and *brent*) perform an increasing growth path within the observation period. The oil price declined from the early 1980s until 1999. However, from then on, a strong upward movement is observable, and it is very likely that the oil prices will continue to increase. One can expect that, due to limited resources, also the raw material prices will increase in the long run. In contrast to this, interest rates may have a non-trending development. In fact, world interest rates were increasing from 1960 to 1980 and fell thereafter, reaching a historic low in 2004. In the following years, the downward pressure of this time series reversed again, which is an indication for stationarity.

One way of handling non-stationarity in time series is to compute first differences

$$\Delta_{12}^{1}Y_t \;=\; logY_t - logY_{t-12} \tag{8}$$

and second differences

$$\Delta_{1}^{2}Y_t \;=\; (1-L)(logY_t - logY_{t-12}). \tag{9}$$

The time series *wdexm*, *wdfcf*, *wdpri*, *wdirst*, *brent* and *wdpro* were transformed to year-by-year plus month-by-month differences with the symbol Δ_{12}^{1} and Δ_{1}^{2}. Taking first differences year-by-year (Equation 8 and Figure 3) yields time series that are shaped like traditional business cycles. The shaded areas of Figure 3 show the lower turning points of the cycles, when the world economy run through the two most severe recessions. Despite the problem of over-differencing, the time series have been transformed to their second differences (Equation 9 and Figure 4).

Testing for unit roots is the first step of time series model building. Visual evidence of the Figures 2 and 3 suggest that the observed time series my have a trend and a cycle. The ADF-test — reported in Table 1 top — suggests that only *wdpro* and *brent* incorporate a constant and a linear trend in both samples. In the case of *wdexm* and *wdirst*, the results are mixed. The other time series do not incorporate deterministic patterns. After differencing (Equation 8), with the exclusion of *wdpri* in SS2, all time series turn out to be stationary (see Table 1 middle). The whole data set transformed into second differences (Equation 9) is stationary (see Table 1 bottom).

The analysis is based on three different data sets. The group of I(1) series, is named X_t and consists of the variables *wdexm*, *wdfcf*, *wdpri*, *brent* and *wdpro* in logarithmic form. The stationary data set, named DX_t, consists of X_t in first differences (Equation 8) plus the time series *wdirst* in logarithmic form. The data set DDX_t consists of the variables *wdexm*, *wdfcf*, *wdpri*, *brent* and *wdpro* in second differences (Equation 9) and the series *wdirst* in first differences (Equation 8).

5 Model estimation

This section describes the model selection procedures. The aim is to find a data generation process (DGP), which is capable to explain the growth paths

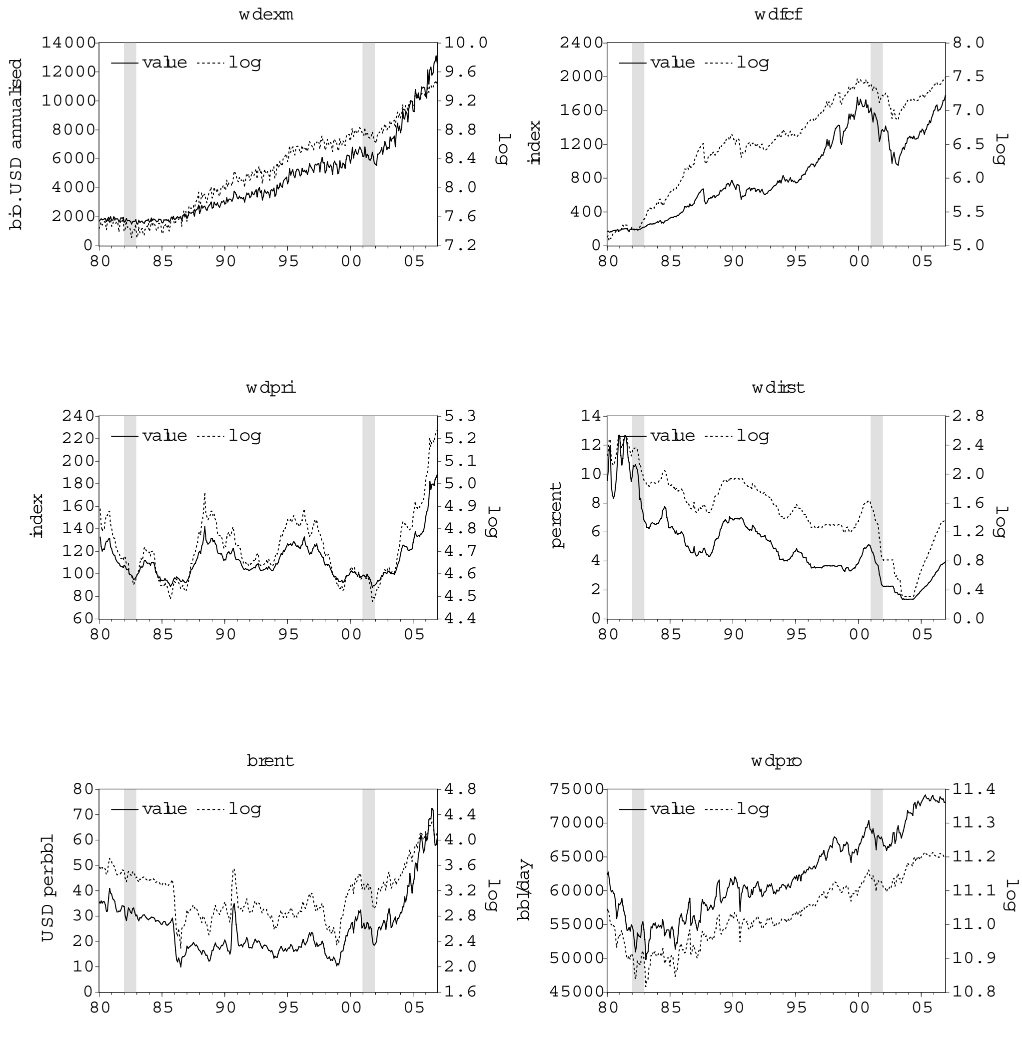


Figure 2: Variables in levels and logs

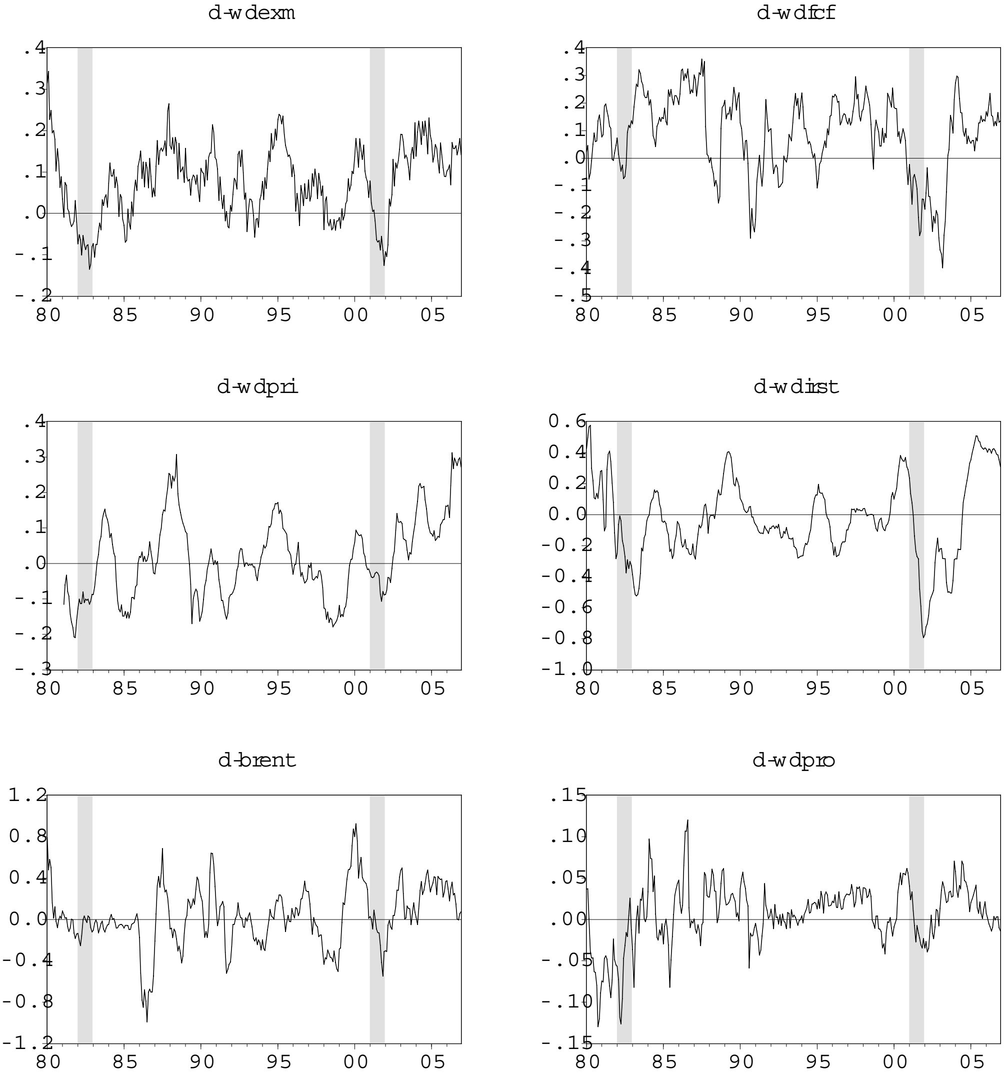


Figure 3: Variables in first differences from a year ago

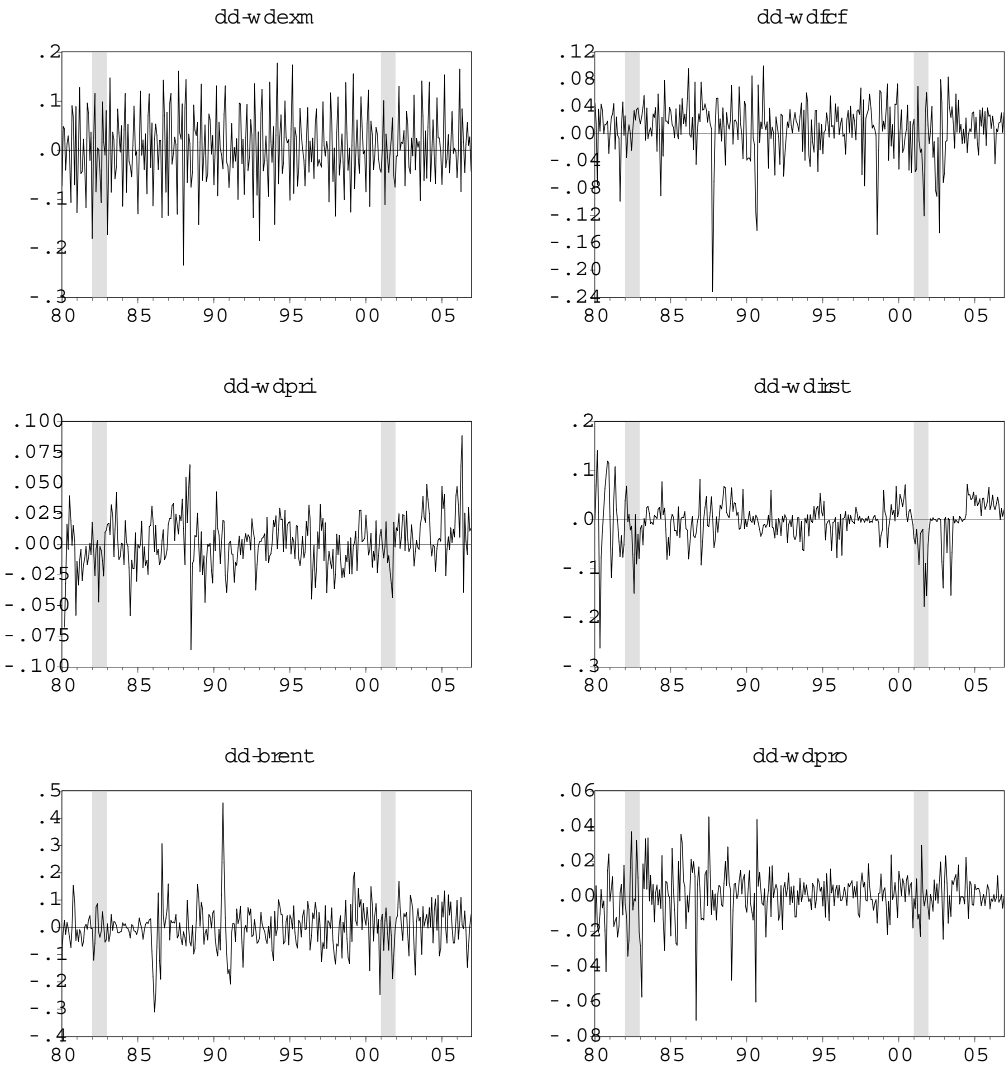


Figure 4: Variables in second differences

Table 1: ADF-test

H_0: time series has a unit root

		MacKinnon one-sided p-values	
		SS1 (1982-2003)	SS2 (1985-2006)
$logY_t$	assumption: exogenous is a constant and a linear trend		
	$wdexm$	0.121	0.621
	$wdfcf$	0.768	0.359
	$wdpri$	0.638	0.996
	$wdirst$	0.957	0.103
	$brent$	0.071	0.160
	$wdpro$	0.000	0.001
$\Delta^1_{12}Y_t$	assumption: exogenous is a constant		
	$wdexm$	0.048	0.080
	$wdfcf$	0.130	0.121
	$wdpri$	0.037	0.317
	$wdirst$	0.034	0.187
	$brent$	0.001	0.024
	$wdpro$	0.003	0.001
$\Delta^2_1Y_t$	assumption: exogenous is a constant		
	$wdexm$	0.005	0.003
	$wdfcf$	0.000	0.000
	$wdpri$	0.000	0.000
	$wdirst$	0.000	0.000
	$brent$	0.000	0.000
	$wdpro$	0.000	0.000

of the set of variables considering the past development and the interrelation of the time series world trade ($wdexm$), world foreign capital flows ($wdfcf$), world commodity prices ($wdpri$), world short-term interest rates ($wdirst$), the oil price ($brent$) and the oil production ($wdoil$). As the true DGP is unknown, the development path of the six variables has been estimated with three different types of models. The methods under consideration are autoregressive processes (ARs), unrestricted vector autoregressive models (VARs) and the error correction mechanisms (ECMs). When estimating the parameters of the DGPs, decisions have to be taken regarding the data set to use, the lag length and the number of cointegrated vectors.

Small-scale DGPs have come to be widely used in macroeconomics. However, a body of recent work suggests that such DGPs may be prone to instabilities. Shifts in deterministic components are one of the primary sources of mis-specification, and unforeseen structural breaks and regime shifts seem responsible for many of the more dramatical historical episodes of macroeconomic forecasting failure. In the face of such instabilities, a variety of estimation methods might be used, to improve the accuracy of forecasts from a DGP. (Clements & Hendry 2001) showed that some models offer greater protection against unforeseen structural breaks than others. In particular, models in first and second differences might robustify forecasts against breaks. The authors derived forecast-error biases and variances for VARs in these differences to demonstrate that when forecasting after structural breaks, they can outperform ECMs. Hence, in the analysis the parameter estimations of the DGPs will be based on data sets in levels (X_t) and its transformations into first (DX_t) and second differences (DDX_t).

In the model selection procedure, the determination of the lag length (p) of a DGP is critical. If p is too small, the model is mis-specified; if p is too large, the model is over-parameterised. It is standard in applied work to select forecasting models by ranking candidate models by their prediction mean squared error (PMSE) in simulated out-of-sample forecasts (SOOS). Alternatively, forecast models may be selected using information criteria (IC). (Inoue & Kilian 2006) compared the asymptotic and finite-sample properties of these methods in terms of their ability to minimize the true out-of-sample PMSE, allowing for possible mis-specification of the forecast models under consideration. The authors show that under suitable conditions the IC method will select the best approximating model among the candidate models. In contrast, under the standard assumptions the SOOS method whether based on fixed or rolling regressions, will select over-parameterised models with positive probability, resulting in excessive finite sample PMSEs. Following the authors' findings, in the underlying analysis the lag order will be selected using IC. The principle of parsimony comes into play when there is the choice between two or more forecast models with the same IC.[3]

The lag length of the ARs is determined as:

$$AIC_{ar} = -2\ln(\hat{\sigma}^2/T) + 2(k/T) \quad (10)$$

assuming that the maximum likelihood function is used for $\hat{\sigma}^2$ with the k parameters estimated using T observations. For systems of equations, the AIC is computed using the full system log likelihood. The log likelihood value is computed assuming a multivariate normal distribution:

$$AIC_{var} = -2\ln(|\hat{\Sigma}_p|/T) + 2pn^2/T \quad (11)$$

$|\hat{\Sigma}_p|$ denotes the determinant of the residual covariance matrix for the VAR(p), with p=1,2,...,K and pn^2 is the number of coefficient parameters.

Once the specifications of the model have been chosen, the parameters of the models are estimated using OLS. The model estimation procedure, together with the determination of the lag length and the rank, is based on the sub-samples SS1 and SS2. The estimation results are summarized in Table 2.

5.1 ARs

The first assumption is that there is no interrelation or feedback mechanism among the variables $wdexm$, $wdfcf$, $wdpri$, $wdirst$, $brent$ and $wdpro$. A widely used class of models in that regard are autoregressive processes. Such models relate a dependent variable to its past values. The development of the data set DX_t and DDX_t will be estimated with the AR-processes of Equation 12 and Equation 13.

$$DX_t = c + \sum_{i=1}^{p} \phi_p L^p(DX_t) + \epsilon_t \quad (12)$$

$$DDX_t = c + \sum_{i=1}^{p} \phi_p L^p(DDX_t) + \epsilon_t \quad (13)$$

[3] The principle of parsimony states that of any two models of different dimensions, but with the same population PMSE, always the more parsimonious model is preferred on the grounds that this model is likely to have smaller PMSEs in the finite sample.

where c is the constant, ϕ is the vector of coefficients, p is the unknown lag order and ϵ is the residual which is assumed to be normally distributed with $\epsilon_t \sim N(0, \sigma^2)$. To find the best fitting models, the AR-processes have been estimated for alternating lag orders ranging from 1 to 24. See Figures 5 and 6.

5.2 Unrestricted VARs

When analysing the existence of relationships among a set of variables one strategy is to treat all variables as endogenous within a VAR. Hence, the data sets DX_t and DDX_t have been explained by VAR-systems as described in the Equations 14 and 15.

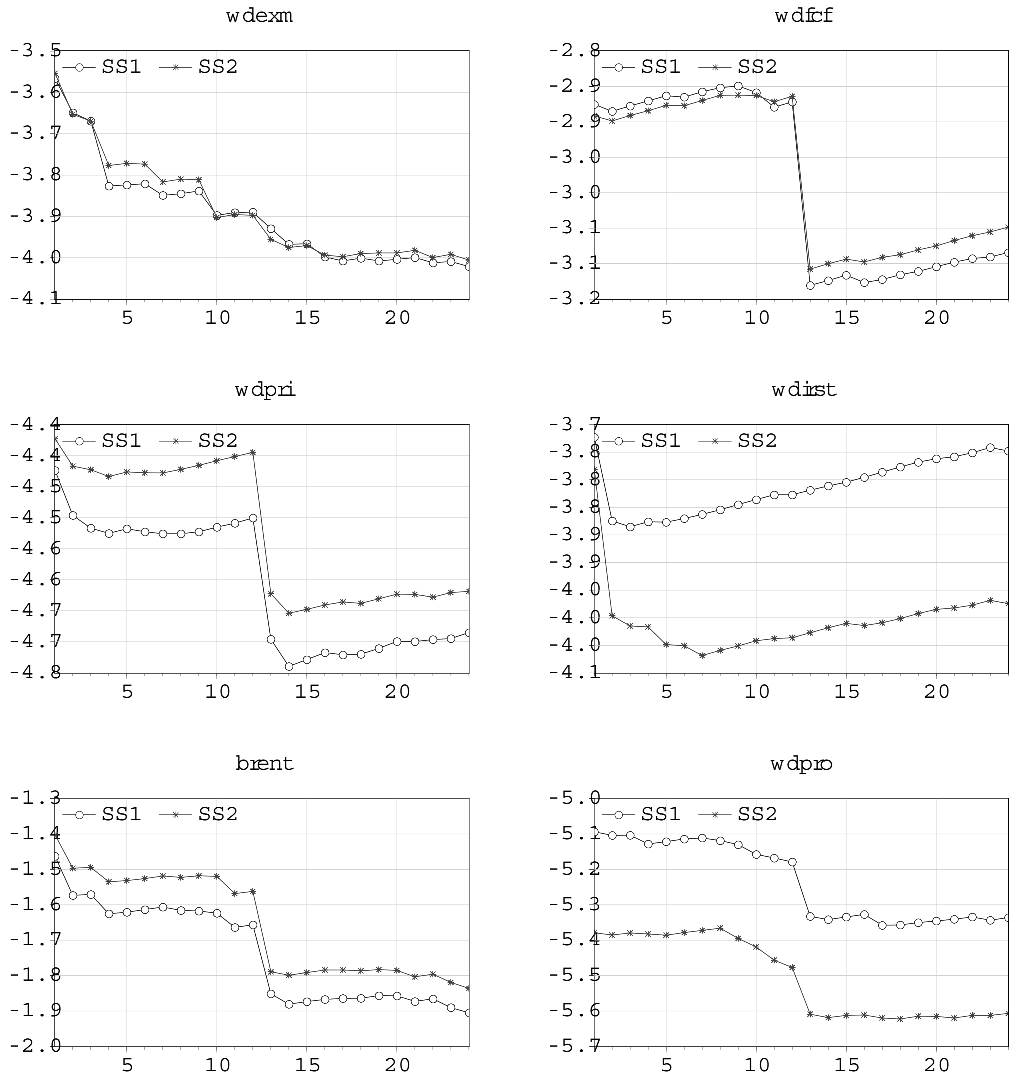
$$DX_t = C + \sum_{i=1}^{p} \Phi_i DX_{t-i} + \varepsilon_t \qquad (14)$$

$$DDX_t = C + \sum_{i=1}^{p} \Phi_i DDX_{t-i} + \varepsilon_t \qquad (15)$$

where C is a 6×1 matrix of constants, Φ is a 6×6 matrix of coefficients, p is the unknown lag order and ε is a 6×1 matrix of residuals, which are assumed to be normally distributed with $\varepsilon_t \sim N(0, \Sigma^2)$. The VAR-systems have been alternatively estimated for lag orders ranging from 1 to 6. For the sample SS1 the multivariate generalisation of the IC suggest to use a lag order of $p = 2$ for the VAR-DX. However, as the next AIC-value remains very close to the previous value, a lag order of $p = 3$ has been selected. The same decision was taken, when choosing the lag order of the VAR-DDX for the sample SS2. In this case a lag order of $p = 2$ has been selected. See Figure 7.

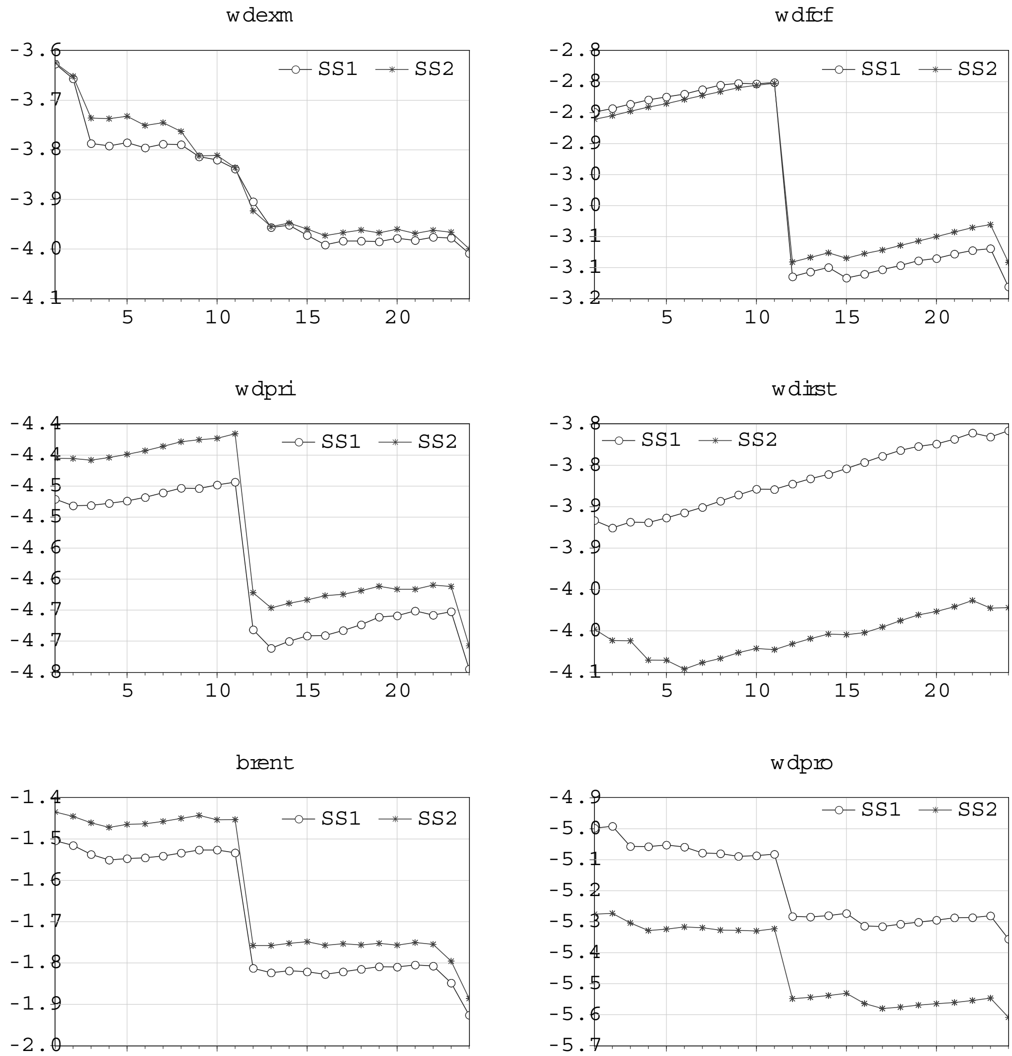
5.3 ECMs

Now the data sets X_t and DX_t, have been estimated with ECMs. In a non-stationary world subject to structural breaks, where model and mechanisms differ, ECMs are a risky device from which to forecast. Equilibrium shifts entail systematic forecast failures, as forecasts will tend to move in the opposite direction to data. (Hendry 2006) explains the empirical success of differenced devices and of model transformations based on additional differ-



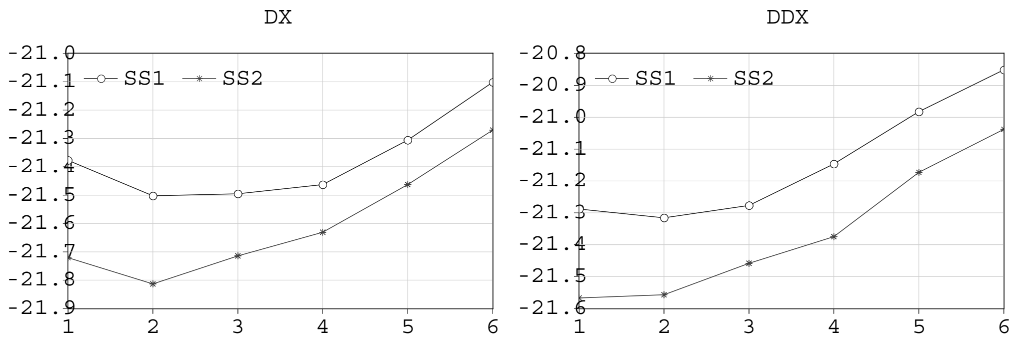
note: left axis AIC-values, bottom axis lags

Figure 5: Lag order selection of AR-DX



note: left axis AIC-values, bottom axis lags

Figure 6: Lag order selection of AR-DDX



note: left axis AIC-values, bottom axis lags

Figure 7: Lag order selection of VAR-DX and VAR-DDX

encing as reducing forecast-error biases, at some cost in increased forecast-error variances. When estimating ECM-X

$$\Delta X_t \quad = \quad C + \Pi X_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta X_{t-j} + \sum_{s=1}^{11} \delta_s D_s + \varepsilon_t \tag{16}$$

$$\Pi = \sum_{i=1}^{p} \Phi_i - I, \Gamma_i = -\sum_{i+1}^{p} \Phi_j \tag{17}$$

The variables in X are ordered as follows: *wdexm*, $wdfcf$, *wdpri*, *wdirst*, *brent*, and *wdpro*. C is a $k \times 1$ matrix of constants, Π is the long-term pattern matrix, Γ is the short-term pattern matrix, δ is the coefficient matrix of the seasonal dummies (D_s) and ε are the residuals of each equation which are assumed to be normally distributed with $\varepsilon_t \sim N(0, \Sigma^2)$ and p is the unknown lag order.

As the interest rate series is by definition I(0), it has to be excluded from the equations, which explain the long-run relationship of the ECM. However, the variable should be considered in the VAR-part of the system. Therefore, the following restriction has been imposed:

$$\Pi_{k,4} = 0$$

In ECM-DX all variables are stationary; hence, no restrictions in the long-term relationship are necessary. The dummies (D_s), which control for seasonality, have been dropped.

$$\Delta DX_t \quad = \quad C + \Pi DX_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta DX_{t-j} + \varepsilon_t \tag{18}$$

In both ECMs the lag length p also the rank (k) is unknown and has to be determined. When doing so, all external factors have been excluded from the estimation procedure of the Equations 16 and 18. Then the number of cointegrating relations have been tested and whether there is an intercept or a constant or both in the cointegrating relation or in the data. Each combination has been alternatively estimated for lag orders ranging from 1 to 6. The results are plotted in the Figures 8 to 11. The IC suggests a lag order of 2 for both DGPs. Both ECMs have two equilibrium relationships. One equation with a linear trend in the data, with a constant and a trend in the cointegrating equations, the other with no linear trend in the data, a constant and no trend in the cointegrating equations.

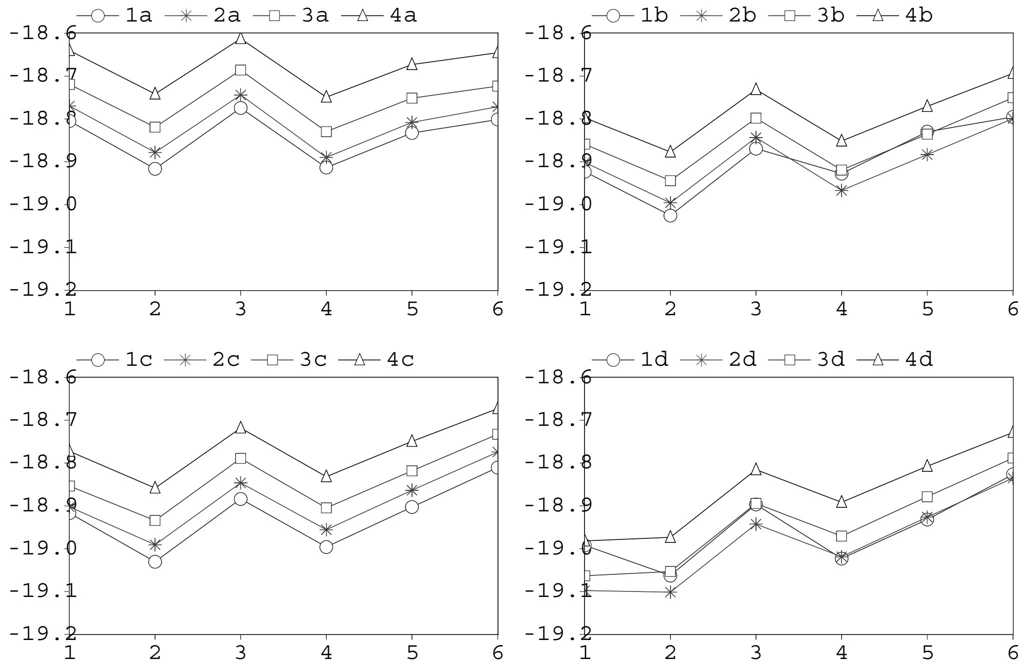
6 Forecasting

Once the time series models have been selected, one may generate one-step ahead forecasts. Alternatively to the one-step ahead (iterated) forecasting method one could also apply multiperiod ahead (direct) forecasting methods. According to (Marcellino, Stock & Watson 2006), iterated forecasts are more efficient if the one-step ahead model is correctly specified, but direct forecasts are more robust to model mis-specifications. However, the iterated forecasts typically outperform the direct forecasts, particularly, if the models can select long lag specifications. The relative performance of the iterated forecasts improves with the forecast horizon.

The parameters of the selected models, as reported in Table 2, have been estimated for the period 1982 to 2003 leaving the years 2004 to 2006 as the forecasting evaluation period. This period is considered as the unknown future. The forecasting procedure is one-step ahead.

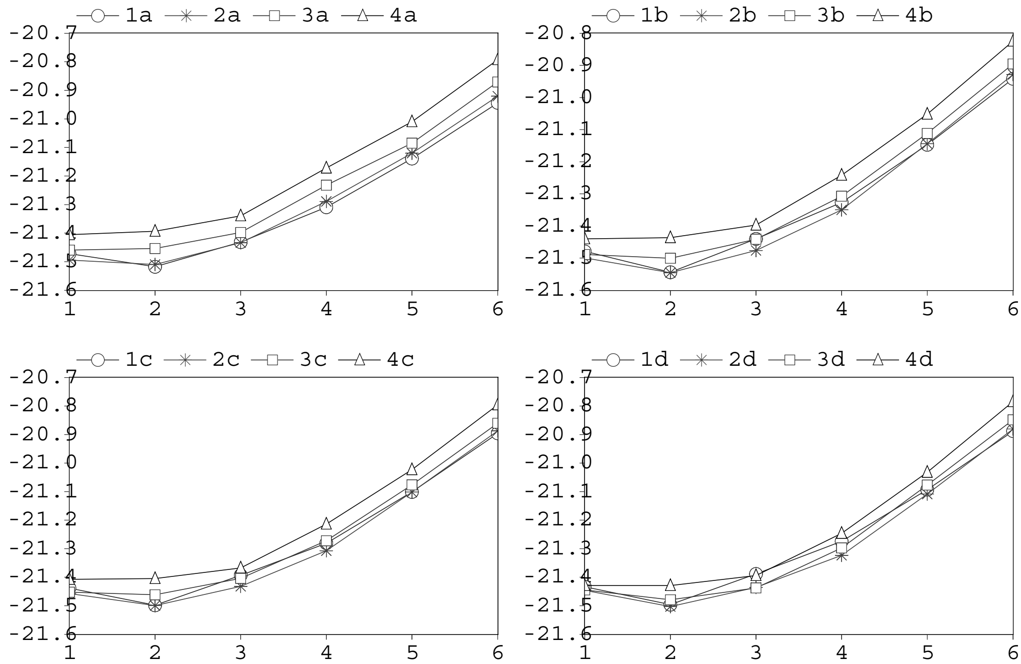
$$\hat{y}_{n+h} = Y_{n+h-1} \tag{19}$$

$\hat{y}_{n+h}$ are the forecasts with $h = 1, 2, \ldots, 36$. Y_{n+h-1} is the information set. As the forecast horizon extends to more than one month, one-step ahead forecasting requires dynamic model solutions. During the forecasting procedure



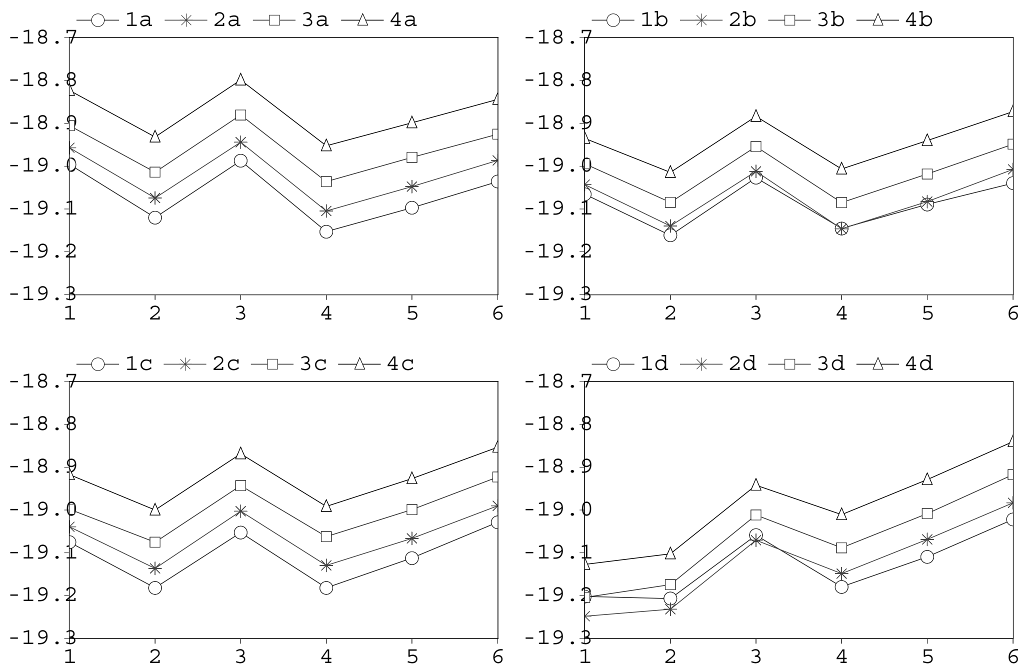
note: left axis AIC-values, bottom axis lags.
The numbers 1 to 4 are the rank specifications; a=no deterministic trend in the data, and no intercept or trend in the cointegrating equation; b=no deterministic trend in the data, and an intercept but no trend in the cointegrating equation; c=linear trend in the data, and an intercept but no trend in the cointegrating equation; d=linear trend in the data, and an intercept and a trend in the cointegrating equation.

Figure 8: Lag order and rank selection of ECM-X for SS1



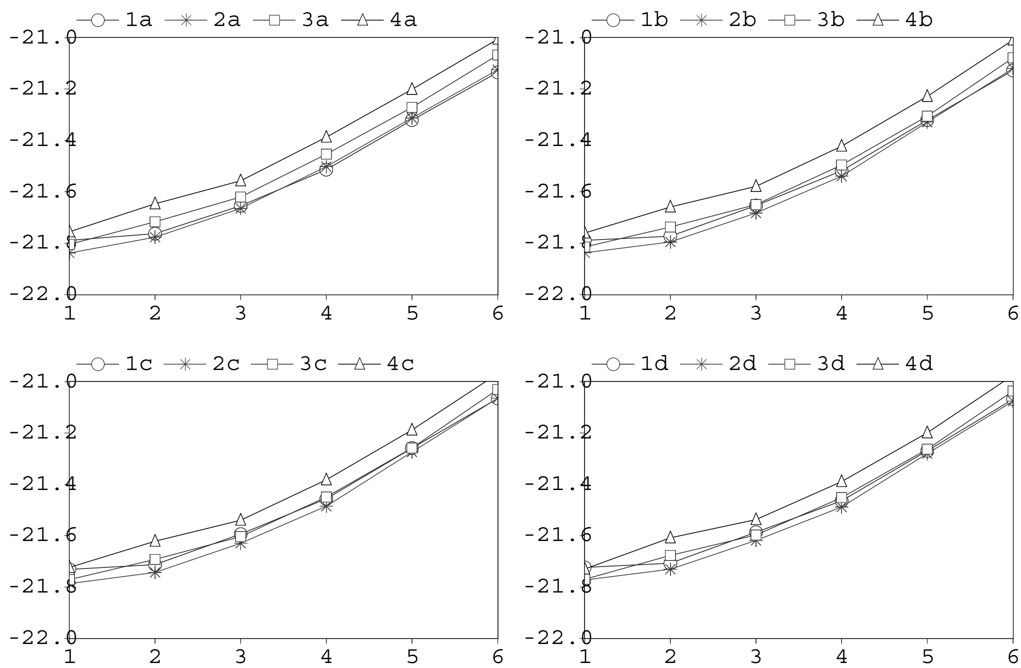
note: left axis AIC-values, bottom axis lags.
The numbers 1 to 4 are the rank specifications; a=no deterministic trend in the data, and no intercept or trend in the cointegrating equation; b=no deterministic trend in the data, and an intercept but no trend in the cointegrating equation; c=linear trend in the data, and an intercept but no trend in the cointegrating equation; d=linear trend in the data, and an intercept and a trend in the cointegrating equation.

Figure 9: Lag order and rank selection of ECM-DX for SS1



note: left axis AIC-values, bottom axis lags.
The numbers 1 to 4 are the rank specifications; a=no deterministic trend in the data, and no intercept or trend in the cointegrating equation; b=no deterministic trend in the data, and an intercept but no trend in the cointegrating equation; c=linear trend in the data, and an intercept but no trend in the cointegrating equation; d=linear trend in the data, and an intercept and a trend in the cointegrating equation.

Figure 10: Lag order and rank selection of ECM-X for SS2



note: left axis AIC-values, bottom axis lags.
The numbers 1 to 4 are the rank specifications; a=no deterministic trend in the data, and no intercept or trend in the cointegrating equation; b=no deterministic trend in the data, and an intercept but no trend in the cointegrating equation; c=linear trend in the data, and an intercept but no trend in the cointegrating equation; d=linear trend in the data, and an intercept and a trend in the cointegrating equation.

Figure 11: Lag order and rank selection of ECM-DX for SS2

the lag order and the rank of the underlying models, always remain fixed. Also the estimates for the parameters have been kept fixed. However, the whole procedure has been repeated with re-estimated parameters in every new forecasting step. At the same time one new observation is added and one is dropped at the beginning of the time horizon, such that the number of observations did not change. The logic behind this approach is that for models exhibiting structural changes, older observations are less likely to be relevant for the present incarnation of the DGP. In particular, using older observations could imply a type of model mis-specification (and perhaps bias in the forecast) that can be alleviated by simply dropping those observations.

The results of forecasting have been converted to their levels as shown in Figure 12, together with the observed data. All forecasts of $wdexm$, $wdfcf$ and $wdpro$ point into the same direction as the observed data. Regarding the world commodity prices ($wdpri$) only a few DGPs could forecast the strong upturn of time series from 2003 onwards. Also only few DGPs were capable to forecast the turning point in the development of the interest rates. Most of the DGPs could not predict the sharp upturn of the oil price in the years 2004 to 2006.

7 Evaluation of forecasts

As already mentioned, the best approximating forecasting model among other competitive models may be selected by information criteria (IC). In Table 2 all IC-results are listed. The best forecasting ability among the multivariate models, when the estimates are based on SS1, is the ECM-DX closely followed by the VAR-DX. If the coefficient estimates are based on the time span SS2, the VAR-DX is expected to deliver the best forecasting results, followed by the ECM-DX.

In order to check this expectation, a more traditional model selection measure is being introduced. The root mean square percentage error (RM-SPE) based measures (see Equation 20) are currently the most commonly used criterion for the assessment of accuracy in macroeconomic forecasting (Clements & Hendry 1998) and (Franses 1998).

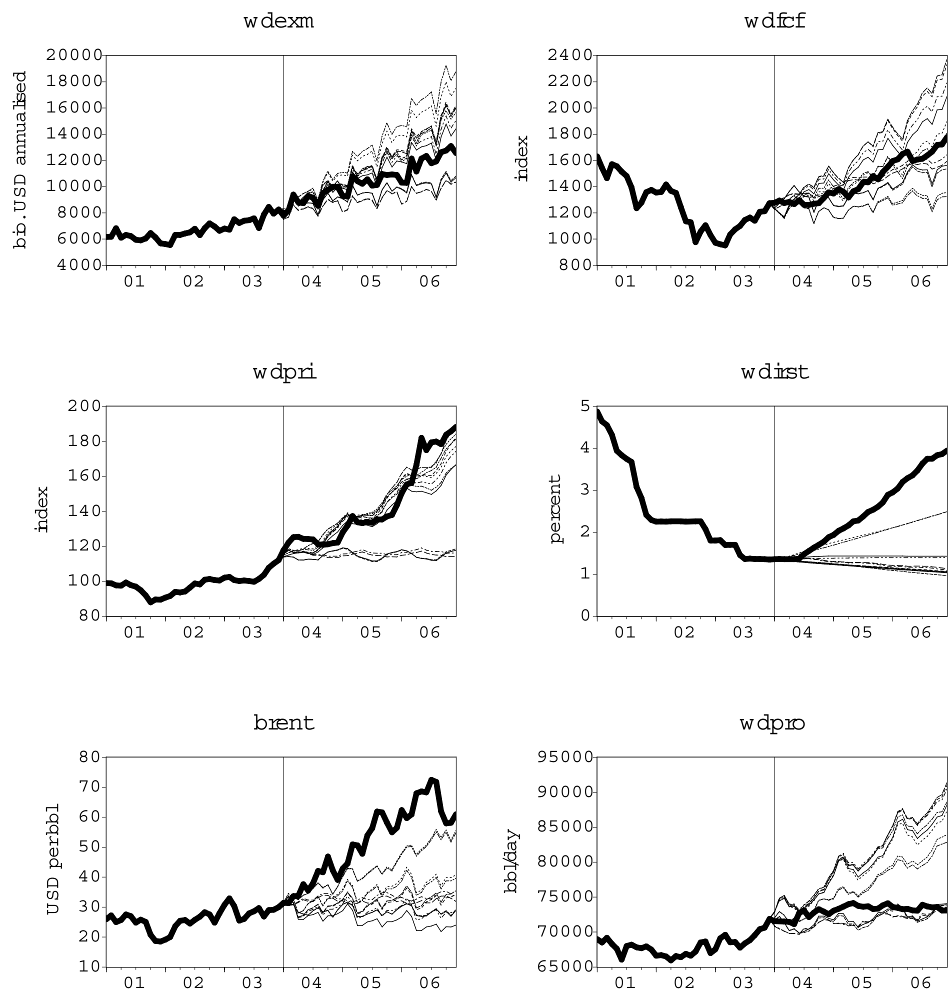
$$MSPE_h = \frac{1}{n}\sum[\frac{Y_t - Y_t^f}{Y_t}]^2, RMSPE = \sqrt{MSPE} \tag{20}$$

where Y_t is the observed data in time t and Y_t^f is the forecast in time t. This

Table 2: DGPs

DGP's		lag order		rank		ICs	
		SS1	SS2	SS1	SS2	SS1	SS2
AR-DX	*wdexm*	4	4			-3.826	-3.777
	wdfcf	13	13			-3.131	-3.108
	wdpri	14	14			-4.740	-4.654
	wdirst	3	3			-3.868	-4.012
	brent	14	14			-1.885	-1.799
	wdpro	13	13			-5.345	-5.609
AR-DDX	*wdexm*	13	13			-3.945	-3.955
	wdfcf	12	12			-3.114	-3.091
	wdpri	13	13			-4.711	-4.646
	wdirst	2	6			-3.876	-4.046
	brent	12	12			-1.813	-1.758
	wdpro	12	12			-5.283	-5.548
VAR-DX		3	2			-21.500	-21.813
VAR-DDX		2	2			-21.316	-21.557
ECM-X		2	2	2,d	2,d	-19.101	-19.232
ECM-DX		2	2	2,b	2,b	-21.546	-21.795

note: b=no deterministic trend in the data, and an intercept but no trend in the cointegrating equation; d=linear trend in the data, and an intercept and a trend in the cointegrating equation.



note: the bold line is the observed data, the other plots are forecasts.

Figure 12: Forecasting results

method is only useful for series with small relative changes, which is the case here.

Figure 13 shows the development of the percentage deviations of the forecast from the observed data set (RSPE) in respect to an increasing time horizon. The first column of Figure 13 shows the RSPEs, which result from the forecasts generated from the four ARs. The second and third column contains the RSPEs of the four VARs and the ECMs. The horizontal line is the 20 percent deviation of the forecast from the observed data. At a first glance, one can see, that the RSPE is relatively low in the first year. This applies for all forecasts. The RSPE increases when h increases, resulting in higher RSPEs in most of the cases.

More detailed information on forecasting biases are reported in the Tables 3 to 6. The tables contain the RMSPEs for the individual years and for the whole forecasting period. The tables also contain averages of the RMSPEs across all types of DGPs and across variables. (Clements & Hendry 2002) suggest that combining forecasts adds value, and can even dominate the best individual device. The authors show that simple rules for combining forecasts, such as averages with equal weights, often is in line with more elaborate rules based on the relative past performance of the forecasts to be combined.[4]

When comparing the forecasting performance of the different DGP-types, it was found that at the beginning of the forecasting horizon the AR-DDXs, with fixed or re-estimated coefficients, generate the best results. The percentage deviation from the observed data set accounts in both cases only 5.9 percent. This outcome supports the view, that AR-DDXs in second differences have a better performance after a break compared to models in first differences. Such breaks occurred in the cases of *wdpri* and *brent* at the beginning of the forecasting horizon. The VAR-DX-rolling with a deviation of

[4]There are a number of explanations for this. First, if two models provide partial, but completely overlapping, explanations, then some combinations of the two might do better than either alone. In particular, if two forecasts are differently biased (one upwards, one downwards). Secondly, in non-stationary time series, most forecasts will fail to move in the same direction when forecasting over a period within which a break unexpectedly occurs. Combination is unlikely to provide a substantial improvement over the best individual forecasts in such a setting. However, what will occur when forecasting after a deterministic shift depends on the extent of model miss-specification, data correlation, the size of the breaks and so on, so combination may help. Thirdly, averaging reduces the variance to the extent that separate sources of information are used. Since all models are differently mis-specified, such variance reduction remains possible.

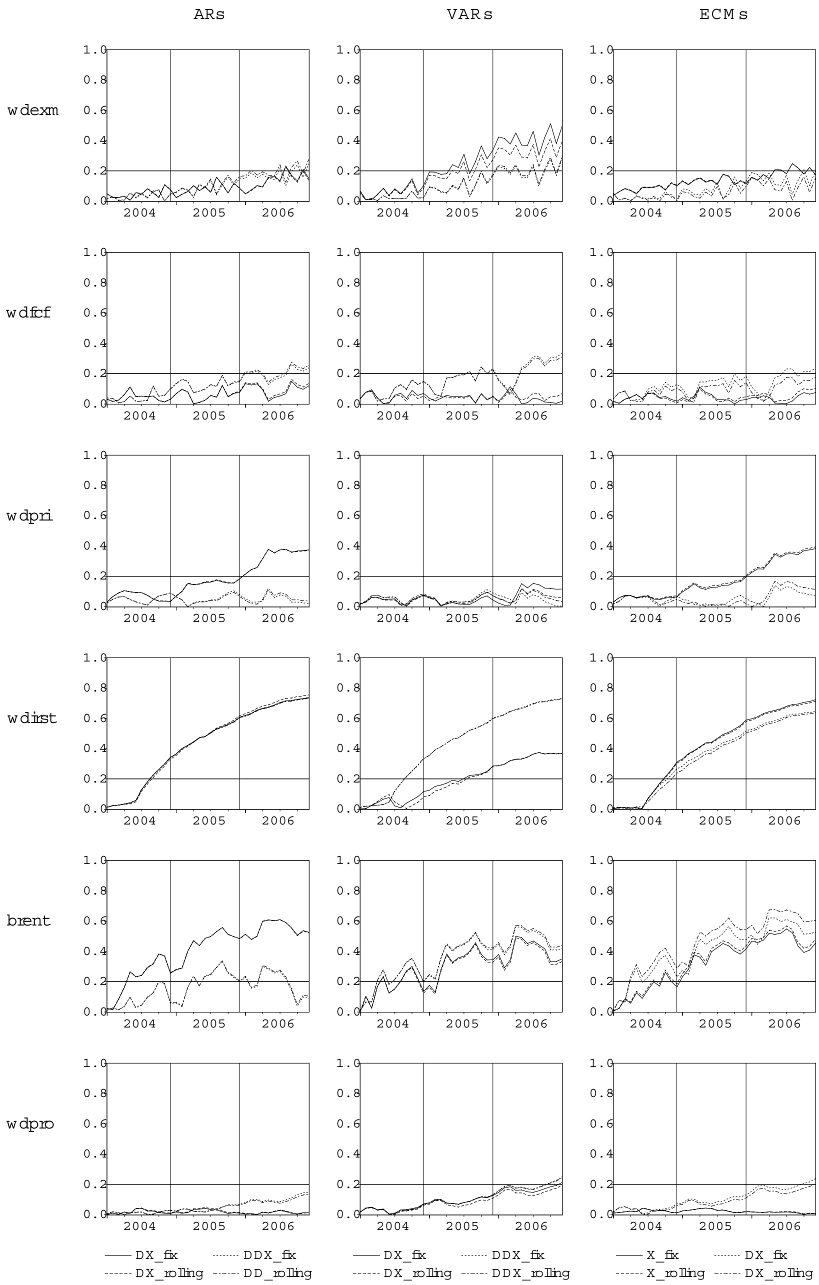


Figure 13: Root squared percentage errors (RSPEs)

6.3 percent generates the second best result, followed by the ECM-X-fix with deviation of 7.1 percent. However, when the forecasting horizon increases the VAR-DX-rolling starts to outperform the AR-DDXs. For the whole time span 2004 to 2006, on average, the VAR-DX-rolling generates the smallest RMSPE in particular because this model is able to forecast the turning point of $wdirst$ at the beginning of the forecasting horizon correctly. The second best result delivers the AR-DDX-fix.

Comparing the forecasting performance of the ECMs, it was found that the forecasting ability of the ECM-DX-rolling outperforms the ECM-X when the forecasting horizon increases. This outcome is in line with the view of (Hendry 2006), that ECMs based on a data set in differences outperform ECMs based on data sets in levels. The result also is in line with the outcome of the IC model selection procedure (Table 2), where the ECM-DX is supposed to be the best approximating model.

When comparing the RMSPE from all models based on fixed and recursive coefficient estimates it turned out that both methods deliver similar results, which is an indication for stability. The results also suggest, that the pooling of forecasts as recommended by (Clements & Hendry 2002) is not applicable here, because all forecasts have similar biases, in particular when forecasting the variables $wdirst$ and $brent$.

If one intends to generate forecasts for the unknown future, say from January to December 2006, a simple AR-DDX would be a sufficient device. When forecasting two or three years ahead, the VAR-DX-rolling would generate the best forecasting results.

8 Conclusion

The external sector of an open economy like Austria is closely linked to the development of global flows of goods and capital. Hence, the intention of this empirical analysis is to make the forecasting of the external sector of one country simpler. A top-down approach has been developed, which means, that first the global demand is subject to forecast. Then it depends on the competitiveness of the individual country how successful the external sector performs. Hence, the world is treated as a closed economy with its own business cycle. The theory suggests that investment activities and monetary policy influence the development of the business cycle. The oil price and other raw material prices also play a key role in the economic development

Table 3: RMSPE, first year

DGPs	*wdexm*	*wdfcf*	*wdpri*	*wdirst*	*brent*	*wdpro*	*avg.*	
AR-DX-fix	0.047	0.042	0.067	0.136	0.220	0.017	0.088	
AR-DX-rolling	0.048	0.043	0.068	0.128	0.220	0.018	0.088	
AR-DDX-fix	0.033	0.045	0.050	0.136	0.077	0.013	0.059	***
AR-DDX-rolling	0.034	0.044	0.050	0.137	0.078	0.013	0.059	***
VAR-DX-fix	0.067	0.052	0.044	0.046	0.162	0.035	0.068	
VAR-DX-rolling	0.061	0.044	0.045	0.040	0.159	0.029	0.063	
VAR-DDX-fix	0.025	0.086	0.048	0.127	0.204	0.032	0.087	
VAR-DDX-rolling	0.025	0.087	0.049	0.129	0.206	0.032	0.088	
ECM-X-fix	0.078	0.040	0.059	0.100	0.128	0.022	0.071	
ECM-X-rolling	0.081	0.035	0.062	0.097	0.139	0.023	0.073	
ECM-DX-fix	0.024	0.078	0.047	0.089	0.218	0.036	0.082	
ECM-DX-rolling	0.022	0.066	0.046	0.077	0.250	0.031	0.082	
Avg. of above	0.045	0.055	0.053	0.104	0.172	0.025	0.076	
Avg. of ARs	0.041	0.044	0.059	0.134	0.149	0.015	0.074	
Avg. of VARs	0.045	0.067	0.047	0.086	0.183	0.032	0.076	
Avg. of ECMs	0.051	0.055	0.054	0.091	0.184	0.028	0.077	
Avg. of fix	0.046	0.057	0.053	0.106	0.168	0.026	0.076	
Avg. of rolling	0.045	0.053	0.053	0.101	0.175	0.024	0.075	
Avg. of DX	0.064	0.043	0.058	0.091	0.171	0.024	0.075	
Avg. of DDX	0.027	0.068	0.048	0.116	0.172	0.026	0.076	

note: *** is the best forecasting model

Table 4: RMSPE, second year

DGPs	*wdexm*	*wdfcf*	*wdpri*	*wdirst*	*brent*	*wdpro*	*avg.*	
AR-DX-fix	0.080	0.058	0.148	0.493	0.454	0.022	0.209	
AR-DX-rolling	0.080	0.059	0.150	0.494	0.454	0.027	0.211	
AR-DDX-fix	0.096	0.128	0.053	0.492	0.204	0.040	0.169	
AR-DDX-rolling	0.105	0.129	0.048	0.490	0.208	0.037	0.170	
VAR-DX-fix	0.248	0.042	0.035	0.200	0.329	0.094	0.158	
VAR-DX-rolling	0.205	0.039	0.048	0.183	0.319	0.078	0.145	***
VAR-DDX-fix	0.103	0.167	0.052	0.484	0.400	0.093	0.217	
VAR-DDX-rolling	0.109	0.166	0.042	0.483	0.407	0.094	0.217	
ECM-X-fix	0.132	0.042	0.139	0.460	0.373	0.028	0.196	
ECM-X-rolling	0.135	0.039	0.148	0.453	0.392	0.029	0.199	
ECM-DX-fix	0.083	0.133	0.031	0.404	0.444	0.097	0.199	
ECM-DX-rolling	0.060	0.099	0.019	0.385	0.503	0.082	0.191	
Avg. of above	0.120	0.092	0.076	0.418	0.374	0.060	0.190	
Avg. of ARs	0.090	0.094	0.100	0.492	0.330	0.032	0.190	
Avg. of VARs	0.166	0.104	0.044	0.338	0.364	0.090	0.184	
Avg. of ECMs	0.103	0.078	0.084	0.426	0.428	0.059	0.196	
Avg. of fix	0.124	0.095	0.076	0.422	0.367	0.062	0.191	
Avg. of rolling	0.116	0.089	0.076	0.415	0.381	0.058	0.189	
Avg. of DX	0.147	0.047	0.111	0.381	0.387	0.046	0.186	
Avg. of DDX	0.093	0.137	0.041	0.456	0.361	0.074	0.194	

note: *** is the best forecasting model

Table 5: RMSPE, third year

DGPs	*wdexm*	*wdfcf*	*wdpri*	*wdirst*	*brent*	*wdpro*	*avg.*	
AR-DX-fix	0.142	0.095	0.333	0.689	0.553	0.012	0.304	
AR-DX-rolling	0.136	0.107	0.332	0.704	0.550	0.013	0.307	
AR-DDX-fix	0.174	0.201	0.047	0.688	0.188	0.105	0.234	
AR-DDX-rolling	0.196	0.214	0.055	0.684	0.197	0.095	0.240	
VAR-DX-fix	0.412	0.032	0.097	0.343	0.400	0.170	0.242	
VAR-DX-rolling	0.328	0.049	0.070	0.343	0.385	0.151	0.221	***
VAR-DDX-fix	0.198	0.236	0.046	0.683	0.473	0.191	0.305	
VAR-DDX-rolling	0.210	0.223	0.062	0.680	0.487	0.188	0.308	
ECM-X-fix	0.190	0.040	0.322	0.667	0.476	0.014	0.285	
ECM-X-rolling	0.190	0.060	0.332	0.659	0.497	0.014	0.292	
ECM-DX-fix	0.144	0.163	0.079	0.599	0.552	0.187	0.287	
ECM-DX-rolling	0.104	0.116	0.105	0.588	0.620	0.161	0.282	
Avg. of above	0.202	0.128	0.157	0.611	0.448	0.108	0.276	
Avg. of ARs	0.162	0.154	0.192	0.691	0.372	0.056	0.271	
Avg. of VARs	0.287	0.135	0.069	0.512	0.436	0.175	0.269	
Avg. of ECMs	0.157	0.095	0.210	0.628	0.536	0.094	0.287	
Avg. of fix	0.210	0.128	0.154	0.612	0.440	0.113	0.276	
Avg. of rolling	0.194	0.128	0.159	0.610	0.456	0.104	0.275	
Avg. of DX	0.233	0.064	0.248	0.568	0.477	0.062	0.275	
Avg. of DDX	0.171	0.192	0.066	0.654	0.420	0.155	0.276	

note: *** is the best forecasting model

Table 6: RMSPE, average from 2004 to 2006

DGPs	*wdexm*	*wdfcf*	*wdpri*	*wdirst*	*brent*	*wdpro*	*avg.*	
AR-DX-fix	0.089	0.065	0.183	0.439	0.409	0.017	0.200	
AR-DX-rolling	0.088	0.069	0.183	0.442	0.408	0.019	0.202	
AR-DDX-fix	0.101	0.124	0.050	0.439	0.156	0.053	0.154	
AR-DDX-rolling	0.112	0.129	0.051	0.437	0.161	0.049	0.157	
VAR-DX-fix	0.242	0.042	0.059	0.196	0.297	0.100	0.156	
VAR-DX-rolling	0.198	0.044	0.054	0.189	0.288	0.086	0.143	***
VAR-DDX-fix	0.109	0.163	0.049	0.431	0.359	0.105	0.203	
VAR-DDX-rolling	0.115	0.159	0.051	0.430	0.366	0.105	0.204	
ECM-X-fix	0.133	0.040	0.173	0.409	0.325	0.021	0.184	
ECM-X-rolling	0.135	0.045	0.181	0.403	0.343	0.022	0.188	
ECM-DX-fix	0.084	0.125	0.052	0.364	0.405	0.107	0.190	
ECM-DX-rolling	0.062	0.094	0.057	0.350	0.457	0.091	0.185	
Avg. of above	0.122	0.092	0.095	0.377	0.331	0.065	0.180	
Avg. of ARs	0.098	0.097	0.117	0.439	0.284	0.035	0.178	
Avg. of VARs	0.166	0.102	0.053	0.312	0.328	0.099	0.177	
Avg. of ECMs	0.104	0.076	0.116	0.382	0.383	0.060	0.187	
Avg. of fix	0.126	0.093	0.094	0.380	0.325	0.067	0.181	
Avg. of rolling	0.118	0.090	0.096	0.375	0.337	0.062	0.180	
Avg. of DX	0.148	0.051	0.139	0.346	0.345	0.044	0.179	
Avg. of DDX	0.097	0.132	0.052	0.409	0.317	0.085	0.182	

note: *** is the best forecasting model

and there is a co-movement among oil consumption and global output.

The development of this set of variables has been explained by ARs and small-scale VARs and ECMs. Assuming independency it was found, that each variable sufficiently could be explained by its past development. If one also considers the interrelation of the variables, the appropriate DGPs to use are unrestricted VARs in first or second differences or ECMs in levels and first differences. When estimating such models, the determination of the lag length and the rank has been based on ICs.

For the DGPs under consideration the forecasts of *wdexm*, $wdfcf$ and *wdpro* point into the same direction as the observed data. Regarding the world commodity prices (*wdpri*) only a few DGPs could forecast the strong upturn of time series from 2003 onwards. Also only few DGPs were capable to forecast the turning point in the development of the interest rates. Most of the DGPs could not predict the sharp upturn of the oil price in the years 2004 to 2006.

When comparing the forecasting performance of the different DGP-types, it was found that at the beginning of the forecasting horizon the AR-DDXs, with fixed or re-estimated coefficients, generate the best results. The percentage deviation from the observed data set accounts in both cases only 5.9 percent. This outcome supports the view, that DGPs in second differences have a better performance after a break compared to models in first differences. Such breaks occurred in the cases of *wdpri* and *brent* at the beginning of the forecasting horizon. The VAR-DX-rolling with a deviation of 6.3 percent generates the second best result, followed by the ECM-X-fix with deviation of 7.1 percent. However, when the forecasting horizon increases the VAR-DX-rolling starts to outperform the AR-DDXs. For the whole time span 2004 to 2006, on average, the VAR-DX-rolling generates the smallest RMSPE in particular because this model is capable of forecasting the turning point of $wdirst$ at the beginning of the forecasting horizon correctly. The AR-DDX-fix delivers the second best result. According the RMSPEs, the ECMs do not deliver competitive results in particular because the models are not able to forecast *brent* correctly. Comparing the forecasting performance of the ECMs, it was found that the forecasting ability of the ECM-DX-rolling outperforms the ECM-X when the forecasting horizon increases. This outcome is in line with the view of (Hendry 2006) that ECMs based on a data set in differences outperform ECMs based on data sets in levels.

When comparing the RMSPEs from DGPs with fixed and re-estimated coefficients it turned out that both methods deliver similar results, which is an indication for stability. The results also suggest, that the pooling of forecasts as recommended by (Clements & Hendry 2002) is not applicable here, because all forecasts have similar biases, in particular when forecasting the variables *wdirst* and *brent*.

If one intends to generate forecasts for the unknown future, say from January to December 2007, a simple AR-DDX would be a sufficient device, in particular when breaks occurred at the end of the observation period. When forecasting two or three years ahead, the VAR-DX-rolling appears to be the best approximating DGP.

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