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UNIFIED GERMANY AND THE EURO AREA

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CONTENTS

Abstract

In this paper we compare alternative approaches for the construction of time series of macroeconomic variables for Unified Germany prior to 1991, and then use them for the construction of corresponding time series for the euro area. The resulting series for Germany and the euro area are compared with existing ones on the basis of both descriptive statistics and results of econometric analyses conducted with the alternative time series. We find that more sophisticated time series methods for backdating can yield sizeable gains.

Key words: Backdating, Factor Model, Unified Germany, Euro Area

JEL Classification: C32, C43, C82.

Non-technical summary

After the introduction of the euro, the attention of macroeconomists and policy makers is focusing more and more on explaining and monitoring the behaviour of euro area macroeconomic variables. This requires the availability of long enough time series, which makes the results of econometric and economic analyses informative and accurate.

Typically, euro area variables are constructed as (possibly weighted) averages of the corresponding time series of the single member countries. A major problem for this approach is represented by the German unification, whose effects are often either not taken into consideration or addressed with simple methods. In this paper we apply more sophisticated techniques to backdate German data prior to the re-unification. Specifically, based on the empirical results in Angelini, Henry and Marcellino (2006), two approaches are particularly promising in this context: Chow and Lin (1971) type of procedures or factor based approaches.

The idea underlying both methods is to regress the series of interest, which contains missing observations at the beginning of the sample, on a set of series covering the whole sample. The parameters of the regression are computed over the (possibly short) sample where both the target series and the regressors are available. The estimated parameters are then used jointly with the values of the regressors to provide estimates of the missing observations in the series of interest.

When the set of potentially significant explanatory variables is large (compared with the sample size), a pre-selection has to be made, and it can be based on the correlation of the target series with the regressors computed over the sample when both the target and the regressors are available. An alternative procedure to overcome the curse of dimensionality problem is to model the large amount of available information with a factor model, where all variables are driven by a limited number of common factors, and use the estimated factors as regressors.

In our context, we have collected about 20 real variables and 30 nominal variables for West Germany, while the estimation sample is of 15 observations (or less when dynamics is taken into account). Therefore, we preselect (at most) five or six West German regressors based on their correlation with the series of interest for unified Germany, or use (at most) three or four factors estimated from the set of nominal or real West German series. We have also considered univariate and multivariate time series models (AR and VAR) for the unified German series and applied the Kalman smoother to backdate the missing observations. This is basically equivalent to reverting the order of the observations in the time series and compute dynamic forecasts for them with a forecast horizon from h=1 to h=84 (to recover quarterly data in the '70s and '80s). However, this approach has two key problems in our context. First, due to the small sample available, the estimators of the parameters of dynamic models can be substantially biased. Second, due to stationarity, the dynamic forecasts converge rather soon to the unconditional mean of the variables so that, for example, the backdated values for the '70s and early '80s are all equal. The latter problem is particularly relevant in a univariate context, but it is also partly present in a VAR framework.

The empirical results indicate that the variables used in the Chow-Lin procedure have the highest explanatory power for the unified Germany inflation and GDP growth series after 1991, which suggests that the Chow-Lin backdated series could be the most reliable in this context. However, a bootstrap experiment highlights the good performance also of the factor based backdated series, even when the data are generated with a Chow-Lin type of mechanism.

We then consider VARs for growth, inflation and a short term interest rate, where early values for the first two variables are backdated in several ways. We then evaluate whether or not results concerning model specification, Granger causality, impulse response analysis and forecasting are affected by the choice of a specific backdating method. It turns out that there are some interesting differences related with the choice of the backdating procedure. In particular, when the Chow-Lin approach is adopted, a restrictive monetary policy shock significantly decreases growth, while the effect is not statistically significant with the other types of backdated series. Moreover, forecasts for growth and inflation after 1999 are more accurate when using the Chow-Lin backdated series for the '70s and '80s. Interestingly, the worst forecasting performance is achieved when estimation starts in 1991, i.e. observations prior to German re-unification are completely discarded, which highlights the importance of using a longer sample combined with a proper backdating procedure.

We then use the Chow-Lin and factor based backdated series for unified Germany to construct euro area GDP and inflation series prior to 1991. We again compare the resulting series on the basis of descriptive statistics, and of the coefficients, impulse response functions and forecasts in a VAR for growth, inflation and a short term interest rate. The descriptive analysis indicates that, while the differences for inflation are minor, the series for growth currently used in the area wide model has a higher mean. As a consequence, the cumulated growth for the euro area over the period 1970-1991 is about 80% based on the latter, but only about 60% with the Chow-Lin or factor based series. The pattern of peaks and troughs in the levels of GDP is instead similar.

Another interesting finding is that VAR forecasts for euro area growth over the period 1999-2004 are more accurate with the Chow-Lin than with the series used in the area wide model, the gains in terms of mean squared forecast error are about 20%. These gains are associated with parameter constancy in the growth equation of the VAR when estimated with the Chow-Lin backdated series, while stability is rejected in favour of a break in 1991:2 (when the backdated and actual series are joined) for estimation with the area wide model series or the factor based series.

Finally, we summarize the results obtained when backdating several other macroeconomic variables for Germany and the euro area. In particular, we focus on the components of aggregate demand (private consumption, investment, imports, exports, and government consumption), and on their associated deflators. We then compare the performance of our reconstructed time series for the euro area in VAR analysis, for forecasting, and to estimate some of the equations in a forward looking version of the area wide model. Overall, in this context the factor based method seems to produce the most reliable results for backdating.

1 Introduction

After the introduction of the euro, the attention of macroeconomists and policy makers is focusing more and more on explaining and monitoring the behaviour of euro area macroeconomic variables. This requires the availability of long enough time series, which makes the results of econometric and economic analyses informative and accurate.

Typically, euro area variables are constructed as (possibly weighted) averages of the corresponding time series of the single member countries. A major problem for this approach is represented by the German unification, whose effects are often either not taken into consideration or addressed with simple methods. For example, in the well know area wide dataset prepared by Fagan, Henry and Mestre (2001, FHM) for the estimation of an area wide model, and later used in a vast range of empirical macroeconomic analyses on the working of euro area, the series for unified Germany are obtained by just rescaling those for West Germany. Similarly, in the German block of the ESCB multi-country model (Vetlov and Warmedinger (2006)), West Germany data are used prior to 1991 and united Germany data after 1991, combined with a step dummy variable to account for the unification. Perhaps, the simple treatment of the unification problem is based on the economic reasoning that the East Germany economy accounted for only about 10% of unified Germany (in real GDP terms) in 1991. However, from an econometric point of view, an improper treatment of the problem can introduce a substantial measurement error, which in turn can bias all the results of the analysis. [1]

In this paper we propose to apply more sophisticated techniques to backdate German data prior to the re-unification. Specifically, based on the empirical results in Angelini, Henry and Marcellino (2006), two approaches are particularly promising in this context: Chow and Lin (1971) type of procedures or factor based approaches.

The idea underlying both methods is to regress the series of interest, which contains missing observations at the beginning of the sample, on a set of series covering the whole sample. The parameters of the regression are computed over the (possibly short) sample where both the target series and the regressors are available. The estimated parameters are then used jointly with the values of the regressors to provide estimates of the missing observations in the series of interest. The key assumption is that the parameters remain stable over time. While this assumption is questionable, and unfortunately untestable, it is strictly required for the estimation of the missing observations. Notice also that additional accounting constraints, e.g. that the sum of the levels of GDP for East and West Germany must add up to the level of GDP for unitied Germany, cannot be imposed prior to 1991 because of lack of data for East Germany.

In our context, the sample size is 1970:1-1994:4, data for West Germany are available over the whole sample while data for unified Germany after 1991 only, so that the overlapping sample contains 16 observations (15 for growth rates). Data for West Germany are no longer available after 1994, which constraints the length of the overlapping period.

When the set of potentially significant explanatory variables is large (compared with the sample

[1] The construction of euro area time series presents other problems, not considered in this paper to focus on the main issue of German unification, such as the proper choice of a weighting scheme or the treatment of seasonality, see e.g. Beyer, Doornik and Hendry (2001), Bruggemann and Lutkepohl, H. (2006).

size), a pre-selection has to be made, and it can be based on the correlation of the target series with the regressors computed over the sample when both the target and the regressors are available.

An alternative procedure to overcome the curse of dimensionality problem is to model the large amount of available information with a factor model, where all variables are driven by a limited number of common factors, and use the estimated factors as regressors. Specifically, Angelini et al. (2006) suggested to estimate the factors using the Stock and Watson (2002a, 2002b) principal component based estimator. Under some mild technical conditions, see Bai and Ng (2006), factor estimation creates no generated regressor problems, and the estimated factors are good substitutes for the unknown true factors.

In our context, we have collected about 20 real variables and 30 nominal variables for West Germany, described in the Data Appendix, while the estimation sample is of 15 observations (or less when dynamics is taken into account). Therefore, we preselect (at most) five or six West German regressors based on their correlation with the series of interest for unified Germany, or use (at most) three or four factors estimated from the set of nominal or real West German series. Similar choices performed well in the simulation experiments of Angelini et al. (2006) and in their empirical applications.

We have also considered univariate and multivariate time series models (AR and VAR) for the unified German series and applied the Kalman smoother to backdate the missing observations. This is basically equivalent to reverting the order of the observations in the time series and compute dynamic forecasts for them with a forecast horizon from h=1 to h=84 (to recover quarterly data in the '70s and '80s). However, this approach has two key problems in our context. First, due to the small sample available, the estimators of the parameters of dynamic models can be substantially biased. Second, due to stationarity, the dynamic forecasts converge rather soon to the unconditional mean of the variables so that, for example, the backdated values for the '70s and early '80s are all equal. The latter problem is particularly relevant in a univariate context, but it is also partly present in a VAR framework.

In Section 2 we present the results for unified Germany GDP growth and inflation (measured as the growth rate of the GDP deflator). We compare the Chow-Lin and factor based backdated series with those by FHM on the basis of descriptive statistics, and present the results of a bootstrap experiment that is helpful to evaluate the relative merits of the alternative backdating methods. The empirical results indicate that the variables used in the Chow-Lin procedure have the highest explanatory power for the unified Germany inflation and GDP growth series after 1991, which suggests that the Chow-Lin backdated series could be the most reliable in this context. However, the bootstrap experiment highlights the good performance of the factor based backdated series, even when the data are generated with a Chow-Lin type of mechanism.

We also consider VARs for growth, inflation and a short term interest rate, where early values for the first two variables are backdated in several ways. We then evaluate whether or not results concerning model specification, Granger causality, impulse response analysis and forecasting are affected by the choice of a specific backdating method. It turns out that there are some interesting differences related with the choice of the backdating procedure. In particular, when the Chow-Lin approach is adopted, a restrictive monetary policy shock significantly decreases growth, while the effect is not statistically significant with the other types of backdated series. Moreover, forecasts for growth and inflation after 1999 are more accurate when using the Chow-Lin backdated series for the '70s and '80s. Interestingly, the worst forecasting performance is achieved when estimation starts in 1991, i.e. observations prior to German re-unification are completely discarded, which highlights the importance of using a longer sample combined with a proper backdating procedure.

In Section 3 we use the Chow-Lin and factor based backdated series for unified Germany to construct euro area GDP and inflation series prior to 1991. We again compare the resulting series with those by FHM on the basis of descriptive statistics, and of the coefficients, impulse response functions and forecasts in a VAR for growth, inflation and a short term interest rate. The descriptive analysis indicates that, while the differences for inflation are minor, the FHM series for growth has a higher mean. As a consequence, the cumulated growth for the euro area over the period 1970-1991 is about 80% based on the FHM series, but only about 60% with the Chow-Lin or factor based series. The pattern of peaks and troughs in the levels of GDP is instead similar.

Another interesting finding is that VAR forecasts for euro area growth over the period 1999-2004 are more accurate with the Chow-Lin than with the FHM series, the gains in terms of mean squared forecast error are about 20%. These gains are associated with parameter constancy in the growth equation of the VAR when estimated with the Chow-Lin backdated series, while stability is rejected in favour of a break in 1991:2 (when the backdated and actual series are joined) for estimation with either the FHM or the factor based series.

In Section 4 we summarize the results obtained when backdating several other macroeconomic variables for Germany and the euro area. In particular, we focus on the components of aggregate demand (private consumption, investment, imports, exports, and government consumption), and on their associated deflators.

We then compare the performance of the FHM data and of our reconstructed time series for the euro area in VAR analysis, for forecasting, and to estimate some of the equations in a forward looking version of the area wide model of FHM. Overall, in this context the factor based method seems to produce the most reliable results for backdating.

Finally, in Section 5 we review the main findings of the paper and conclude.

2 Backdating GDP growth and inflation for unified Germany

In this Section we provide an overview of the methodology for backdating unified Germany time series, discuss the properties of alternative backdated series for inflation and GDP growth, evaluate the relative merits of the different proposals in a Monte Carlo experiment, and analyze the results of common empirical analysis using the backdated unified Germany time series.

2.1 An overview of the methodology

We assess four methods for backdating data, which exploit an increasing amount of information.

First, we consider the value of GDP growth and of (the GDP deflator) inflation for West and unified Germany in 1991:2, say $y^{WG}_{1991:2}$ and $y^{UG}_{1991:2}$, and construct the weight

$$w_L = \frac{y^{UG}_{1991:2}}{y^{WG}_{1991:2}}. \tag{1}$$

Then, we backdate the values for y_t^{UG} using the simple formula

$$y_t^{UG} = w_L y_t^{WG}, \tag{2}$$

for t=1970:1,...,1991:1. We will refer to this method as y^{WEFIX}, for fixed weight.

A modified version of this simple method is used by FHM to backdate the German series that are later used in the construction of the euro area variables. Specifically, in the case of GDP growth, they calculate the weight starting from the levels of the variables in 1991:1 (rather than the growth rate), namely

$$w_{FHM} = \frac{y\_lev_{1991:1}^{UG}}{y\_lev_{1991:1}^{WG}}. \tag{3}$$

Then, they backdate the level of GDP for unified Germany as

$$y\_lev_t^{UG} = w_{FHM} y\_lev_t^{WG}, \tag{4}$$

for t=1970:1,...,1991:1, and use it to compute the growth rate of GDP. Notice that equation (4) implies that the growth rate of unified Germany prior to 1991 is equal to that of West Germany (which in turn is equal to growth in East Germany), while with (2) the growth rates can differ, which can be more plausible from an economic point of view. While the correlation of the FHM GDP growth series with y^{WEFIX} is larger than 0.90 in absolute value, we will see later on that their method can substantially overestimate the level of GDP for Unified Germany prior to 1991, and also that of the euro area.[2]

The second backdating method we consider requires to estimate by OLS a regression of y^{UG} on y^{WG} over the sample 1991:2-1994:4:

$$y_t^{UG} = \alpha + \beta y_t^{WG} + e_t, \tag{5}$$

and to compute the backdated values as

$$y_t^{UG} = \widehat{\alpha} + \widehat{\beta} y_t^{WG}, \tag{6}$$

for t=1970:1,...,1991:1. We will refer to this method as y^{CLFIX}. Notice that both y^{WEFIX} and y^{CLFIX} are a linear combination of y^{WG}, though with different weights, so that they will be perfectly correlated. However, the latter can be expected to produce better results, since the weight is constructed using information over four years rather than on a single quarter.

Third, we estimate by OLS a regression of y^{UG} on x^{WG}, over the sample 1991:2-1994:4, where x^{WG} includes a few macroeconomic variables for West Germany, selected among a larger set of regressors on the basis of their correlation with y^{UG}:

$$y_t^{UG} = \alpha + \beta_1 x_{1t}^{WG} + \beta_2 x_{2t}^{WG} + ... + \beta_j x_{jt}^{WG} + e_t. \tag{7}$$

The backdated values are calculated as

$$y_t^{UG} = \widehat{\alpha} + \widehat{\beta}_1 x_{1t}^{WG} + \widehat{\beta}_2 x_{2t}^{WG} + ... + \widehat{\beta}_j x_{jt}^{WG}, \tag{8}$$

[2] For inflation, FHM backdate nominal and real GDP series as described above, take their ratio that gives the GDP deflator, and compute its growth rate.

for t=1970:1,...,1991:1. We will refer to this method as y^{CL}, since it is similar to the Chow and Lin's (1971) proposal for interpolation. The previous method, y^{CLFIX}, can be considered as a simplified version of this one, where the set of regressors is fixed and only contains y^{WG}.

Finally, we estimate by OLS a regression of y^{UG} on f^{WG}, over the sample 1991:2-1994:4, where f^{WG} includes a few factors estimated using the Stock and Watson (2002a, 2002b) method applied to a set of macroeconomic variables for West Germany (the same set from which x^{WG} is chosen). The regression becomes:

$$y_t^{UG} = \alpha + \beta_1 f_{1t}^{WG} + \beta_2 f_{2t}^{WG} + ... + \beta_k f_{kt}^{WG} + e_t, \tag{9}$$

and the backdated values are computed as

$$y_t^{UG} = \widehat{\alpha} + \widehat{\beta}_1 f_{1t}^{WG} + \widehat{\beta}_2 f_{2t}^{WG} + ... + \widehat{\beta}_k f_{kt}^{WG}, \tag{10}$$

for t=1970:1,...,1991:1. We will refer to this method as y^{DFM}, since the factors are estimated assuming a dynamic factor model for the set of available regressors for West Germany. Following the same line of reasoning as in Stock and Watson (2002a, 2002b) in a forecasting context, the fact that the estimated rather than the true factors are used in the procedure does not affect the quality of the fit of the regression, at least asymptotically, see also Bai (2003) and Bai and Ng (2006).

Notice that the factor based procedure is similar to that underlying y^{CL}, but the set of regressors is different. The relative performance of the two methods will depend on whether y^{UG} is related to all the available regressors (which cannot all be used since their number is larger than the number of observations in the sample period), or to just a small subset of them. In the former case y^{DFM} is expected to be the best, in the latter y^{CL}. Angelini et al. (2006) provide some simulation results on this intuitive result in a related context.

The information on y^{UG} after 1991 is not directly exploited in the construction of the backdated values. However, y^{UG} can be added to x^{WG} to form an unbalanced panel (since the early observations on y^{UG} are missing), and the factors can be extracted from this unbalanced panel using an EM algorithm developed by Stock and Watson (2002a, 2002b). Basically, in the first step the procedure computes y^{DFM} using x^{WG} only; then y^{DFM} is added to set of regressors in x^{WG}, factors are re-extracted, y^{DFM} is computed with the new set of factors, a new set of values for y^{UG} are obtained, and they are used to construct another balanced panel, another set of factors, etc. The procedure is repeated until the estimates of the factors do not change substantially in successive iterations. However, the simulation results in Angelini et al. (2006) indicate that this method does not yield any gains with respect to the basic factor approach when the percentage of missing observations in the y series is substantial, as in our context.

It is worth mentioning that all the regression models we have considered are static. In principle dynamics can be included, but the specification and estimation of a dynamic model for y^{UG} with only 15 observations is unreliable. Moreover, as we will see in more details in the next subsection, there is no evidence of serial correlation in the errors of the models (7), and (9), even though the results of the tests should be interpreted with care because of the small sample size.

Whenever the levels of the variables are of interest, they can be obtained by back-cumulation of the backdated growth rates, starting with the actual level values for unified Germany in 1991:1.

Finally, it is worth commenting on a common procedure to handle the problem of German reunification, namely, the use of West Germany data prior to 1991 and united Germany data after 1991, combined with the inclusion of a dummy variable in the model of interest, see e.g. the German block of the ESCB multi-country model (Vetlov and Warmedinger (2006)). In our notation, this corresponds to the equation

$$y_t^w = \alpha + \beta_0 D_t + \beta_1 x_{1t}^w + \beta_2 x_{2t}^w + ... + \beta_j x_{jt}^w + e_t, \tag{11}$$

where D_t is a step dummy whose value is 0 before 1990:4 (or 1991:1 for growth rates) and 1 afterward, while w is WG before 1990:4 (or 1991:1 for growth rates) and UG afterwards. Hence, the hypothesis is that (only) the growth rate of the variables can change after the unification. However, since the estimate of the parameter β_0 is model dependent, the effects of the unification are also made model dependent, while with any of the backdating methods that we have considered a single series for united Germany is produced and used in any later econometric analysis. This seems to be preferable from an economic point of view, but the dummy method could still produce good results from an empirical point of view, and we will also consider this issue in subsection 2.5.

2.2 Some preliminary results

We have collected a set of series for West Germany over the sample 1970-1994, at the quarterly level, to be used for the implementation of the backdating procedures described in the previous section. For backdating (the GDP deflator) inflation we have 31 series, for GDP growth 22 series. They are listed and described in the Data Appendix and we will refer to them as to the nominal and real variables for West Germany, respectively. The 31 nominal variables include series such as deflators for GDP, private and government consumption, investment, exports and imports, total Producer Price Index (PPI) and sectorial breakdowns, different measures of cost of living, Wholesale Price Index (WPI), compensation per employees, average earnings and unit labour costs. The 22 real variables are GDP and its components, total industrial production and sectorial breakdowns, retail sales, employment and the unemployment rate, and surveys such as business confidence and production expectations.

A first issue to be considered is whether the nominal and real variables for West Germany can be well represented by a factor model, i.e., whether they can be well summarized by a few principal components. Table 1 reports the percentage of variance explained by each principal component, the cumulative proportion of explained variance, and the eigenvalues associated with each principal component. The first principal component explains 31% of the total variance of the 31 nominal series, a values that increases to about 50% for the 22 real variables. The drop in the size of the eigenvalues and in the percentage of the explained variance indicates that the information in the nominal series can be well summarized by four principal components (the cumulated percentage of explained variance is about 77%), by just three components for the real series (the cumulated percentage of explained variance is about 78%).

Overall, these results indicate that West Germany time series can indeed be summarized by a few factors, estimated as the first three or four principal components of the variables. While more sophisticated statistical criteria could be used for the determination of the number of factors, e.g.

Bai and Ng (2002), due to the relatively small sample size we prefer to rely on the descriptive analysis of variance reported above.

The second issue we consider is whether the nominal and real West Germany series are correlated with the unified Germany inflation and GDP growth, over the overlapping period 1991:2-1994:4, for a total of 15 quarters. From Table 2, there are, respectively, 19 and 20 West Germany time series whose correlation with unified Germany inflation or GDP growth is higher than 0.30 in absolute value. Unfortunately, since there are only 15 observations in the overlapping time period, not all these variables can be used as regressors in the Chow-Lin type backdating procedure. Therefore, we have selected the five West German series most correlated with unified German inflation, and the six series most correlated with GDP growth. Adding or excluding one or two variables from these sets, or basing their selection on the partial correlation with the target, does not substantially alter the empirical results reported below. Notice also that the fact that many time series are correlated with the target variable indicates that the factor based backdating approach can be particularly suited in this context.

Finally, in Table 3 we summarize the results from the estimation over the period 1991:2-1994:4 of the models (5), (7), and (9), which relate the unified Germany variables to either the corresponding variable for West Germany, or to the few most correlated West German variables, or to the estimated factors. Five comments can be made. First, over such a short sample it is not possible to test for the presence of a unit root in the variables, and therefore we assume, based on economic theory, that the variables are stationary. When this hypothesis is tested over the period 1970-1991 using West German series, it is not rejected by ADF tests with BIC lag length selection at the 10% levle. Second, in all models the regressors are significant at the 10% level, which justifies their use in the backdating procedure. Moreover, the significance of other regressors in addition to the corresponding West Germany variable (e.g. in addition of West Germany inflation in the equation for united Germany inflation) implies that backdating methods based on a simple rescaling of the corresponding West German variable are inefficient. Third, the goodness of fit is best for the models with few German variables, which indicates that the Chow-Lin type procedure could produce the best results. However, we will see that the results of the Monte Carlo experiment on the ranking of the backdating methods are less clear cut. Fourth, the p-values of an LM test for no correlation in the residuals do not reject this hypothesis, which provides support in favour of the static specification of the models (5), (7), and (9). Finally, along the lines of Boivin and Ng (2006) in a forecasting context, the factor analysis can be based only on the West Germany time series whose correlation with Unified Germany inflation or GDP growth is higher than a given value, say 0.30, in absolute value. We find that variable pre-selection improves the performance of the factor-based approach, for example, the adjusted R^2 of equation (9) increases. However, the ranking of the alternative backdating procedures emerging from the subsequent analysis is basically unaffected.

2.3 Inflation and GDP growth for unified Germany

The four alternative backdated series for unified Germany inflation and GDP growth are graphed in Figures 1 and 2, respectively, while Table 4 presents descriptive statistics.

First, notice that y^{WEFIX} and y^{CLFIX} are perfectly correlated, as noted before, since they are obtained with a fixed weight multiplied for the West German series. However, in the case of GDP growth, the weight is negative for y^{WEFIX}, since in the first quarter of 1991 there was positive growth in West Germany but overall negative growth in unified Germany. As a consequence, most of the backdated y^{WEFIX} values are negative, which is not credible. Therefore, we will focus on y^{CLFIX} in the comparison. Fagan et al. (2001) adopt a slightly different approach: they calculate the weight starting from the levels of the variables in 1991:1 (rather than the growth rate), backdate the level of GDP for unified Germany, and use it to compute the growth rate. The result is very similar to y^{CLFIX}, the correlation of the two series is larger than 0.95.

Overall, the correlation of the alternative backdated series is high, the lowest value is about 0.79 for inflation (between y^{CLFIX} and y^{DFM}) and 0.78 for GDP growth (between y^{CL} and y^{DFM}). This is confirmed by the fact that the first principal component explains about 89% of the variability of the four inflation series, 88% for GDP growth. The mean and ranges of the variables are also similar. However, the median value for GDP growth is rather smaller according to y^{CL}, and the variable is more volatile. Moreover, y^{CLFIX} is less volatile for both inflation and GDP growth, since it is based on a single regressor.

The persistence of the inflation series, measured by the estimated coefficient in an AR(1) model, ranges from -0.14 for y^{CL} to 0.016 for y^{CLFIX} (it is 0.05 with the original Fagan et al. (2001) data), but the values are never statistically different from zero. The corresponding range for GDP growth is wider, from a strongly statistically significant -0.33 for y^{DFM} to a non significant 0.05 for y^{CL} (it is -0.05 and not significant with the original Fagan et al. (2001) data).

The differences in the dynamics of the backdated growth series are then reflected in the levels of GDP, which are graphed in Figure 3. While the overall pattern is the similar and peaks and troughs appear to happen around the same dates, the fluctuations are much more marked with y^{CL}, which also presents a substantial slowdown over the period 1983-1987.

Overall, y^{CL} and y^{DFM} appear as more reliable backdated series. There appear to be some interesting differences across the two methods for backdating GDP growth, less so for inflation, but even for the latter variable the values are sometimes significantly different across the alternative backdated series, e.g. around 1974-75.

2.4 A bootstrap experiment

To evaluate the relative performance of the Chow-Lin and factor based backdating approaches in our context, we now conduct a Monte Carlo experiment, similar to those in Angelini et al. (2006) but specifically designed to mimic the features of our empirical application.

The variable to be backdated is labeled y_t^o while the set of variables to be used as regressors are grouped into the vector X_t. We consider two different generating mechanisms (DGMs):

$$\begin{aligned} X_t &= \Lambda F_t + e_t, \\ y_t^o &= \beta' F_t + \varepsilon_t, \end{aligned} \tag{12}$$

and

$$\begin{aligned} X_t &= \Lambda F_t + e_t, \\ y_t^o &= \beta' Z_t + \varepsilon_t. \end{aligned} \tag{13}$$

In the first specification (12) both the y and the X variables are generated by a factor model. The number of factors is set equal to 3 for GDP growth and 4 for inflation. The factors are generated as independent AR(1) processes with roots equal to those obtained in the empirical application, the elements of Λ and β are kept fixed at the values obtained in the empirical application, while the error terms e_t and ε_t are independent draws from a normal distribution with zero mean and variances equal to the estimated values in the empirical application. In the second specification (13) $Z_t = (x_{1t}, ..., x_{kt})'$, where $k = 5$ for inflation and $k = 6$ for GDP growth, so that y depends on some of the variables in X rather than on the factors.

When the DGM is (12) we expect the factor based approach to be the best, but the Chow-Lin method should also perform well since the number of regressors is larger than the number of factors, so that the former can provide a good approximation for the latter. When the DGM is (13) the Chow-Lin method is expected to generate the lowest loss function, but the factor based backdating approach could also perform well when the factors have a high explanatory power for the Z variables, since the model for y_t^o in (13) can be written as:

$$y_t^o = \beta' S \Lambda F_t + \beta' S e_t, + \varepsilon_t,$$

where S is a selection matrix such as

$$S = \begin{pmatrix} 1 & 0 & 0 & ... & 0 \\ 0 & 1 & 0 & ... & 0 \\ 0 & 0 & 1 & ... & 0 \end{pmatrix}.$$

In our context with a small sample size for the estimation of the β parameters, the factor method could even outperform the Chow-Lin approach since it is based on a more parsimonious model for y.

The sample size and the number of observations of y to be backdated are set equal to those in the empirical application, i.e., to 99 and 84 respectively. For each of the four experiments (GDP growth or inflation, DGM is (12) or (13)) we run 1000 replications, and rank the estimators on the basis of the average absolute and mean square backdating error (MAE and MSE, respectively). We also compute percentiles of the distribution of the absolute and mean square disaggregation error, which provides additional information on the robustness of the performance of the estimators.

The results are reported in Table 5 and the picture is fairly similar for inflation and GDP growth. In particular, when the generating mechanism is DFM there are sizeable gains from the use of the factor approach for backdating compared to CL. When instead the DGM is of the Chow-Lin type, the two backdating procedures generate very similar losses. The DFM could be even slightly better for GDP growth when evaluated on the basis of the average RMSE and MAE, but this finding is due to a few outliers and CL is the best on the basis of the median RMSE and MAE. As mentioned, the good performance of the DFM approach, even with the Chow-Lin type of DGM, is due to the use of a more parsimonious model in the presence of a very short estimation sample.

Overall, the results of the Monte Carlo experiments, combined with the high correlation of the backdated variables when using the actual series, suggest that the data are likely generated by a Chow-Lin type of DGM, and we have seen that in this case it is indeed difficult to discriminate between the two backdating procedures.

2.5 Using the backdated series

We now analyze the effects of using different backdated series in common empirical analyses. The starting point is a VAR for unified Germany, using inflation, GDP growth and a short term interest rate. The latter is taken from the dataset used for the Fagan et al. (2001) area wide model, while for inflation and GDP growth we compare three cases: y^{CL}, y^{DFM} and the series used by Fagan et al. (2001), which will be labeled y^{FHM}. The estimation sample is 1970:1-2004:2, and the series for growth and inflation only differ over the period 1970:1-1991:1.

For the choice of the lag length of the VAR we compare the outcome of three criteria: the final prediction error (FPE), the AIC and the Schwarz criterion. They are reported in Table 6, for up to eight lags. The FPE and AIC indicate four lags when using either FHM or DFM, five for CL. The Schwarz criterion, which assigns a higher premium to parsimony, suggests two lags for all types of backdated inflation and GDP growth. Overall, there are no major differences with respect to the choice of the lag length across the three types of backdated variables. Since several fourth lags of the variables are statistically significant in the different VARs, we will proceed with a VAR(4) specification for all the three cases.

In Table 7 we summarize the estimation results for the three VARs. In each case, the explanatory power is largest for the interest rate, intermediate for inflation and lowest for GDP growth. Ranking the equations across backdating methods on the basis of the AIC and Schwarz criteria, FHM produces the lowest loss for the interest rate (where the dependent variable is the same across equations), DFM for inflation and GDP growth (but the DFM dependent variables have also the smallest variances). At the system level, the DFM is associated with the lowest value of AIC and Schwarz criteria, and with the highest likelihood.

In Table 8 we report the results of Granger causality tests, which indicate some interesting differences across the three VARs. Specifically, while inflation is never significant in the growth equation, for DFM output growth is also not significant in the inflation and interest rate equations, while it is strongly significant with FHM and CL.

We can also use the estimated VARs to compute the response of the three variables to a monetary policy shock. The latter is identified with a Choleski orthogonalization, where the interest rate is ordered last. The economic rationale is that monetary policy can react to contemporaneous output and inflation shocks, in line with a simple version of the Taylor rule, while output and inflation react with at least a one period delay to the monetary shock. The impulse response functions are reported in the first three panels of Figure 4. The major difference across VARs is in the reaction of output growth, which is stronger and significantly negative after 3-4 quarters when using the CL backdated variables, an important finding for monetary policy. In the fourth panel of Figure 4 we report the impulse response functions from a VAR (with BIC lag length selection equal to 4) where the West and united Germany series are simply joined, and a step dummy is inserted into the model to take the unification into account. There are no major differences in the reaction of output and inflation, which closely resemble those for the CL case.[3] In the final panel of Figure 4 we report the response functions from a VAR (with BIC lag length selection equal to 4) estimated after unification

[3] Actually, the correlation of the joined series and of the CL series over the whole sample are 0.86 for GDP growth and 0.90 for inflation.

only. In this case the pattern of the reaction of output is similar, while the impact effect on inflation becomes negative but still not statistically significant. Moreover, the size of the responses is fairly different, reflecting the fact the size of the interest rate is different (smaller) when computed after 1991. However, as we will see, the forecast performance of this model is in general inferior to that of the other models, so that there results should be interpreted with care.

An additional interesting topic to be analyzed is whether there is a structural break in the VAR equations in 1991:2, when the backdated series are joined with the original ones. In Table 9 we report the outcome of Chow tests for the null hypothesis of constant parameters in the equations of the VARs based on the FHM, CL and DFM methods. The null hypothesis of parameter stability is never rejected at the 5% significance level, except for the DFM inflation equation.

Finally, we evaluate the (one-step ahead) forecasting performance of the VARs specified with the three different types of backdated variables. The forecast period is 1999-2004, so that the target variable is the same in the three VARs and the root mean squared forecast error (RMSE) and mean absolute forecast error (MAE) are directly comparable across the VARs. We also add a fourth VAR, which is estimated over the shorter sample starting in 1991, so that only actual values for unified Germany are used. This is interesting to evaluate whether longer time series but with backdated data produce more accurate forecasts than shorter time series with only actual values.

The RMSE and MAE for forecasting GDP growth, inflation and the interest rate are reported in Table 10. CL is the best for both growth and inflation, with the forecasts based on the shorter sample of actual values being the worst in these two cases, with losses of about 40% with respect to CL. For the interest rate CL is instead the worst, with FHM being the best and the forecast based on the short sample a close second best. The overall disappointing performance of DFM forecasts is in line with the results of the Granger causality tests, which indicated more non-causality for this choice of backdated series.

In summary, based on the fit of the equations, the absence of structural breaks and the superior forecasting performance of the resulting VAR, the CL backdated time series seem to represent the best choice for unified Germany inflation and GDP growth. These findings are also in line with the good explanatory power of the West Germany variables underlying the CL approach for the unified Germany inflation and growth over the overlapping period 1991-94. The simulation results appear to favour on average the DFM approach over CL, in particular for inflation, but this outcome could be due to the different loss function used in the Monte Carlo experiments (the mean squared or absolute backdating error) and the fact that they do not take into account the uncertainty on the loadings of the factors, the Λ matrix. The empirical results also indicate that the choice of the backdating procedure matters, both for estimation and inference, and for the computation of impulse response functions, and for forecasting.

3 Euro area series for GDP growth and inflation

3.1 Constructing the series

To construct euro area series for GDP growth and inflation based on alternative measures for unified Germany, we subtract from the Fagan et al. (2001) euro area series the values that they have used for unified Germany and add the values that we have obtained in the previous Section, using their weight for Germany. The resulting four alternative euro area inflation and GDP growth series are graphed in Figures 5 and 6, respectively, with also the original Fagan et al. (2001) variables. Table 11 presents descriptive statistics on the five versions of each variable.

The descriptive statistics for inflation are very similar across the different definitions of the variables, and the persistence is also stable (the range is 0.79-0.85). These results are not surprising given that the lowest correlation across the series is 0.992 and the first principal component explains more than 995% of the variability of all the five inflation series.

In the case of GDP growth, the correlation values remain very high, about 0.95 (with the exception of y^{WEFIX} for the reason mentioned in Section 2), and the first principal component explains about 89% of the variability of all the series, even more if y^{WEFIX} is excluded. However, the descriptive statistics indicate that both the mean and the median of the FHM euro area GDP growth series are substantially higher then those obtained with the alternative series for Germany. The persistence in different series is also fairly different, the range is 0.18-0.38.

The higher mean of the Fagan et al. (2001) euro area GDP growth is then reflected in the levels of GDP, which are graphed in Figure 7. The overall pattern is similar, and peaks and troughs appear to happen around the same dates, but the FHM series is much steeper than the alternative ones, the cumulated growth is about 80% versus 60% of the other series. This is quite important since most "great ratios" in economics, such as the saving rate or the investment ratio, are based on the levels of GDP. We will see in the following Section that this result is mostly due to the Consumption component of GDP, while the other components are fairly similar across backdating method.

Overall, there are only minor differences in the alternative series for area wide inflation resulting from the alternative backdated series for unified Germany, while there are substantial differences in the growth rate of GDP, which is higher in the FHM series underlying the Fagan et al. (2001) area wide model. As expected, this pattern reflects that for the backdated unified German series.

3.2 Using the backdated series

As for unified Germany, the starting point of our investigation of the effects of using alternative euro area series is the formulation of a VAR for inflation, GDP growth and a short term interest rate. This is, for example, a subset of the variables analyzed using the FHM data in Peersman and Smets (2003).

The estimation sample is 1970:1-2003:1, for which the Fagan et al. (2001) series are available and can be used as a benchmark to compare what happens when using the y^{CL} and y^{DFM} series for unified Germany.

In Table 12 we compare the outcome of the final prediction error (FPE), the AIC and the Schwarz criterion for lag length selection. The Schwarz criterion indicates again two lags for all types of euro area inflation and GDP growth, while FPE and AIC are minimized by either two or three lags. However, again several fourth lags of the variables are statistically significant in the different VARs, so that we maintain a VAR(4) specification also for the three euro area VARs.

In Table 13 we provide some information on the estimated VARs. As for Germany, the explanatory power is largest for the interest rate, but now similar results are obtained for inflation while the adjusted R^2 of the growth equations remains low, the range is 0.17 for DFM to 0.28 for CL. Ranking the three equations for each variable on the basis of the AIC and Schwarz criteria, FHM produces the lowest loss for the interest rate and inflation, DFM for GDP growth. At the system level, as in the case of Germany, the DFM based VAR generates the lowest value of AIC and Schwarz criteria, and the highest likelihood.

In Table 14 we report the p-values of Granger causality tests, which do not reject the null hypothesis of no causality for inflation in the interest rate equation, for inflation in the growth equation (except for CL), and for growth in the inflation equation only for DFM. Therefore, the regressors are "mostly" significant in the CL VAR, which suggests that the latter could also perform well in forecasting.[4]

In terms of forecasting, the RMSE and MAE in Table 15a, suggest that there are minor differences for inflation (as expected since all the euro area inflation series are highly correlated), minor differences for interest rates (again, the series for this variable are equal), but serious losses from the use of the FHM series for forecasting euro area GDP growth, over 20%, with CL performing slightly better than DFM.

The better forecasting performance for GDP growth of CL than DFM and, in particular, of the FHM euro area series could be due to the presence of structural breaks in the estimated equation. In fact, the Chow test for no break in 1991:2, whose p-values are presented in Table 16, does not reject the null hypothesis only for the CL growth equation. Instead, the hypothesis of constant parameters in the inflation and interest rate equations is never rejected.

Another issue that deserves investigation in a forecasting context is whether simpler univatiate AR models can provide even better forecasts, see e.g. Marcellino (2006) for supporting evidence on this for US inflation and GDP growth. In Table 15b we report forecasts based on AR(4) models for inflation and AR(2) models for GDP growth (the third and fourth lags are never significant). Indeed, the forecasts are systematically better in terms of RMSE and MAE than those based on the VAR models. Moreover, there are small differences across the backdating methods, the lowest loss for inflation is achieved by simply dropping data prior to 1991, and this method is comparable with the use of CL data for growth.

Finally, comparing the impulse response functions of growth, inflation and interest rate to a monetary policy shock, obtained from the three VARs, only minor differences emerge, see Figure 8. The differences are also minor both when using joined West and unified Germany series to construct euro area data with a step dummy included into the VAR (fourth panel of the Figure), and when starting estimation in 1991 after the German reunification. However, in the latter case, as for Germany, there is a substantial reduction in the size of the monetary shock, but also a deterioration in the forecasting performance of the model with respect to the other VARs, in particular for the interest rate (see Table 15a).

In summary, the results in this Section indicate that the construction of the German inflation series to be included in the corresponding euro area variable is not particularly important, in the sense that euro area inflation series incorporating different values for German inflation are highly correlated and the results related to estimation, inference and forecasting are fairly similar. Instead,

[4] Similar results are obtained with a VAR(2), the preferred choice based on the Schwarz criterion.

there are sizeable differences for GDP growth, and in the VAR context the CL backdated series for Germany produce the best results in terms of stability of the parameters of the growth equation, significance of the other variables in this equation, and forecasting performance. Even slightly more accurate forecasts can however be constructed, based on AR models estimated after 1991.

4 Other euro area series

In this Section we comment on the construction and use of other backdated unified Germany and, in particular, euro area series. Specifically, we focus on the components of aggregate demand (private consumption, PCE, investment, ITR, imports, MTR, exports, XTR, and government consumption, GCR), and on their associated deflators (respectively, PCD, ITD, MTD, XTD and GCD).

4.1 Constructing the series

As for GDP growth and inflation, we consider a few alternative backdating procedures for each of the five demand components and their deflators: y^{WEFIX}, which is based on a simple rescaling of the corresponding West German variable in 1991:1, y^{CLFIX}, where the rescaling is based on the coefficient of a regression of the unified Germany on the corresponding West Germany time series over 1991-1994, y^{CL}, where the West German series mostly correlated with each unified Germany variable are combined using regression based weights, and y^{DFM}, where the factors estimated from a set of West German real or nominal variables using principal component analysis are combined to produce the backdated unified Germany series of interest. To this set we add the backdated series used by FHM, which are derived with a procedure similar to that for y^{WEFIX}.

Then, we subtract from the FHM euro area series the values they have used for unified Germany and add, in turn, y^{WEFIX}, y^{CLFIX}, y^{CL}, and y^{DFM}. The resulting variables are labeled AW-X-M, where X is PCE, ITR, MTR, etc, and M is WEFIX, CL, etc. The original FHM variables are labeled AWPCE, AWITR, AWMTR, etc. For the sake of brevity, we focus on the comparison of the euro area variables.

Tables 17a and 17b report descriptive statistics on the five versions of each of the five euro area real and nominal variables. Starting with the real variables, from Table 17a the main differences across methods are for consumption. Both the mean and the median values are smaller for AWPCECL and AWPCEDFM than for the FHM AWPCE, and the cumulated growth over 1970-1991 is 18 points smaller for AWPCECL than for AWPCE (21 points smaller when measured over 1970-2003). Lower average growth values are obtained also for imports and exports, but they compensate so that the differences across backdating methods in terms of next exports are not very large. The average values for investment and government consumption are also similar, but the CL and DFM series are less volatile than the original DFM series. Therefore, the differences in area wide GDP growth backdated series emerging from the analysis of Section 3 are mostly due to the consumption component.

About the WEFIX and CLFIX series, the former produce unreliable values for PCE, XTR and MTR, while the latter are fairly similar to the CL variables.

A principal component analysis of the five backdated series for each variable reveals that one component is sufficient to capture most of the variance of all series, even more so when CLFIX and WEFIX are dropped from the analysis. Correlation coefficients provide a similar picture.

For the five deflators, the descriptive statistics of the original FHM series and of the y^{CL} and y^{DFM} are fairly similar for PCD and GCD, see Table 17b, mimicing the results for the GDP deflator. Instead, the average and median growth of ITD, MTD and XTD are lower for y^{CL} and y^{DFM} than for FHM, and the volatility is also lower. In the case of the deflators, y^{WEFIX} and y^{CLFIX} also yield similar results to y^{CL} and y^{DFM}.

Finally, we evaluate how much commonality there is across the euro area real variables as a group, and the group of nominal variables (backdated as in FHM, CL or DFM). We model each set of five real or nominal variables by means of a factor model and, following Stock and Watson (2002a, 2002b), we estimate the factors as the first principal components of the variables. While the method was developed for a large number of variables, it typically performs well also for a small number of series. As an alternative, this can be just considered as an analysis of variance exercise.

From Table 18a, the first principal component explains between 62% (CL) and 70% (DFM) of the variability of the five real variables, with an intermediate value of 66% for the FHM series. The second component explains between 18% and 23%. The major drop in the eigenvalue associated with the first and second component suggests that one component could be sufficient, i.e. that a one factor model can be a proper representation for the five variables independently of the backdating method.

From Table 18b, even larger values are obtained for the five nominal variables, the range is between 78% for CL and 83% for FHM, with 79% for DFM. Therefore, a one factor model can provide a proper specification also for the deflators of the demand components.

The estimated factors, i.e. the first principal components extracted from the real and nominal variables, will be used later on in a forecasting exercise for euro area GDP growth and inflation.

4.2 Using the backdated series

We start this subsection on the consequences of the use of the alternative backdated euro area series in empirical analysis by modelling each set of real and nominal variables as a VAR. This is an interesting exercise since it allows to model the dynamic interactions among the demand components or their deflators. As in the previous analysis of euro area GDP growth and inflation, the estimation sample is 1970:1-2003:1 since the publicly available FHM series end in 2003.

The comparison of the FPE, AIC and Schwarz criteria for the choice of the lag length of the VAR for the real variables, reported in Table 19a, indicates one or even zero lags, and the outcome is the same across the different versions of the euro area time series. There is substantial concordance across backdating procedures also for the nominal variables, but in this case the FPE and AIC indicate four lags while the Schwarz criterion just one. For the sake of simplicity and comparability, we will consider a VAR(1) for each version of both the real and nominal variables.

The estimation results of the VAR(1) for each version of the five real and nominal variables are summarized in Table 20. For the real variables, the adjusted coefficients of determination are systematically higher for the DFM equations, the estimated standard deviation of the errors are lower, and the AIC and Schwarz criteria are lower both equation by equation and for the VAR as a whole. For the nominal variables the results are more varied, with the highest adjusted R^2 for the FHM versions of GCD, ITD and XTD and the DFM versions of MTD and PCD, but the differences across methods are in general small. Similar differences across variables emerge for the standard deviation of the residuals and information criteria, while at the system level the DFM VAR is again associated with the highest likelihood and lowest AIC and Schwarz criteria.

Overall, the DFM series appear to produce the best results in terms of fit when used in a VAR context.

In Tables 21a and 21b we report the results of Granger causality tests, which in our VAR(1) framework are basically t-tests and F-tests for the significance of each regressor and of all of them into the equations for each of the five real or nominal variables. The Tables show that there are marked differences both in the t-tests and in the F-tests across alternative backdated euro area series. For example, the regressors are jointly statistically significant for FHM and CL Government Consumption, but not for DFM. On the contrary, the regressors are strongly statistically significant for DFM PCE, but not for FHM or CL. These findings indicate that the choice of the backdating method can substantially alter the dynamic relationships across the variables, and those based on the more sophisticated CL or DFM methods can be more reliable. The estimation results indicate that the DFM euro area series could be the best choice in this context.

The second exercise we consider is the use of the estimated factors extracted from the different versions of the real and nominal variables for forecasting (one-step ahead) euro area GDP growth and inflation. Specifically, we regress each (different version of each) variable on one lag of the (corresponding version of the) real and nominal principal components. We also include in the comparison a model estimated after 1991, with principal components also estimated with data after 1991, so that there are no backdating problems but at the cost of using a shorter sample. In all cases the forecast sample is 1999-2003, as in Section 3 and such that all the series of GDP growth and inflation become the same. The resulting root mean square error (RMSE) and mean absolute error (MAE) are reported in Table 22.

For GDP growth the lowest RMSE and MAE are produced by the DFM backdated time series, with gains of about 20% with respect to the FHM series. For inflation, the best approach appears to be to start estimation after 1991. However, from Table 15, the best forecasting models for GDP growth and inflation remain those based on the univariate AR models estimated either after 1991 or with CL data.

The final exercise we consider to evaluate the role of alternative backdated series is estimation of a key equation in the area wide macroeconomic model, the Investment equation. We consider a specification similar to that in the forward looking area wide model currently under evaluation at the ECB (in particular, see Sgherri (2006)). It is derived assuming profit maximization subject to three constraints. First, a Cobb-Douglas production function with constant returns to scale,

$$Y_t = a_t K_{t-1}^{s_k} L_t^{1-s_k}, \tag{14}$$

where a represents total factor productivity, K the capital stock, L labor, and s_k the share of capital. Second, an equation derived from the standard capital accumulation identity, which indicates the required investment to maintain the capital stock at the optimal level,

$$I_t = (g + \delta) K_{t-1}, \tag{15}$$

where I is investment, g is the equilibrium growth rate and δ the depreciation rate. Third, a law of motion for the capital stock,

$$K_t = \left[1 - A\left(\frac{I_t}{I_{t-1}} - (1+g)\right)\right] I_t + (1-\delta)K_{t-1}, \tag{16}$$

where $A(.)$ is the adjustment cost function defined as

$$A_t = \frac{\chi}{2}\left[\frac{I_t}{I_{t-1}} - (1+g\right]^2 I_{t-1}, \tag{17}$$

with χ measuring the size of the adjustment costs.

The solution is an Investment equation of the type

$$\frac{I_t}{I_{t-1}} = \frac{1}{1+\eta}E\left(\frac{I_{t+1}}{I_t}\right) + \frac{\eta}{1+\eta}\left(\frac{I_{t-1}}{I_{t-2}}\right) + \frac{\chi}{1+\eta}\left[\frac{I_{t-1}}{Y_{t-1}} - \frac{s_k(g+\delta)(1+g)}{(r+\delta+\phi)}\right], \tag{18}$$

where r is the real interest rate, ϕ a possibly non zero premium, and in equilibrium it is

$$\frac{s_k Y(1+g)}{K} = (r+\delta+\phi). \tag{19}$$

For estimation, we use the specification

$$\frac{I_t}{I_{t-1}} = \frac{1}{1+\eta}E\left(\frac{I_{t+1}}{I_t}\right) + \frac{\eta}{1+\eta}\left(\frac{I_{t-1}}{I_{t-2}}\right) + \frac{\chi}{1+\eta}\left[\frac{I_{t-1}}{Y_{t-1}} - \frac{.413895(g_t+0.01)(1+g_t)}{(r_{t-1}+0.01+0.01231)}\right] + dummies + e_t, \tag{20}$$

where the values for s_k, g_t, and ϕ are obtained from the other equations of the model. Since the expected value of the future dependent variable appears as a regressor, we substitute it with its true values, and estimate the parameters with GMM, with a proper correction to take into account autocorrelated and possibly heteroskedastic errors. The instrument set includes the dummies plus the first three lags of nominal short-term interest rate, quarterly inflation, real wages, investment-to-output ratios, employment-to-output ratios, gross changes in investment and employment.

Estimation results are reported in the columns of Table 23 for, respectively, the FHM, Chow-Lin and factor based data. The most interesting result is that with the Chow-Lin data the null hypothesis $\eta = 0$ cannot be rejected, so that a pure forward looking specification is supported by these data. However, the same hypothesis is rejected by both the FHM and the factor based data, and the latter provide the best fit in terms of standard deviation of the equation residuals.

In summary, interesting differences across backdating methods emerge also for the demand components and their deflators, both in terms of descriptive statistics for the variables, and for the results of subsequent econometric analyses using the backdated series. For the demand components and their deflators, the factor based backdated values appear to be the most reliable.

5 Conclusions

In this paper we have considered two main alternative approaches for backdating macroeconomic time series for unified Germany prior to 1991. The former, based on Chow-Lin (1971), uses information on a limited number of West Germany variables that are highly correlated with those for unified Germany over the sample 1991-94 and are also available prior to 1991. The latter, relies on the same principle but using information from a larger set of macroeconomic variables for West Germany, summarized by a few estimated factors.

The descriptive statistics indicate that the alternative backdated inflation series for unified Germany are fairly similar, while there are some differences for GDP growth. In particular, there are more marked fluctuations in the Chow-Lin series, which also presents a substantial slowdown over the period 1983-1987. When the backdated series are used in subsequent econometric analyses, the fit of the equations, the absence of structural breaks, the pattern of the impulse response functions and the superior forecasting performance suggest that the Chow-Lin backdated time series represent the best choice for unified Germany inflation and GDP growth.

The backdated German time series are also quite important for the construction of historical data for the euro area. Our findings indicate that the construction of the German inflation series to be included in the corresponding euro area variable is not particularly important, in the sense that euro area inflation series incorporating different backdated values for German inflation are highly correlated, and the results related to estimation, inference and forecasting are fairly similar. Instead, there are sizeable differences for GDP growth, and the Chow-Lin backdated series for Germany produces the best results at the euro area level, in terms of stability of the parameters of the growth equation in a VAR for GDP growth, inflation and the short term interest rate; significance of the other variables in this equation; and forecasting performance.

The same procedures can be adopted to backdate other German and euro area real and nominal variables, and we have considered in details the demand components and their associated deflators. In this case, the results are more varied but, overall, the factor based approach to backdating appears to produce better results.

For all the variables that we have considered, the simple approach of realigning the unified German series to those of West Germany with a fixed weight produces the worst results in terms of fit and forecasts. This finding highlights the importance of the adoption of more sophisticated backdating methods, even though in some cases, e.g. for forecasting inflation, it can be sufficient to use simple univariate AR models estimated with post German re-unification data.

To conclude, it is worth mentioning that the implementation of the backdating methods that we propose in this paper is simple, and that the same methods can be also applied to backdate the variables of the new actual and potential members of the euro area, such as Slovenia, for which long historical macroeconomic time series are often not available.

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Data Appendix

Variables are denoted as follows: DEWB stands for West Germany, DEU for unified Germany, AW for Area Wide, G denotes growth rates, and Q levels. Data sources are: the BIS for West Germany, since this database has the longest available balanced sample ending in 1994:4; Eurostat for unified Germany; an updated version of the Fagan et al. (2001) dataset for the euro area. Data is generally seasonally adjusted directly by the source, if not by X-11. Monthly data is aggregated to the quarterly frequency.

List of variables in price dataset

CEEDEWBG COST OF LIVING EXL. ENERGY (CEE)
CESDEWBG COST OF LIVING EXCL. SEASONAL FOODS (CES)
COCDEWBG COST OF LIVING CLOTHING AND FOOTWEARE (COC)
CODDEWBG COST OF LIVING OTHER DURABLE AND NON DURABLE GOODS (COD)
COEDEWBG COST OF LIVING GAS AND ELECTRICTY (COE)
COFDEWBG COST OF LIVING FOOD (COF)
COHDEWBG COST OF LIVING HOUSING AND GARAGE RENT (COH)
COLDEWBG COST OF LIVING (COL)
COPDEWBG COST OF LIVING SERVICES AND HEAALTH (COP)
CORDEWBG COST OF LIVING RECREATIONAL AND CULTURE (COR)
COSDEWBG COST OF LIVING SERVICES AND HOUSING (COS)
COTDEWBG COST OF LIVING PUBLIC TRANSPORT (COT)
ERNDEWBG HOURLY EARNINGS (ERN)
GCDDEWBG GOVERNMENT CONSUMPTION DEFLATOR
ITDDEWBG PRIVATE INVESTMENT DEFLATOR
MTDDEWBG IMPORTS DEFLATOR
PCDDEWBG PRIVATE CONSUMPTION DEFLATOR
PPIDEWBG PPI FINISHED GOODS
PPBDEWBG PPI OUTPUT AND BASIC PRODUCTION (PPB)
PPCDEWBG PPI OUTPUT CONSUMER GOODS (PPC)
PPFDEWBG PPI FARM PRODUCTS (PPF)
PPKDEWBG PPI CAPITAL GOODS (PPK)
PPMDEWBG PPI MANUFACTURING (PPM)
ULCDEWBG ULC
UWSDEWBG UNIT WAGE AND SALARY COSTS (UWS)
WINDEWBG COMP. OF EMPLOYEES
WPIDEWBG WPI
WURDEWBG WAGE RATES (WUR)
XTDDEWBG EXPORTS DEFLATOR
YEDDEUG GDP DEFLATOR

YEDDEWBG GDP DEFLATOR

List of variables in real dataset

CIDEWBQ BUSINESS CONFIDENCE AND BUSINESS CLIMATE INDUSTRY AND TRADE(BCI)

BCSDEWBQ BUSINESS CONFIDENCE BUSINESS CLIMATE EXCL FOOD AND BEVERAGES (BCS)

CARDEWBG CAR REGISTRATIONS (CAR)

GCRDEWBG GOVERNMENT CONSUMPTION

GDPDEUESAG REAL GDP

GDPDEWBG REAL GDP

ICCDEWBG IND'L PRODUCTION CONSTRUCTION (ICC)

ICGDEWBG IND'L PRODUCTION CONSUMER GOODS (ICG)

IKGDEWBG IND'L PRODUCTION CAPITAL GOODS (IKG)

IMMDEWBG IND'L PRODUCTION MINING (IMM)

IIPDEWBG IND'L PRODUCTION TOTAL (IIP)

IPCDEWBG IND'L PRODUCTION EXCL. CONSTRUCTION (IPC)

IPEDEWBG IND'L PRODUCTION ELECTRICITY AND GAS (IPE)

IPGDEWBG IND'L PRODUCTION BASIC AND PRODUCER GOODS (IPG)

IPMDEWBG IND'L PRODUCTION MANUFACTURING (IPM)

IPPDEWBG IND'L PRODUCTION AND REPAIR OF MOTOR VEHICLES (IPP)

ITRDEWBG PRIVATE INVESTMENT

LNNDEWBG TOTAL EMPLOYMENT

MTRDEWBG REAL IMPORTS

PCEDEWBG PRIVATE CONSUMPTION EXPENDITURE

PPSDEWBQ PRODUCTION EXPECTATIONS IN MANUFACTURING (PPS)

RSLDEWBG RETAIL SALES

UNRDEWBG UNEMPLOYMENT RATE

XTRDEWBG REAL EXPORTS

BCIDEWBQ BUSINESS CONFIDENCE AND BUSINESS CLIMATE INDUSTRY AND TRADE(BCI)

BCSDEWBQ BUSINESS CONFIDENCE BUSINESS CLIMATE EXCL FOOD AND BEVERAGES (BCS)

CARDEWBG CAR REGISTRATIONS (CAR)

GCRDEWBG GOVERNMENT CONSUMPTION

GDPDEUESAG REAL GDP

GDPDEWBG REAL GDP

ICCDEWBG IND'L PRODUCTION CONSTRUCTION (ICC)

Table 1: Principal Component Analysis of the West German Series

Nominal Variables						
	Comp 1	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
Eigenvalue	9,018	5,564	4,726	3,013	1,762	1,381
Variance Prop.	0,312	0,192	0,163	0,104	0,061	0,048
Cumulative Prop.	0,312	0,504	0,667	0,772	0,832	0,880

Real Variables						
	Comp 1	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
Eigenvalue	10,246	3,379	2,407	1,528	0,893	0,663
Variance Prop.	0,499	0,165	0,117	0,074	0,043	0,032
Cumulative Prop.	0,499	0,664	0,781	0,855	0,899	0,931

Note: The table reports the eigenvalues associated with each of the first size principal components, the percentage of variance explained by each component, and the actual percecntage of explained variance.

Table 2: Correlation of West German time series and Unified Germany inflation and GDP growth, 1991-1994

YEDDEUG	
IIPDEWBG	-0,49
CORDEWBG	-0,39
COTDEWBG	-0,29
PPBDEWBG	-0,21
COSDEWBG	-0,08
WPIDEWBG	-0,05
COEDEWBG	0,06
MTDDEWBG	0,08
PPFDEWBG	0,08
COHDEWBG	0,13
COLDEWBG	0,21
COFDEWBG	0,23
CEEDEWBG	0,24
XTDDEWBG	0,24
PCDDEWBG	0,27
PPMDEWBG	0,31
CESDEWBG	0,34
CODDEWBG	0,36
COPDEWBG	0,39
PPCDEWBG	0,39
WINDEWBG	0,42
PPIDEWBG	0,45
GCDDEWBG	0,51
COCDEWBG	0,53
ITDDEWBG	0,53
WURDEWBG	0,54
YEDDEWBG	0,57
PPKDEWBG	0,62
ULCDEWBG	0,74
ERNDEWBG	0,80
UWSDEWBG	0,82
YEDDEUG	1,00

GDPDEUESAG	
UNRDEWBG	-0,50
IPEDEWBG	0,12
BCIDEWBQ	0,24
IMMDEWBG	0,29
BCSDEWBQ	0,33
IPPDEWBG	0,33
LNNDEWBG	0,33
ICGDEWBG	0,34
PPSDEWBQ	0,35
XTRDEWBG	0,39
IKGDEWBG	0,50
PCEDEWBG	0,51
RSLDEWBG	0,54
IPMDEWBG	0,55
CARDEWBG	0,56
GCRDEWBG	0,57
IPCDEWBG	0,62
ICCDEWBG	0,64
MTRDEWBG	0,64
IPGDEWBG	0,66
ITRDEWBG	0,74
GDPDEWBG	0,87
GDPDEUESAG	1,00

See the Data Appendix, for complete series list and description.

Table 3: Regression models for Unified Germay, Inflation and GDP growth

Inflation			
Model	1	2	3
Regressors	YEDDEWBG	ERNDEWBG UWSDEWBG ULCDEWBG YEDDEWBG PPKDEWBG	PC1 PC2 PC3 PC4
F-test (p.value)	0,026	0,002	0,005
Adjusted R-squared	0,274	0,753	0,649
Schwarz criterion	1,428	0,704	0,980
Durbin-Watson stat	2,710	1,580	2,957
Breusch-Godfrey (p.value)	0,447	0,756	0,230

GDP Growth			
Model	1	2	3
Regressors	GDPDEWBG	GDPDEWBG ITRDEWBG IPGDEWBG MTRDEWBG IPCDEWBG ICCDEWBG	PC1 PC2 PC3
F-test (p.value)	0,00	0,00	0,08
Adjusted R-squared	0,73	0,87	0,29
Schwarz criterion	1,65	1,38	2,82
Durbin-Watson stat	1,70	1,91	1,80
Breusch-Godfrey (p.value)	0,36	0,33	0,03

Note: F-test (p.value) reports the p.value of an F-Test for the joint significance of the regressors.
Breusch Goodfrey (p.value) reports the p.value of the LM test for no correlation in the residuals up to order two.

See the Data Appendix, for complete series list and description.

Table 4: Descriptive statistics on alternative backdated series for Unified Germany Inflation and GDP Growth

Inflation	YEDCL	YEDCLFIX	YEDDFM	YEDWEFIX
Mean	0.98	0.98	0.97	0.94
Median	0.89	0.88	0.91	0.78
Maximum	2.99	3.09	3.39	4.30
Minimum	0.06	0.19	0.00	-0.32
Std. Dev.	0.55	0.44	0.59	0.70
Sum	80.96	81.56	80.76	78.42
Sum Sq. Dev.	24.95	16.08	28.57	40.62

GDP Growth	GDPCL	GDPCLFIX	GDPDFM	GDPWEFIX
Mean	0.25	0.30	0.28	-0.29
Median	0.21	0.40	0.33	-0.34
Maximum	3.91	2.80	3.43	1.14
Minimum	-2.83	-2.17	-3.00	-1.73
Std. Dev.	1.24	0.87	1.00	0.50
Sum	20.59	24.70	23.22	-23.71
Sum Sq. Dev.	125.71	62.24	81.67	20.69

Correlation Matrix	YEDCL	YEDCLFIX	YEDDFM	YEDWEFIX
YEDCL	1.00	0.84	0.82	0.84
YEDCLFIX	0.84	1.00	0.79	1.00
YEDDFM	0.82	0.79	1.00	0.79
YEDWEFIX	0.84	1.00	0.79	1.00

Correlation Matrix	GDPCL	GDPCLFIX	GDPDFM	GDPWEFIX
GDPCL	1.00	0.85	0.78	-0.85
GDPCLFIX	0.85	1.00	0.84	-1.00
GDPDFM	0.78	0.84	1.00	-0.84
GDPWEFIX	-0.85	-1.00	-0.84	1.00

Principal Component Analysis	Comp 1	Comp 2	Comp 3	Comp 4
Eigenvalue	1.18	0.10	0.05	0.00
Variance Prop.	0.89	0.07	0.04	0.00
Cumulative Prop.	0.89	0.96	1.00	1.00

Principal Component Analysis	Comp 1	Comp 2	Comp 3	Comp 4
Eigenvalue	3.09	0.27	0.14	0.00
Variance Prop.	0.88	0.08	0.04	0.00
Cumulative Prop.	0.88	0.96	1.00	1.00

Note: YEDCL is the GDP Deflator for Unified Germany backdated using the Chow-Lin method
YEDCLFIX is the GDP Deflator for Unified Germany backdated using the Chow-Lin method with fixed weight
YEDDFM is the GDP Deflator for Unified Germany backdated using the DFM method
YEDWEFIX is the GDP Deflator for Unified Germany backdated using a fixed weight
GDPCL is the GDP growth for Unified Germany backdated using the Chow-Lin method
GDPCLFIX is GDP growth for Unified Germany backdated using the Chow-Lin method with fixed weight
GDPDFM is the GDP growth for Unified Germany backdated using the DFM method
GDPWEFIX is the GDP growth for Unified Germany backdated using a fixed weight

Table 5: Monte Carlo results for Chow-Lin and factor-based backdating procedures

INFLATION

DFM generating process

MSE	average	0,05	0,25	0,5	0,75	0,95
DFM:	49,32	29,83	37,96	45,21	54,69	79,13
Chow-Lin:	68,23	38,19	49,28	61,16	79,45	118,03

MAE	average	0,05	0,25	0,5	0,75	0,95
DFM:	0,51	0,40	0,45	0,50	0,55	0,66
Chow-Lir	0,60	0,45	0,52	0,58	0,66	0,81

Chow-Lin generating process

MSE	average	0,05	0,25	0,5	0,75	0,95
DFM:	43,89	26,42	34,03	40,13	49,64	73,93
Chow-Lin:	43,32	22,98	30,51	38,44	50,23	80,60

MAE	average	0,05	0,25	0,5	0,75	0,95
DFM:	0,48	0,38	0,43	0,47	0,52	0,63
Chow-Lir	0,48	0,35	0,40	0,46	0,52	0,66

GDP Growth

DFM generating process

MSE	average	0,05	0,25	0,5	0,75	0,95
DFM:	44,04	28,44	35,69	41,55	49,25	66,72
Chow-Lin:	59,72	34,05	44,66	54,08	68,65	103,85

MAE	average	0,05	0,25	0,5	0,75	0,95
DFM:	0,48	0,39	0,44	0,48	0,52	0,61
Chow-Lir	0,56	0,42	0,49	0,54	0,61	0,75

Chow-Lin generating process

MSE	average	0,05	0,25	0,50	0,75	0,95
DFM:	66,11	46,16	54,91	62,72	73,09	96,64
Chow-Lin:	68,27	36,60	49,63	61,64	78,21	115,83

MAE	average	0,05	0,25	0,50	0,75	0,95
DFM:	0,59	0,50	0,54	0,58	0,63	0,73
Chow-Lir	0,60	0,45	0,52	0,58	0,65	0,80

Note: The table reports the mean and percentiles of the empirical distribution of the MSE and MAE computed over 1000 replications.

Table 6: Lag order selection in VARs for Unified Germany

	FPE			AIC			Schwarz		
	FHM	CL	DFM	FHM	CL	DFM	FHM	CL	DFM
Lag									
0	1,775	1,666	1,293	9,087	9,024	8,771	9,154	9,090	8,837
1	0,142	0,137	0,113	6,563	6,524	6,335	6,829	6,790	6,601
2	0,107	0,103	0,074	6,274	6,243	5,906	6.740*	6.709*	6.372*
3	0,101	0,090	0,068	6,224	6,106	5,818	6,889	6,771	6,483
4	0.084*	0,085	0.063*	6.040*	6,043	5.748*	6,904	6,907	6,613
5	0,091	0.084*	0,064	6,112	6.028*	5,760	7,176	7,092	6,824
6	0,098	0,092	0,072	6,187	6,120	5,873	7,451	7,384	7,136
7	0,099	0,095	0,077	6,189	6,145	5,939	7,652	7,608	7,403
8	0,092	0,101	0,076	6,114	6,204	5,928	7,776	7,867	7,590

Note: * indicates lag order selected by the criterion

FPE: Final prediction error
AIC: Akaike information criterion
Schwarz: Schwarz information criterion

FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 7: Estimation results for VARs for Unified Germany

	FHM			CL			DFM		
	GDP	Inflation	Interest rates	GDP	Inflation	Interest rates	GDP	Inflation	Interest rates
Adj. R-squared	0,083	0,516	0,935	0,127	0,454	0,934	0,155	0,502	0,929
S.E. equation	0,886	0,439	0,704	0,949	0,416	0,709	0,808	0,405	0,734
Akaike AIC	2,689	1,286	2,229	2,827	1,178	2,242	2,503	1,121	2,312
Schwarz SC	2,972	1,568	2,512	3,109	1,460	2,525	2,786	1,403	2,595
Log likelihood		-369,135			-371,596			-353,490	
Akaike inf. criterion		6,137			6,174			5,902	
Schwarz criterion		6,985			7,022			6,750	

FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 8: Granger Causality tests in VARs for Unified Germany (p.values)

FHM		CL		DFM	
Dependent variable: GDPFHM		Dependent variable: GDPCL		Dependent variable: GDPDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
YEDFHM	0,606	YEDCL	0,563	YEDDFM	0,573
STIDEUQ	0,032	STIDEUQ	0,000	STIDEUQ	0,005
All	0,119	All	0,002	All	0,037
Dependent variable: YEDFHM		Dependent variable: YEDCL		Dependent variable: YEDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
GDPFHM	0,003	GDPCL	0,039	GDPDFM	0,748
STIDEUQ	0,002	STIDEUQ	0,038	STIDEUQ	0,000
All	0,000	All	0,007	All	0,001
Dependent variable: STIDEUQ		Dependent variable: STIDEUQ		Dependent variable: STIDEUQ	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
GDPFHM	0,017	GDPCL	0,018	GDPDFM	0,245
YEDFHM	0,008	YEDCL	0,001	YEDDFM	0,008
All	0,000	All	0,000	All	0,007

Note:
FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 9: Chow tests for parameter stability in VAR equations for Unified Germany (p.values)

	FHM	CL	DFM
GDP	0,164	0,990	0,197
Inflation	0,304	0,113	0,049
Interest Rates	0,996	0,965	0,994

Note: Break point is in 1991:2
FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 10: Forecasting performance of alternative VARs for Unified Germany

Inflation							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,41	0,38	0,39	0,72	0,35	0,31	0,33	0,61

GDP Growth							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,65	0,55	0,73	0,93	0,58	0,48	0,64	0,74

Interest Rates							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,33	0,39	0,36	0,33	0,27	0,31	0,30	0,26

FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany
91 : Estimation starts in 1991:2 therefore series are NOT backdated

Table 11: Descriptive statistics on alternative euro area series for Inflation and GDP Growth

Inflation	AWYEDCL	AWYEDCLFIX	AWYEDDFM	AWYEDFHM	AWYEDWEFIX
Mean	1,44	1,44	1,44	1,45	1,44
Median	1,29	1,27	1,27	1,28	1,25
Maximum	3,40	3,32	3,20	3,31	3,38
Minimum	0,14	0,14	0,14	0,16	0,14
Std. Dev.	0,86	0,86	0,86	0,88	0,88
Sum	190,02	190,22	190,02	190,76	189,47
Sum Sq. Dev.	96,28	96,84	97,30	100,96	101,74

Correlation Matrix	AWYEDCL	AWYEDCLFIX	AWYEDDFM	AWYEDFHM	AWYEDWEFIX
AWYEDCL	1,00	1,00	0,99	0,99	0,99
AWYEDCLFIX	1,00	1,00	0,99	1,00	1,00
AWYEDDFM	0,99	0,99	1,00	0,99	0,99
AWYEDFHM	0,99	1,00	0,99	1,00	0,99
AWYEDWEFIX	0,99	1,00	0,99	0,99	1,00

Principal Component Analysis	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,98	0,01	0,01	0,00	0,00
Variance Prop.	1,00	0,00	0,00	0,00	0,00
Cumulative Prop.	1,00	1,00	1,00	1,00	1,00

GDP Growth	AWGDPFHM	AWGDPCL	AWGDPCLFIX	AWGDPFM	AWGDPWEFIX
Mean	0,62	0,53	0,54	0,53	0,41
Median	0,60	0,55	0,56	0,54	0,41
Maximum	2,22	2,23	1,83	1,95	1,42
Minimum	-1,60	-1,54	-1,29	-1,23	-1,23
Std. Dev.	0,62	0,62	0,55	0,55	0,41
Sum	81,31	69,85	71,00	70,51	54,57
Sum Sq. Dev.	50,61	50,40	39,62	39,44	21,84

Correlation Matrix	AWGDPFHM	AWGDPCL	AWGDPCLFIX	AWGDPFM	AWGDPWEFIX
AWGDPFHM	1,00	0,94	0,97	0,96	0,68
AWGDPCL	0,94	1,00	0,96	0,95	0,70
AWGDPCLFIX	0,97	0,96	1,00	0,97	0,74
AWGDPDFM	0,96	0,95	0,97	1,00	0,72
AWGDPWEFIX	0,68	0,70	0,74	0,72	1,00

Principal Component Analysis	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,46	0,42	0,06	0,04	0,02
Variance Prop.	0,89	0,08	0,01	0,01	0,00
Cumulative Prop.	0,89	0,98	0,99	1,00	1,00

Note
AWYEDCL is the GDP Deflator for the Euro Area using YEDCL for the Unified German series which is backdated using the Chow-Lin method
AWYEDCLFIX is the GDP Deflator for the Euro Area using YEDCLFIX for the Unified German series which is backdated using the Chow-Lin fixewd weight method
AWYEDDFM is the GDP Deflator for the Euro Area using YEDCDFM for the Unified German series which is backdated using the DFM method
AWYEDFHM is the GDP Deflator for the Euro Area using YEDDFHM for the Unified German series which is backdated as ing Fagan, Mestre and Henry 2001
AWYEDWEFIX is the GDP Deflator for the Euro Area using YEDWEFIX for the Unified German series which is backdated using a fixed weight

AWGDPCL is the GDP growth for the Euro Area using GDPCL for the Unified German series which is backdated using the Chow-Lin method
AWGDPCLFIX is the GDP growth for the Euro Area using GDPCLFIX for the Unified German series which is backdated using the Chow-Lin fixewd weight method
AWGDPDFM is the GDP growth for the Euro Area using GDPCDFM for the Unified German series which is backdated using the DFM method
AWGDPFHM is the GDP growth for the Euro Area using GDPDFHM for the Unified German series which is backdatedas in Fagan, Mestre and Henry 2001
AWGDPWEFIX is the GDP growth for the Euro Area using GDPWEFIX for the Unified German series which is backdated using a fixed weight

Table 12: Lag order selection in VARs for euro area

	FPE			AIC			Schwarz		
	FHM	CL	DFM	FHM	CL	DFM	FHM	CL	DFM
Lag									
0	1,722	1,574	1,298	9,057	8,967	8,775	9,125	9,036	8,843
1	0,012	0,011	0,010	4,107	4,028	3,931	4,380	4,301	4,204
2	0.009*	0,008	0,007	3.772*	3,679	3,551	4.250*	4.157*	4.029*
3	0,009	0.008*	0.007*	3,772	3.634*	3.550*	4,455	4,316	4,232
4	0,009	0,008	0,007	3,801	3,658	3,567	4,688	4,545	4,454
5	0,009	0,008	0,007	3,789	3,651	3,581	4,881	4,742	4,673
6	0,009	0,008	0,008	3,786	3,690	3,653	5,082	4,986	4,950
7	0,010	0,008	0,008	3,846	3,726	3,705	5,347	5,227	5,207
8	0,010	0,009	0,009	3,930	3,840	3,778	5,636	5,546	5,484

Note: * indicates lag order selected by the criterion

FPE: Final prediction error
AIC: Akaike information criterion
Schwarz: Schwarz information criterion

FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 13: Estimation results for VARs for euro area

	FHM			CL			DFM		
	GDP	Inflation	Interest rates	GDP	Inflation	Interest rates	GDP	Inflation	Interest rates
Adj. R-squared	0,201	0,909	0,967	0,280	0,902	0,966	0,172	0,904	0,966
S.E. equation	0,545	0,267	0,582	0,516	0,270	0,585	0,496	0,269	0,590
Akaike AIC	1,721	0,290	1,851	1,610	0,318	1,861	1,531	0,305	1,877
Schwarz SC	2,011	0,580	2,140	1,900	0,608	2,151	1,820	0,595	2,167
Log likelihood		-205,094			-198,277			-193,815	
Akaike inf. criterion		3,814			3,707			3,638	
Schwarz criterion		4,683			4,576			4,507	

Note:
FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 14: Granger Causality tests in VARs for euro area (p.values)

FHM		CL		DFM	
Dependent variable: AWGDP		Dependent variable: AWGDPCL		Dependent variable: AWGDPDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWYED	0,178	AWYEDCL	0,092	AWYEDDFM	0,136
STIAW	0,002	STIAW	0,000	STIAW	0,000
All	0,004	All	0,000	All	0,002
Dependent variable: AWYEDG		Dependent variable: AWYEDCL		Dependent variable: AWYEDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGDP	0,048	AWGDPCL	0,021	AWGDPDFM	0,711
STIAW	0,000	STIAW	0,001	STIAW	0,000
All	0,000	All	0,000	All	0,000
Dependent variable: STIAW		Dependent variable: STIAW		Dependent variable: STIAW	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGDP	0,015	AWGDPCL	0,047	AWGDPDFM	0,071
AWYED	0,513	AWYEDCL	0,235	AWYEDDFM	0,272
All	0,017	All	0,027	All	0,056

Note:
FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 15a: Forecasting performance of alternative VAR(4) for euro area

Inflation							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,26	0,25	0,26	0,36	0,20	0,19	0,22	0,28

GDP Growth							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,65	0,48	0,50	0,50	0,57	0,39	0,40	0,42

Interest Rates							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,31	0,32	0,31	0,52	0,25	0,25	0,24	0,40

Note:
FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany
91 : Estimation starts in 1991:2 therefore series are NOT backdated
Estimation sample: 1970-1998. Forecast sample 1999-2003. One-step ahead forecasts

Table 15b: Forecasting performance of alternative ARs for euro area

Inflation - AR(4)							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,26	0,26	0,26	0,22	0,20	0,20	0,20	0,17

GDP Growth - AR(2)							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,34	0,32	0,33	0,32	0,28	0,27	0,29	0,27

Note:
FHM: AR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: AR with Chow-Lin backdated variables for Unified Germany
DFM: AR with DFM backdated variables for Unified Germany
91 : Estimation starts in 1991:2 therefore series are NOT backdated
Estimation sample: 1970-1998. Forecast sample 1999-2003. One-step ahead forecasts

Table 16: Chow tests for parameter stability in VAR equations for euro area (p.values)

	FHM	CL	DFM
GDP	0,004	0,148	0,044
Inflation	0,337	0,480	0,439
Interest Rates	0,886	0,726	0,796

Note: Break point is in 1991:2

FHM: VAR with backdated variables for Unified Germany as in Fagan, Henry and Mestre 2001
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 17a: Descriptive statistics on alternative euro area series for real variables

Consumption	AWPCEFHM	AWPCECL	AWPCECLFIX	AWPCEDFM	AWPCEWEFIX
Mean	0,63	0,56	0,57	0,56	0,77
Median	0,69	0,53	0,58	0,56	0,81
Maximum	2,09	2,72	1,90	1,91	3,18
Minimum	-1,64	-1,65	-1,65	-1,65	-1,65
Std. Dev.	0,59	0,65	0,55	0,52	0,80
Sum	82,73	72,87	74,33	73,88	101,52
Sum Sq. Dev.	45,89	54,44	38,79	35,39	82,68

Investment	AWITRFHM	AWITRCL	AWITRCLFIX	AWITRDFM	AWITRWEFIX
Mean	0,49	0,47	0,48	0,47	0,46
Median	0,47	0,54	0,45	0,54	0,44
Maximum	5,94	4,47	4,00	4,00	4,00
Minimum	-2,94	-3,03	-3,03	-3,03	-3,03
Std. Dev.	1,47	1,36	1,26	1,24	1,31
Sum	64,00	60,99	62,28	62,02	59,79
Sum Sq. Dev.	280,63	239,96	205,07	200,80	224,10

Government Consumption	AWGCRFHM	AWGCRCL	AWGCRCLFIX	AWGCRDFM	AWGCRWEFIX
Mean	0,70	0,73	0,73	0,73	0,75
Median	0,67	0,66	0,73	0,77	0,67
Maximum	2,45	2,59	1,56	1,56	3,83
Minimum	-1,35	-0,42	-0,42	-0,42	-1,45
Std. Dev.	0,55	0,48	0,35	0,38	0,76
Sum	91,37	94,99	94,98	95,63	98,31
Sum Sq. Dev.	39,67	29,78	15,75	18,34	75,79

Real Exports	AWXTRFHM	AWXTRCL	AWXTRCLFIX	AWXTRDFM	AWXTRWEFIX
Mean	1,39	1,11	1,12	1,12	0,77
Median	1,48	1,16	1,24	1,14	0,73
Maximum	5,61	4,80	4,61	4,36	4,12
Minimum	-4,36	-4,19	-4,30	-3,27	-3,84
Std. Dev.	1,90	1,75	1,70	1,55	1,59
Sum	182,14	144,93	147,28	146,37	100,32
Sum Sq. Dev.	469,01	396,17	373,52	311,48	328,18

Real Imports	AWMTRFHM	AWMTRCL	AWMTRCLFIX	AWMTRDFM	AWMTRWEFIX
Mean	1,30	1,14	1,14	1,15	1,02
Median	1,64	1,64	1,42	1,38	1,32
Maximum	4,90	4,51	3,97	4,59	3,79
Minimum	-7,20	-5,96	-6,01	-5,67	-4,89
Std. Dev.	1,87	1,78	1,75	1,75	1,58
Sum	170,95	149,53	149,14	150,43	133,63
Sum Sq. Dev.	453,18	411,28	400,09	398,70	323,29

Principal Component Analysis Consuption	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,39	0,44	0,08	0,07	0,02
Variance Prop.	0,88	0,09	0,02	0,01	0,00
Cumulative Prop.	0,88	0,97	0,98	1,00	1,00

Principal Component Analysis Investment	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,83	0,09	0,04	0,04	0,00
Variance Prop.	0,97	0,02	0,01	0,01	0,00
Cumulative Prop.	0,97	0,98	0,99	1,00	1,00

Principal Component Analysis Government Consumption	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	3,39	0,99	0,34	0,19	0,10
Variance Prop.	0,68	0,20	0,07	0,04	0,02
Cumulative Prop.	0,68	0,88	0,94	0,98	1,00

Principal Component Analysis Real Exports	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,17	0,70	0,08	0,03	0,02
Variance Prop.	0,83	0,14	0,02	0,01	0,00
Cumulative Prop.	0,83	0,98	0,99	1,00	1,00

Principal Component Analysis Real Imports	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,82	0,10	0,05	0,03	0,01
Variance Prop.	0,96	0,02	0,01	0,01	0,00
Cumulative Prop.	0,96	0,98	0,99	1,00	1,00

Table 17b: Descriptive statistics on alternative euro area series for deflators

Private Consumption Deflator

	AWPCDFHM	AWPCDCL	AWPCDCLFIX	AWPCDDFM	AWPCDWEFIX
Mean	1,50	1,49	1,49	1,49	1,48
Median	1,24	1,27	1,29	1,17	1,27
Maximum	3,80	3,69	3,73	3,54	3,77
Minimum	0,05	0,05	0,05	0,05	0,05
Std. Dev.	0,92	0,91	0,89	0,92	0,90
Sum	196,16	195,03	195,27	195,46	193,47
Sum Sq. Dev.	110,03	108,39	103,14	110,86	105,88

Investment Deflator

	AWITDFHM	AWITDCL	AWITDCLFIX	AWITDDFM	AWITDWEFIX
Mean	1,45	1,38	1,38	1,38	1,44
Median	1,23	1,04	1,09	0,99	1,15
Maximum	4,65	4,49	4,56	4,48	4,69
Minimum	-0,02	-0,01	-0,01	-0,01	-0,01
Std. Dev.	1,11	1,07	1,05	1,07	1,11
Sum	190,10	180,32	181,00	180,87	189,23
Sum Sq. Dev.	159,77	147,71	143,50	149,82	161,61

Government Consumption Deflator

	AWGCDFHM	AWGCDCL	AWGCDCLFIX	AWGCDDFM	AWGCDWEFIX
Mean	1,63	1,58	1,58	1,56	1,67
Median	1,33	1,31	1,33	1,46	1,33
Maximum	6,84	6,47	5,51	4,42	6,77
Minimum	-0,16	-0,14	-0,14	-0,14	-0,14
Std. Dev.	1,24	1,24	1,14	0,98	1,29
Sum	213,14	207,13	207,42	203,99	218,56
Sum Sq. Dev.	199,26	199,46	169,59	125,76	214,89

Exports Deflator

	AWXTDFHM	AWXTDCL	AWXTDCLFIX	AWXTDDFM	AWXTDWEFIX
Mean	1,24	1,11	1,10	1,10	1,10
Median	0,90	0,80	0,80	0,80	0,82
Maximum	7,56	5,60	5,67	5,66	6,12
Minimum	-1,42	-1,26	-1,24	-1,31	-1,32
Std. Dev.	1,53	1,31	1,31	1,31	1,34
Sum	161,82	144,77	144,74	144,68	143,92
Sum Sq. Dev.	305,61	221,74	221,88	224,30	234,04

Imports Deflator

	AWMTDFHM	AWMTDCL	AWMTDCLFIX	AWMTDDFM	AWMTDWEFIX
Mean	1,26	1,05	1,06	1,05	1,08
Median	0,93	0,86	0,88	0,88	0,93
Maximum	16,70	14,00	13,17	12,15	12,46
Minimum	-5,01	-4,21	-3,97	-3,85	-3,68
Std. Dev.	2,52	2,16	2,08	2,00	2,00
Sum	164,97	138,16	138,59	137,56	141,56
Sum Sq. Dev.	822,42	605,42	562,48	522,13	521,92

Principal Component Analysis Consuption Deflator

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,95	0,02	0,02	0,01	0,00
Variance Prop.	0,99	0,00	0,00	0,00	0,00
Cumulative Prop.	0,99	1,00	1,00	1,00	1,00

Principal Component Analysis Investment Deflator

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,95	0,03	0,01	0,00	0,00
Variance Prop.	0,99	0,01	0,00	0,00	0,00
Cumulative Prop.	0,99	1,00	1,00	1,00	1,00

Principal Component Analysis Government Consumption Deflator

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,70	0,22	0,05	0,03	0,00
Variance Prop.	0,94	0,04	0,01	0,01	0,00
Cumulative Prop.	0,94	0,98	0,99	1,00	1,00

Principal Component Analysis Exports Deflator

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,98	0,02	0,00	0,00	0,00
Variance Prop.	1,00	0,00	0,00	0,00	0,00
Cumulative Prop.	1,00	1,00	1,00	1,00	1,00

Principal Component Analysis Imports Deflator

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	4,98	0,02	0,00	0,00	0,00
Variance Prop.	1,00	0,00	0,00	0,00	0,00
Cumulative Prop.	1,00	1,00	1,00	1,00	1,00

Table 18a: Principal component analysis of alternative real series for euro area

Principal Component Analysis Area Wide Model database					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	6,53	1,81	1,01	0,31	0,18
Variance Prop.	0,66	0,18	0,10	0,03	0,02
Cumulative Prop.	0,66	0,85	0,95	0,98	1,00

Principal Component Analysis Chow Lin backdating method					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	5,35	1,94	0,94	0,24	0,13
Variance Prop.	0,62	0,23	0,11	0,03	0,02
Cumulative Prop.	0,62	0,85	0,96	0,98	1,00

Principal Component Analysis DFM backdating method					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	5,11	1,32	0,60	0,23	0,09
Variance Prop.	0,70	0,18	0,08	0,03	0,01
Cumulative Prop.	0,70	0,87	0,96	0,99	1,00

Correlation of Principal Components			
	PC1REALFI	PC1REALCL	PC1REALDFM
PC1REAL	1,00	0,97	0,95
PC1REALCL	0,97	1,00	0,94
PC1REALDFM	0,95	0,94	1,00

Note:
PC1REALFHM: all real variables as in Fagan, Henry and Mestre 2001
PC1REALCL: all real variables using Chow-Lin backdating method
PC1REALDFM: all variables using DFM backdating method

Table 18b: Principal component analysis of alternative nominal series for euro area

Principal Component Analysis Area Wide Model database					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	10,10	1,42	0,38	0,22	0,07
Variance Prop.	0,83	0,12	0,03	0,02	0,01
Cumulative Prop.	0,83	0,94	0,98	0,99	1,00

Principal Component Analysis Chow Lin backdating method					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	7,64	1,44	0,40	0,22	0,09
Variance Prop.	0,78	0,15	0,04	0,02	0,01
Cumulative Prop.	0,78	0,93	0,97	0,99	1,00

Principal Component Analysis DFM backdating method					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Eigenvalue	6,81	1,25	0,28	0,25	0,07
Variance Prop.	0,79	0,14	0,03	0,03	0,01
Cumulative Prop.	0,79	0,93	0,96	0,99	1,00

Correlation of Principal Components			
	PC1NOM	PC1NOMCL	PC1NOMDFM
PC1NOMFHM	1,00	0,99	0,99
PC1NOMCL	0,99	1,00	1,00
PC1NOMDFM	0,99	1,00	1,00

Note:
PC1NOMFHM: all NOM variables as in Fagan, Henry and Mestre 2001
PC1NOMCL: all NOM variables using Chow-Lin backdating method
PC1NOMDFM: all variables using DFM backdating method

Table 19a: Lag order selection in VARs for euro area real series

	FPE			AIC			Schwarz		
	FHM	CL	DFM	FHM	CL	DFM	FHM	CL	DFM
Lag									
0	0,643	0,302	0,093	13,747	12,993	11,816	13.859*	13.105*	11.928*
1	0.568*	0.282*	0.076*	13.624*	12.925*	11.608*	14,296	13,593	12,276
2	0,585	0,298	0,077	13,652	12,977	11,621	14,883	14,202	12,847
3	0,664	0,339	0,078	13,773	13,100	11,626	15,565	14,883	13,409
4	0,604	0,315	0,089	13,670	13,018	11,752	16,021	15,358	14,092

Note: * indicates lag order selected by the criterion

FPE: Final prediction error
AIC: Akaike information criterion
Schwarz: Schwarz information criterion

FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 19b: Lag order selection in VARs for euro area nominal series

	FPE			AIC			Schwarz		
	FHM	CL	DFM	FHM	CL	DFM	FHM	CL	DFM
Lag									
0	0,064	0,063	0,037	11,442	11,421	10,894	11,554	11,533	11,005
1	0,004	0,004	0,003	8,659	8,577	8,267	9.331*	9.246*	8.936*
2	0,003	0,003	0,002	8,413	8,527	7,987	9,644	9,753	9,212
3	0,003	0,003	0,002	8,340	8,498	7,982	10,132	10,280	9,764
4	0.002*	0.002*	0.002*	8.048*	8.098*	7.710*	10,400	10,437	10,050

Note: * indicates lag order selected by the criterion

FPE: Final prediction error
AIC: Akaike information criterion
Schwarz: Schwarz information criterion

FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 20: Estimation results for VARs for euro area real variables

	FHM					CL					DFM				
	GCR	ITR	MTR	XTR	PCE	GCR	ITR	MTR	XTR	PCE	GCR	ITR	MTR	XTR	PCE
Adj. R-squared	0,035	0,160	0,106	0,030	0,002	0,068	0,092	0,092	0,027	-0,016	0,193	0,190	0,136	0,026	0,100
S.E. equation	0,537	1,278	1,770	1,875	0,593	0,458	1,281	1,694	1,725	0,652	0,342	1,113	1,624	1,534	0,498
Akaike AIC	1,639	3,374	4,025	4,140	1,839	1,322	3,379	3,937	3,974	2,029	0,739	3,097	3,852	3,738	1,487
Schwarz SC	1,771	3,506	4,157	4,272	1,972	1,453	3,510	4,069	4,105	2,160	0,870	3,229	3,984	3,870	1,619
Log likelihood	-859,447					-821,947					-731,000				
Akaike inf. criterion	13,684					13,007					11,618				
Schwarz criterion	14,346					13,665					12,277				

Note:
FHM: VAR with AWM backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Estimation results for VARs for euro area deflators

	FHM					CL					DFM				
	GCD	ITD	MTD	XTD	PCD	GCD	ITD	MTD	XTD	PCD	GCD	ITD	MTD	XTD	PCD
Adj. R-squared	0,585	0,814	0,517	0,668	0,872	0,512	0,762	0,509	0,635	0,871	0,518	0,762	0,536	0,635	0,875
S.E. equation	0,795	0,480	1,754	0,884	0,330	0,870	0,523	1,512	0,790	0,331	0,689	0,527	1,366	0,794	0,330
Akaike AIC	2,424	1,417	4,006	2,637	0,665	2,603	1,587	3,709	2,410	0,674	2,139	1,601	3,506	2,421	0,667
Schwarz SC	2,556	1,549	4,139	2,769	0,798	2,735	1,719	3,841	2,542	0,806	2,271	1,733	3,637	2,553	0,799
Log likelihood	-562,348					-564,118					-525,828				
Akaike inf. criterion	9,113					9,071					8,486				
Schwarz criterion	9,775					9,729					9,144				

Note:
FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 21a: Granger Causality tests in VARs for euro area real variables (p.values)

FHM		CL		DFM	
Dependent variable: AWGCR		Dependent variable: AWGCRCL		Dependent variable: AWGCRDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWITR	0,255	AWITRCL	0,052	AWITRDFM	0,719
AWMTR	0,332	AWMTRCL	0,002	AWMTRDFM	0,649
AWXTR	0,787	AWXTRCL	0,015	AWXTRDFM	0,923
AWPCE	0,004	AWPCECL	0,917	AWPCEDFM	0,445
All	0,048	All	0,016	All	0,628
Dependent variable: AWITR		Dependent variable: AWITRCL		Dependent variable: AWITRDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCR	0,012	AWGCRCL	0,087	AWGCRDFM	0,674
AWMTR	0,008	AWMTRCL	0,051	AWMTRDFM	0,568
AWXTR	0,139	AWXTRCL	0,674	AWXTRDFM	0,093
AWPCE	0,091	AWPCECL	0,350	AWPCEDFM	0,005
All	0,000	All	0,015	All	0,001
Dependent variable: AWMTR		Dependent variable: AWMTRCL		Dependent variable: AWMTRDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCR	0,204	AWGCRCL	0,1439	AWGCRDFM	0,7708
AWITR	0,0808	AWITRCL	0,0024	AWITRDFM	0,029
AWXTR	0,3608	AWXTRCL	0,4225	AWXTRDFM	0,3787
AWPCE	0,1444	AWPCECL	0,9432	AWPCEDFM	0,2086
All	0,0743	All	0,02	All	0,097
Dependent variable: AWXTR		Dependent variable: AWXTRCL		Dependent variable: AWXTRDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCR	0,6675	AWGCRCL	0,4608	AWGCRDFM	0,7225
AWITR	0,1334	AWITRCL	0,0261	AWITRDFM	0,3488
AWMTR	0,3996	AWMTRCL	0,7987	AWMTRDFM	0,5034
AWPCE	0,4162	AWPCECL	0,7889	AWPCEDFM	0,7314
All	0,0606	All	0,0814	All	0,2865
Dependent variable: AWPCE		Dependent variable: AWPCECL		Dependent variable: AWPCEDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCR	0,3482	AWGCRCL	0,9877	AWGCRDFM	0,0258
AWITR	0,461	AWITRCL	0,2632	AWITRDFM	0,012
AWMTR	0,8827	AWMTRCL	0,9849	AWMTRDFM	0,5476
AWXTR	0,5169	AWXTRCL	0,7405	AWXTRDFM	0,2503
All	0,5757	All	0,6665	All	0,0012

Note:
FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 21b: Granger Causality tests in VARs for euro area nominal variables (p.values)

FHM		CL		DFM	
Dependent variable: AWGCD		Dependent variable: AWGCDCL		Dependent variable: AWGCDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWITD	0,000	AWITDCL	0,559	AWITDDFM	0,683
AWMTD	0,086	AWMTDCL	0,104	AWMTDDFM	0,080
AWXTD	0,233	AWXTDCL	0,206	AWXTDDFM	0,054
AWPCD	0,003	AWPCDCL	0,000	AWPCDDFM	0,000
All	0,000	All	0,000	All	0,000
Dependent variable: AWITD		Dependent variable: AWITDCL		Dependent variable: AWITDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCD	0,890	AWGCDCL	0,070	AWGCDDFM	0,064
AWMTD	0,909	AWMTDCL	0,250	AWMTDDFM	0,578
AWXTD	0,125	AWXTDCL	0,666	AWXTDDFM	0,147
AWPCD	0,004	AWPCDCL	0,000	AWPCDDFM	0,000
All	0,002	All	0,000	All	0,000
Dependent variable: AWMTD		Dependent variable: AWMTDCL		Dependent variable: AWMTDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCD	0,9369	AWGCDCL	0,3744	AWGCDDFM	0,1236
AWITD	0,8735	AWITDCL	0,8998	AWITDDFM	0,3493
AWXTD	0,0723	AWXTDCL	0,0085	AWXTDDFM	0,0064
AWPCD	0,8298	AWPCDCL	0,789	AWPCDDFM	0,8202
All	0,1046	All	0,0162	All	0,0042
Dependent variable: AWXTD		Dependent variable: AWXTDCL		Dependent variable: AWXTDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCD	0,277	AWGCDCL	0,3918	AWGCDDFM	0,3095
AWITD	0,0685	AWITDCL	0,1653	AWITDDFM	0,3278
AWMTD	0,0001	AWMTDCL	0,0003	AWMTDDFM	0,0002
AWPCD	0,1178	AWPCDCL	0,0232	AWPCDDFM	0,0504
All	0	All	0	All	0
Dependent variable: AWPCD		Dependent variable: AWPCDCL		Dependent variable: AWPCDDFM	
Excluded	Prob.	Excluded	Prob.	Excluded	Prob.
AWGCD	0,4242	AWGCDCL	0,2779	AWGCDDFM	0,3423
AWITD	0,0008	AWITDCL	0,0076	AWITDDFM	0,3016
AWMTD	0,4408	AWMTDCL	0,3037	AWMTDDFM	0,5403
AWXTD	0,216	AWXTDCL	0,3139	AWXTDDFM	0,2532
All	0,0002	All	0,0046	All	0,1991

Note:
FHM: VAR with Fagan, Henry and Mestre 2001 backdated variables for Unified Germany
CL: VAR with Chow-Lin backdated variables for Unified Germany
DFM: VAR with DFM backdated variables for Unified Germany

Table 22: Performance of alternative factor based forecasts

GDP Growth							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,66	0,62	0,54	0,58	0,56	0,52	0,43	0,51

Inflation							
RMSE				MAE			
FHM	CL	DFM	91	FHM	CL	DFM	91
0,55	0,58	0,61	0,31	0,49	0,51	0,53	0,21

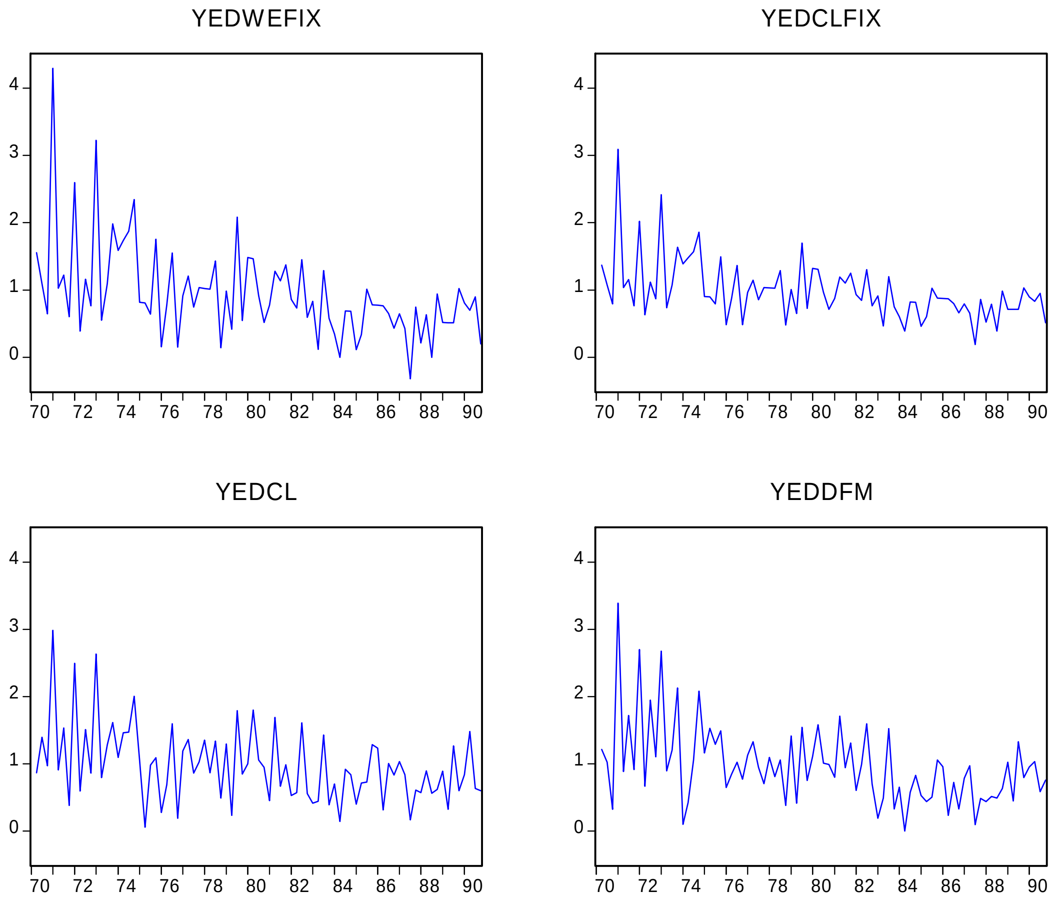
Note:
Each variable is regressed on one lag of factors extracted from the five demand components or their deflators
Forecast sample is 1999-2003
FHM: factors extracted from Fagan et al. (2001) data
CL: factors extracted from Chow-Lin backdated data
DFM: factors extracted from DFM backdated data
91 : Factors extracted from data starting in 1991:2. Estimation starts in 1991:2

Table 23. Estimation of forward looking Investment equation

	FHM	CL	DFM
η	0,117	0,056	0,155
t-stat (p-val)	0,056	0,496	0,098
χ	-0,022	-0,028	-0,015
t-stat (p-val)	0,006	0,006	0,037
st.err	0,0146	0,0177	0,0127
J-stat (p-val)	0,66	0,51	0,49

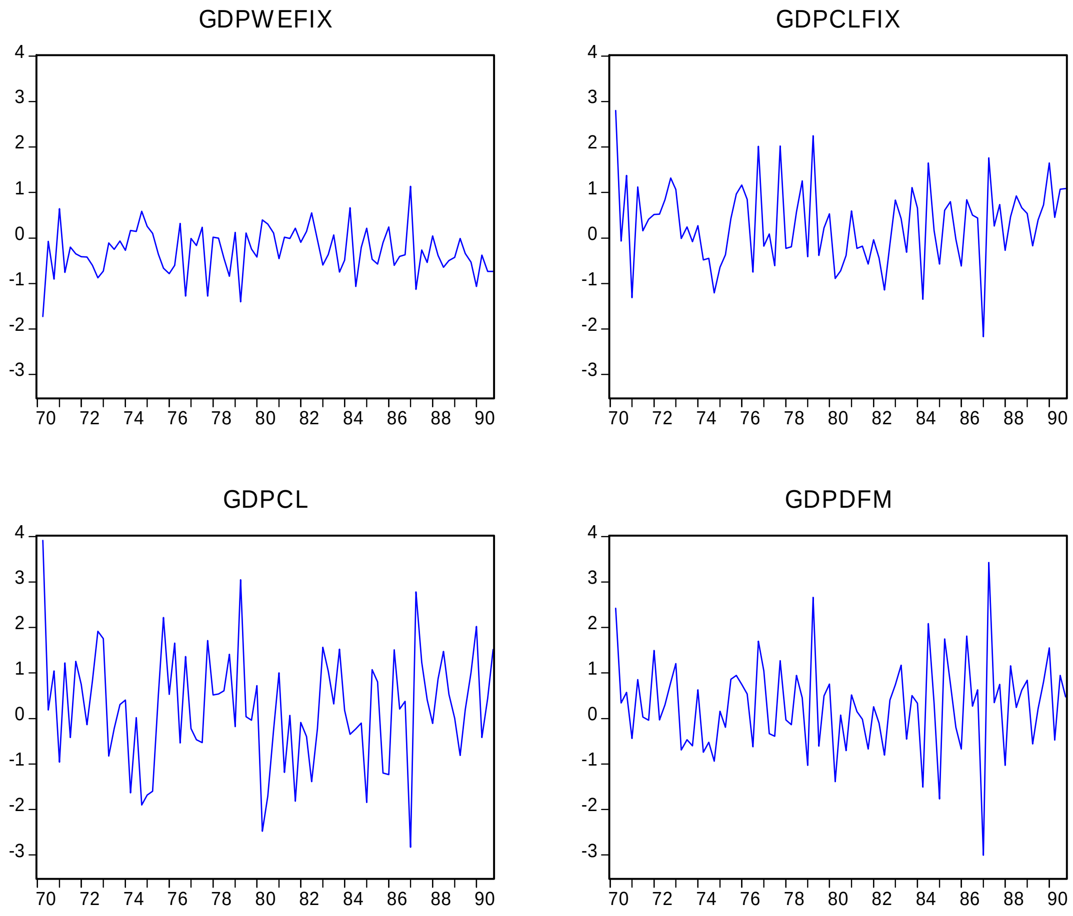
Note: GMM estimation with Heteroskedastic and Autocorrelation Consistent covariance matrix (Bartlett kernel with Newey–West fixed bandwidth).
The sample period is 1973Q3 to 2005Q3. The instrument set includes the dummies plus the first 3 lags of: nominal short-term interest rate, quarterly inflation, real wages, investment-to-output ratios, employment-to-output ratios, gross changes in investment and employment.
The rows labelled t-stat report the p-value of the t-statistics for non significance of the coefficients.
The row labelled J-stat reports the p-value of the Hansen's statistic for instrument validity.

Figure 1: Alternative backdated series for Unified Germany Inflation



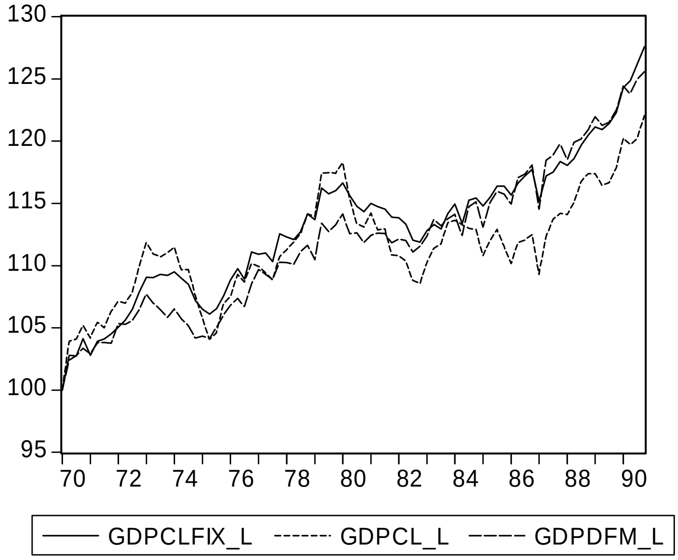
Note: YEDWEFIX is the GDP Deflator for Unified Germany backdated using a fixed weight
YEDCLFIX is the GDP Deflator for Unified Germany backdated using the Chow-Lin method with fixed weight
YEDCL is the GDP Deflator for Unified Germany backdated using the Chow-Lin method
YEDDFM is the GDP Deflator for Unified Germany backdated using the DFM method

Figure 2: Alternative backdated series for Unified Germany GDP Growth



Note: GDPWEFIX is the GDP growth for Unified Germany backdated using a fixed weight
GDPCLFIX is GDP growth for Unified Germany backdated using the Chow-Lin method with fixed weight
GDPCL is the GDP growth for Unified Germany backdated using the Chow-Lin method
GDPDFM is the GDP growth for Unified Germany backdated using the DFM method

Figure 3: Alternative backdated series for Unified Germany GDP Growth levels



Note:
GDPCLFIX_L is the GDP growth in levels for Unified Germany backdated using the Chow-Lin method with fixed weight
GDPCL_L is the GDP growth in levels for Unified Germany backdated using the Chow-Lin method
GDPDFM_L is the GDP growth in levels for Unified Germany backdated using the DFM method

Figure 4: Response functions to a monetary shock in VARs for Unified Germany

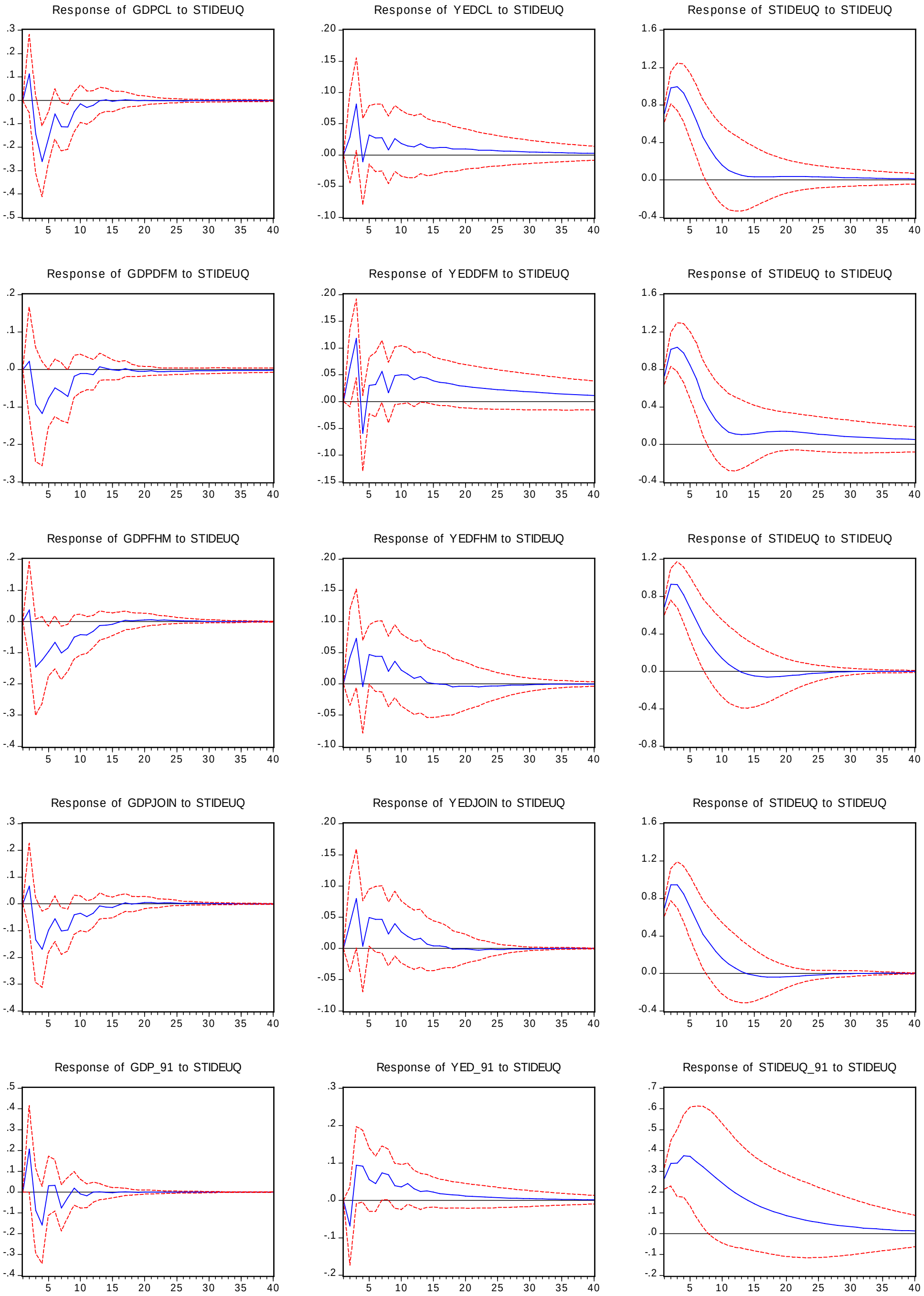
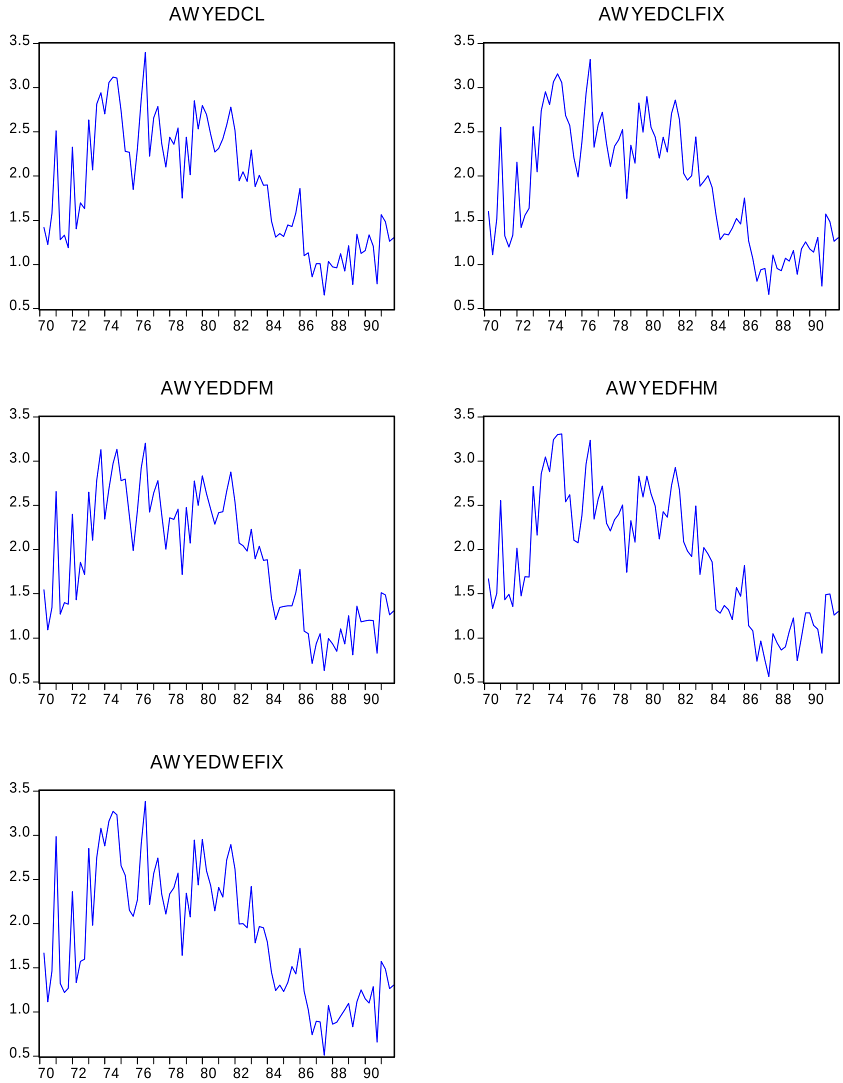
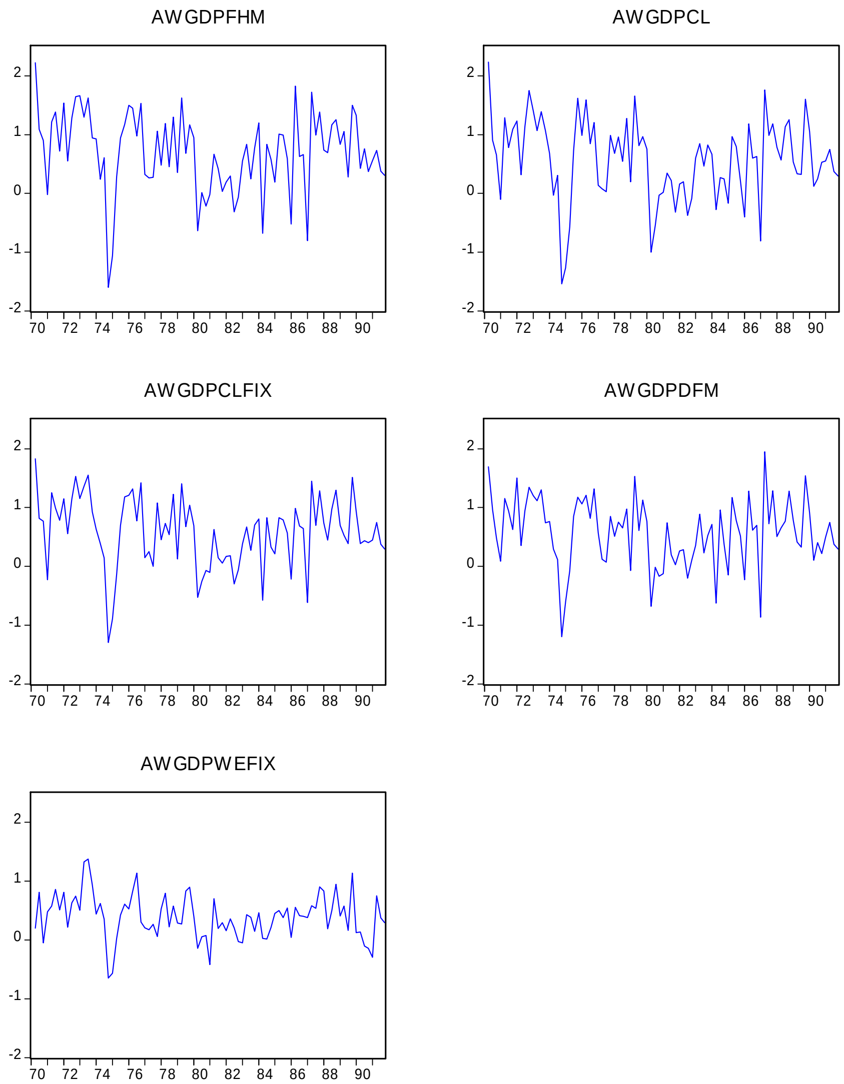


Figure 5: Euro Area Inflation using alternative backdated series for Unified Germany



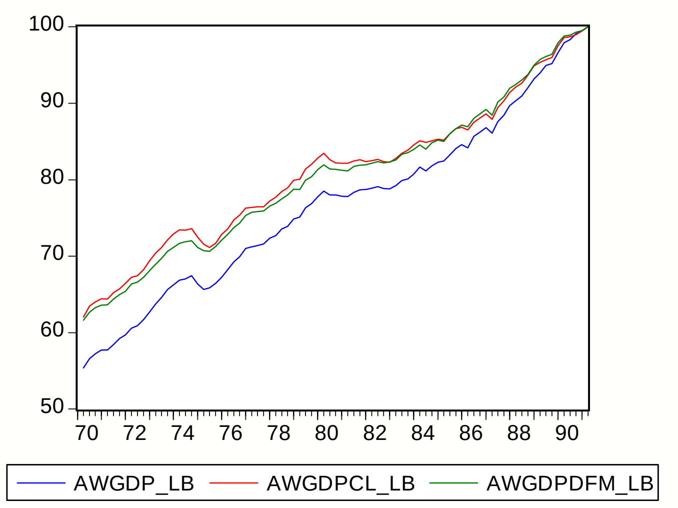
AWYEDCL is the GDP Deflator for the Euro Area using YEDCL for the Unified German series which is backdated using the Chow-Lin method
AWYEDCLFIX is the GDP Deflator for the Euro Area using YEDCLFIX for the Unified German series which is backdated using the Chow-Lin fixewd weight method
AWYEDDFM is the GDP Deflator for the Euro Area using YEDCDFM for the Unified German series which is backdated using the DFM method
AWYEDFHM is the GDP Deflator for the Euro Area using YEDFHM for the Unified German series which is backdated as in Fagan, Henry and Mestre 2001
AWYEDWEFIX is the GDP Deflator for the Euro Area using YEDWEFIX for the Unified German series which is backdated using a fixed weight

Figure 6: Euro Area GDP Growth using alternative backdated series for Unified Germany



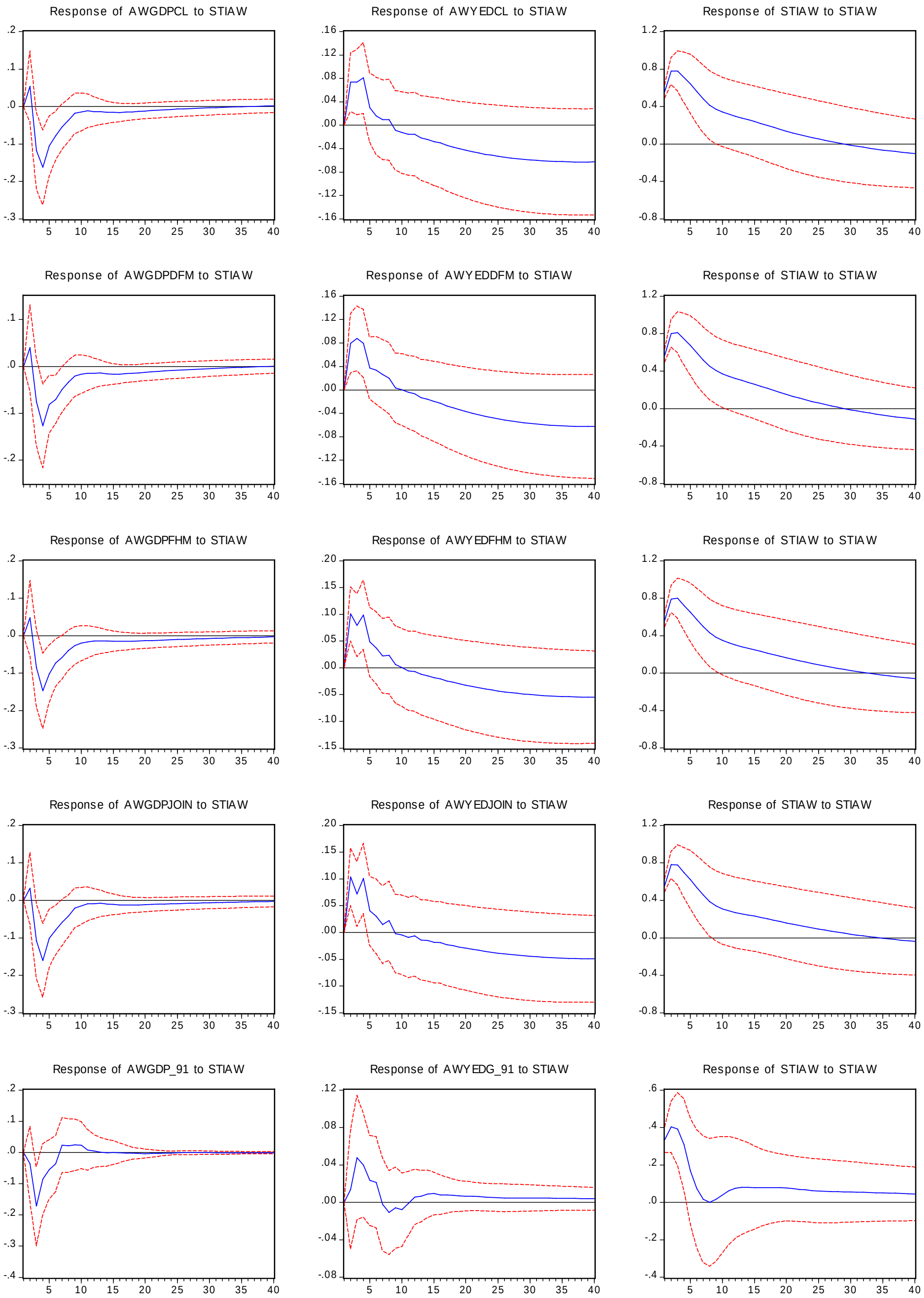
Note:
AWGDPCL is the GDP growth for the Euro Area using GDPCL for the Unified German series which is backdated using the Chow-Lin method
AWGDPCLFIX is the GDP growth for the Euro Area using GDPCLFIX for the Unified German series which is backdated using the Chow-Lin fixewd weight method
AWGDPDFM is the GDP growth for the Euro Area using GDPCDFM for the Unified German series which is backdated using the DFM method
AWGDPFHM is the GDP Deflator for the Euro Area using YEDFHM for the Unified German series which is backdated as in Fagan, Henry and Mestre 2001
AWGDPWEFIX is the GDP growth for the Euro Area using GDPWEFIX for the Unified German series which is backdated using a fixed weight

Figure 7: Euro Area GDP level using alternative backdated series for Unified Germany



Note:
AWGDP_LB is GDP in levels for Euro Area backdated as in Fagan et al. (2001)
AWGDPCL_LB is GDP in levels for Euro Area backdated using the Chow-Lin method to backdate Unifed German series
AWGDPDFM_LB is GDP in levels for Euro Area backdated using the DFM method for Unified German series

Figure 8: Response functions to a monetary shock in VARs for euro area



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