FORECASTING QUARTERLY GERMAN GDP AT MONTHLY INTERVALS USING MONTHLY IFO BUSINESS CONDITIONS DATA

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CESIFO WORKING PAPER NO. 1203
CATEGORY 5: FISCAL POLICY, MACROECONOMICS AND GROWTH
MAY 2004

PRESENTED AT CESIFO CONFERENCE "ACADEMIC USE OF IFO SURVEY DATA"
DECEMBER 2003

CESifo *Working Paper No. 1203*

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Abstract

The paper illustrates and evaluates a Kalman filtering method for forecasting German real GDP at monthly intervals. German real GDP is produced at quarterly intervals but analysts and decision makers often want monthly GDP forecasts. Quarterly GDP could be regressed on monthly indicators, which would pick up monthly feedbacks from the indicators to GDP, but would not pick up implicit monthly feedbacks from GDP onto itself or the indicators. An efficient forecasting model which aims to incorporate all significant correlations in monthly-quarterly data should include all significant monthly feedbacks. We do this with estimated VAR(2) models of quarterly GDP and up to three monthly indicator variables, estimated using a Kalman-filtering-based maximum-likelihood estimation method. Following the method, we estimate monthly and quarterly VAR(2) models of quarterly GDP, monthly industrial production, and monthly, current and expected, business conditions. The business conditions variables are produced by the Ifo Institute from its own surveys. We use early in-sample data to estimate models and later out-of-sample data to produce and evaluate forecasts. The monthly maximum-likelihood-estimated models produce monthly GDP forecasts. The Kalman filter is used to compute the likelihood in estimation and to produce forecasts. Generally, the monthly German GDP forecasts from 3 to 24 months ahead are competitive with quarterly German GDP forecasts for the same time-span ahead, produced using the same method and the same data in purely quarterly form. However, the present mixed-frequency method produces monthly GDP forecasts for the first two months of a quarter ahead which are more accurate than one-quarter-ahead GDP forecasts based on the purely-quarterly data. Moreover, quarterly models based on purely-quarterly data generally cannot be transformed into monthly models which produce equally accurate intra-quarterly monthly forecasts.

JEL classification: E37, C32.

Keywords: mixed-frequency data, VAR models, maximum-likelihood estimation, Kalman filter.

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The opinions expressed in the paper are the authors' and do not reflect any official positions of the Bureau of Labor Statistics.

1 Introduction

This paper illustrates and evaluates a Kalman–filtering method for forecasting German real GDP at monthly intervals. Like U.S. real GDP, German real GDP is produced and publicly released at quarterly intervals, although both U.S. and German economic analysts and business decision makers often want monthly GDP forecasts. Quarterly GDP could be regressed on monthly indicators organized quarterly. Thus, one could: (i) organize all observations on variables at quarterly intervals, with GDP automatically being quarterly and monthly indicators being made quarterly as first–, second–, and third–month quarterly observations; (ii) regress quarterly GDP on the monthly indicators organized quarterly; and, (iii) compute monthly GDP forecasts as the estimated regression evaluated at particular values of the monthly indicators. This description is purposely simple to illustrate the general point that a regression can pick up feedbacks of monthly variables onto quarterly variables but it cannot pick up implicit intra-quarterly monthly feedbacks from quarterly to monthly variables. To avoid this problem, we use a Kalman-filtering method developed by Zadrozny [10] for any number of variables observed at any mixture of frequencies and illustrated in a similar context of forecasting quarterly U.S. real GNP at monthly intervals using a monthly indicator. The method can account for any possible feedbacks, from any variable at any frequency to any other variable at the same or other frequency. The method involves estimating a multivariate time-series model of all variables being considered. The model operates at the highest observed frequency, monthly in this case, and, thus, produces forecasts of any variable at monthly intervals, regardless of the interval at which the variable is observed. Here, data are set up at the highest monthly frequency so that unobserved intra–quarterly monthly values of quarterly GDP are marked as missing. Maximum likelihood estimation (MLE) is used to estimate VAR(2) models. The Kalman filter is used in two ways. First, the Kalman filter is used to compute the likelihood function, under Gaussian or normality assumptions, which is maximized with respect to unknown model parameters. Second, given an estimated model, the Kalman filter is used to produce forecasts of variables, at the higher monthly frequency at which the model operates, any number of months ahead. In both cases, the Kalman filter is applied in a "missing data" form in order to "properly skip over" missing values. Details of these computations are discussed by Zadrozny [10]. The method allows models as general as vector autoregressive moving–average (VARMA) models, although previous and current experience indicates that purely VAR models often suffice for forecasting a variable with the help of other variables, when no restrictions on coefficients, indicated by statistical analysis or economic reasoning, are imposed on the forecasting model.

2 Description of Data

The data, obtained from the Ifo Institute in Munich, Germany, comprise quarterly German real GDP and three monthly indicators of the German economy: German real industrial production (PRD), current German real business conditions (CUR) and expected (6 months in the future) German real business conditions (EXP). The business conditions variables are produced by the Ifo Institute from its own surveys of German business firms. The monthly data cover January 1970 to December 2003 and the quarterly GDP data cover the same period, quarter 1 1970 to quarter 4 2003.

The four variables and their filtered values are displayed in figures 1–9. Figures 1–3 are monthly time plots and figures 4–9 are quarterly time plots. In the monthly graphs, the monthly variables are displayed as continuous lines, with no missing values, and quarterly GDP is displayed as a broken or dashed line, with missing intra–quarterly monthly values. Because each quarter's GDP is fully assigned to the third month of the quarter, GDP is treated as unobserved or missing in the first two intra–quarterly months of a quarter.

There are no missing values after the data are aggregated into quarterly form, so all displayed lines in the quarterly graphs are continuous. GDP is automatically in quarterly form. There are two ways, called "stock" and "flow," for aggregating monthly values to quarterly values. "Stock" means monthly values are skip sampled in the third month of each quarter, so that the value in the third month of a quarter becomes the quarterly value and the values in the first two months of the quarter are discarded. "Flow" means monthly values are aggregated into quarterly form by averaging the monthly values in a quarter. Also, monthly PRD is detrended and deseasonalized in two possible ways, called "AD filtered" and "AD/AMA filtered," to be discussed. Thus, the four ways considered for converting monthly–quarterly data to purely–quarterly data are called stock–AD–filtered, stock–AD/AMA–filtered, flow–AD–filtered, and flow– AD/AMA–filtered.

The variables are graphed in original and filtered forms. Henceforth, we use subscript t to denote months, e.g., PRD_t means PRD in month t, and for now let L^k denote the monthly lag operator applied k times in succession to a monthly variable, e.g., $\mathrm{L}^{12}\mathrm{PRD}_t = \mathrm{PRD}_{t-12}$. We know that the annual differencing operator, defined for monthly time intervals as $\mathrm{AD(L)} = 1 - \mathrm{L}^{12}$, is the product of a single monthly difference, $\mathrm{MD(L)} = 1 - \mathrm{L}$, times a single annual sum, $\mathrm{AS(L)} = 1 + \mathrm{L} + \ldots + \mathrm{L}^{11}$, or $\mathrm{AD(L)} = \mathrm{MD(L)AS(L)}$. Frequency analysis shows that multiplying a variable by MD(L) eliminates its linear deterministic (polynomial) and linear stochastic (unit–root autoregressive) trends and multiplying the variable by AS(L) eliminates its deterministic (harmonic) seasonality, although a variable can have additional stochastic seasonality which cannot be removed by AS(L). This appears to be the case with PRD_t, which is discussed below.

Figure 1 displays the four variables in original monthly form. We see that GDP_t follows an upward trend with additional, relatively small, seasonal variations about the trend. PRD_t also follows an upward trend, with relatively larger seasonal variations about the trend, plus more easily seen cyclical variations. CUR_t and EXP_t both display no apparent trends or seasonality, only cyclical variations. Because in original form the variables are compatible only as GDP_t with PRD_t and CUR_t with EXP_t, there is little hope of obtaining MLE of a VAR model of the four variables in original form, namely GDP_t, PRD_t, CUR_t, and EXP_t. Therefore, to obtain MLE of a VAR model of the four variables, we first linearly filtered GDP_t and PRD_t to eliminate their trends and seasonality, so that the resulting four variables display only cyclical variations and are compatible.

As seen in the figures, the main difference between monthly data versus quarterly data and quarterly-stock data versus quarterly–flow data is smoothness versus noisiness, where "noisiness" means unpredictable high–frequency random variation and "smoothness" means absence of noisiness. As expected, monthly data are noisier than quarterly data and quarterly–stock data are noisier than quarterly–flow data. We expect smoother data to produce better GDP forecasts. Summary table 8 shows that smoother quarterly data produce better long–term GDP forecasts than noisier monthly data, but that choosing stocks instead of flows or AD instead of AD/AMA filtering has insignificant effect on GDP forecast accuracy.

3 Transformation of Data

We filtered GDP_t and PRD_t, respectively, using the single quarterly difference, $\mathrm{QD(L)} = 1$ - L^3, and MD(L), graphed the results, and visually determined that QD(L) and MD(L) remove trends from GDP_t and PRD_t. Because GDP_t is observed only in the third month of a quarter, the shortest time interval over which it can be differenced to remove trend is the quarter. Then, in effect, we filtered $\mathrm{QD(L)GDP}_t$ and $\mathrm{MD(L)PRD}_t$ using AS(L). Actually, we restarted the filtering and directly annually differenced GDP_t and PRD_t using AD(L), which amounts to the same operation. Then, we graphed the results and visually determined that AD(L) removes trends and seasonality from GDP_t and PRD_t. Although we do not display the intermediate QD(L)- and MD(L)–filtered results, figure 2 displays the final monthly AD–filtered GDP_t and PRD_t, denoted $\mathrm{AD}(\mathrm{GDP}_t)$ and $\mathrm{AD}(\mathrm{PRD}_t)$, and the original unfiltered CUR_t and EXP_t. Because $\mathrm{AD}(\mathrm{GDP}_t)$, $\mathrm{AD}(\mathrm{PRD}_t)$, CUR_t, and EXP_t display only cyclical variations, in this mixed form the four variables are compatible and suitable for estimating a VAR model.

AD filtered means GDP_t and PRD_t are filtered using only AD(L) and CUR_t and EXP_t are unfiltered. Initial model estimation resulted in PRD_t residuals with a significantly negative autocorrelation coefficient at the annual lag, indicating AD(L) does not remove all seasonality from PRD_t. Therefore, we extended AD(L) to an "airline model," with an additional estimated annual (seasonal) first–order moving–average term, to remove any remaining significant stochastic seasonality from PRD_t. We denote airline–model filtered PRD_t by $\mathrm{AD/AMA}(\mathrm{PRD}_t)$, where AMA refers to annual moving average. The term "airline model" comes from Box and Jenkins [1] and is often the "default" model in a search for the best ARIMA seasonal–adjustment model.

We extended monthly $\mathrm{AD}(\mathrm{PRD}_t)$ to monthly $\mathrm{AD/AMA}(\mathrm{PRD}_t)$ as follows. We supposed $\mathrm{AD}(\mathrm{PRD}_t)$ is generated by the seasonal–adjustment model $\mathrm{AD}(\mathrm{PRD}_t) = \left(1 - \phi_1\mathrm{L} - \phi_2\mathrm{L}^2 - \phi_3\mathrm{L}^3\right)^{-1}\left(1 + \theta\mathrm{L}^{12}\right)\varepsilon_t$, where the nonseasonal AR(3) component $\left(1 - \phi_1\mathrm{L} - \phi_2\mathrm{L}^2 - \phi_3\mathrm{L}^3\right)^{-1}$ accounts for cyclicality, the seasonal MA(1) component $1 + \theta\mathrm{L}^{12}$ accounts for stochastic seasonality, and ε_t is a white–noise disturbance distributed $\mathrm{NIID}\left(0, \sigma_\varepsilon^2\right)$. Note that both the univariate seasonal–adjustment models and the multivariate VAR models for GDP forecasting were estimated using mean–adjusted and standardized data (divided by standard deviation after mean adjustment). The data and the estimated AR(3) component are stationary, which means that $1 - \phi_1\lambda - \phi_2\lambda^2 - \phi_3\lambda^3 = 0$ implies $|\lambda| > 1$, and the seasonal MA(1) is estimated as invertible, which means that $|\theta| < 1$. AD/AMA(PRD_t) is defined as $\left(1+\theta \mathrm{L}^{12}\right)^{-1}\mathrm{AD}(\mathrm{PRD}_t)$ and is approximated by four terms: AD/AMA(PRD_t) = missing, for $t = 1, \ldots, 48$, and AD/AMA(PRD_t) = $\mathrm{PRD}_t - \left(1+\hat{\theta}\right)\mathrm{PRD}_{t-12} + \hat{\theta}\left(1+\hat{\theta}\right)\mathrm{PRD}_{t-24} - \hat{\theta}^2\left(1+\hat{\theta}\right)\mathrm{PRD}_{t-36} + \hat{\theta}^3\left(1+\hat{\theta}\right)$ PRD_{t-48}, for $t = 49, \ldots, 408$, where monthly $\hat{\theta} = -.5033$ is estimated jointly with the AR parameters, using MLE.

Similarly, we extended quarterly AD(PRD_s) to quarterly AD/AMA(PRD_s), using the analogous model $\mathrm{AD}(\mathrm{PRD}_s) = \left(1 - \phi_1\mathrm{L} - \phi_2\mathrm{L}^2 - \phi_3\mathrm{L}^3\right)^{-1}\left(1+\theta\mathrm{L}^4\right)$ ε_s, where subscript s denotes quarters and L now denotes the quarterly lag operator. AD/AMA(PRD_s) is defined as $\left(1+\theta\mathrm{L}^4\right)^{-1}\mathrm{AD}(\mathrm{PRD}_s)$ and is approximated by four terms: AD/AMA(PRD_s) = missing, for $s = 1, \ldots, 16$, and AD/AMA(PRD_s) = $\mathrm{PRD}_s - \left(1+\hat{\theta}\right)\mathrm{PRD}_{s-4} + \hat{\theta}\left(1+\hat{\theta}\right)\mathrm{PRD}_{s-8} - \hat{\theta}^2$ $\left(1+\hat{\theta}\right)\mathrm{PRD}_{s-12} + \hat{\theta}^3\left(1+\hat{\theta}\right)\mathrm{PRD}_{s-16}$, for $s = 17, \ldots, 136$, where $\hat{\theta} = -.6769$ using quarterly stock data and $\hat{\theta} = -.5041$ using quarterly flow data.

Both monthly and quarterly AD–filtered data comprise AD(GDP), AD (PRD), CUR, and EXP and monthly and quarterly AD/AMA–filtered data comprise AD(GDP), AD/AMA(PRD), CUR, and EXP. Because AD/AMA (PRD) is smoother than AD(PRD), as seen for example in the quarterly figures 4–9, we might expect more accurate GDP forecasts using AD/AMA(PRD). But, because this was not always the case, we did not further extend the AD/AMA model and filter to a more detailed seasonal–adjustment model and filter (cf., Flaig [4]). Thus, present forecasting results indicate some seasonal adjustment is necessary to put all variables in compatible cyclical form in order to estimate a forecasting model, but table 8 shows that a more thorough seasonal adjustment does not necessarily improve short– or long–term forecasts. Of course, a government statistical agency responsible for producing seasonally–adjusted data is obliged to produce thoroughly adjusted data, whatever the consequences in subsequent applications.

Because log–form data are often more homogeneous (have more constant variances or homoskedasticity), hence, are often easier to fit, we also considered log–form data. Because non–missing original values of GDP_t and PRD_t values are positive, these variables were transformed directly to natural logs. However, because values of CUR_t and EXP_t are negative, zero, or positive fractions, they were indirectly transformed into logs as follows. For example, consider CUR_t and suppose d_t, u_t, and i_t denote the fractions of survey respondents who, respectively, said current business conditions declined, are unchanged, or improved. Then, $\mathrm{CUR}_t = i_t - d_t$, such that u_t is ignored. However, because $d_t + u_t + i_t = 1$ and assuming $u_t = 0$, $i_t/d_t = (1+\mathrm{CUR}_t)/(1-\mathrm{CUR}_t) > 0$, so that $\ln\left[(1+\mathrm{CUR}_t)\,/\,(1-\mathrm{CUR}_t)\right]$ is well defined and can be considered the "log" of CUR_t and similarly for EXP_t.

Thus, we computed AD–filtered $\ln(\mathrm{GDP}_t)$ and $\ln(\mathrm{PRD}_t)$, as in the unlogged cases, and unfiltered $\ln(\mathrm{CUR}_t)$ and $\ln(\mathrm{EXP}_t)$. Resulting graphs of monthly, original and filtered, log–form data were very close to those in figures 1–3. Also, monthly model estimates were very similar, regardless whether the data were log transformed or not. Thus, we did not conduct further analysis with the log–form data.

4 Estimation of VAR Models

In principle, we searched for the best combination of monthly indicators for forecasting GDP (we now denote filtered GDP and PRD more simply as "GDP" and "PRD," without AD or AD/AMA). In practice, we restricted the search to three of seven possibilities: models of GDP, PRD, CUR, and EXP; models of GDP, PRD, and CUR; and, models of GDP and PRD. First, we dropped EXP because it is considered the less informative Ifo variable and is somewhat redundant statistically, given CUR. Then, we dropped CUR to see what difference using any Ifo variables makes in forecasting GDP. Finally, we kept PRD because it is often the first choice of a monthly indicator when forecasting GDP.

We aimed for "adequate" estimated VAR models, by which we mean the following. As usual, our ideal was models with minimum numbers of parameters and zero–mean, constant–variance, and independently–distributed residuals. For each of the three variable sets, we estimated unrestricted VAR(1) models, whose residuals showed significant serial correlations, and, then, estimated unrestricted VAR(2) models, whose residuals showed mostly insignificant correlations except for a few higher-lag correlations which could not be accounted for with lower–order VAR models. Thus, we accepted estimated VAR(2) models as adequately fitting the three sets of variables. In reaching this conclusion, we inspected graphs of residual own– and cross–serial correlations, evaluated p values of Ljung–Box Q statistics [6] and evaluated information criteria. Although Ljung–Box Q statistics were developed to test for significant residual own-serial correlations, we also used them to test for significant residual cross–serial correlations. We did not test for significance of individual estimated parameters or remove any.

For the eighteen final estimated VAR(2) models, in table 1 we report only R_e^2 (the usual R–squared called "estimation R squared," which is distinguished in section 5 from $\mathrm{R}_{f,h}^2$, called "forecasting R squared"). We do not report estimated parameters because, as usual in VAR models, they are very imprecise and, thus, provide little reliable information about feedbacks among variables. We also computed implied estimated AR characteristic roots which were all expectedly and firmly stationary. Although R_e^2 does not account for degrees of freedom used in estimation, only pertains to individual variables, and does not pertain to complete estimated models, nevertheless, higher values of R_e^2 are generally associated with more accurate GDP forecasts as seen by comparing table 1 with tables 2–8. We used "in sample" data from January 1970 to December 1993 to estimate models and "out of sample" data from January 1994 to December 2003 to produce and evaluate GDP forecasts.

We implemented the MLE using a FORTRAN 77 program, compiled the program using the Lahey–Fujitsu FORTRAN 95 complier version 5.6, and executed the program on a personal computer with a Pentium 4 central processor, running at about 2 gigahertz speed and controlled by the Windows XP operating system. Using a 10^{-8} convergence criterion, estimating the largest models, with 4 variables and 42 parameters, took about 4000 iterations or less than 20 minutes from start to finish. We started all iterations by setting parameter values to .01. If iterations stalled (reached a point in parameter space where the likelihood function appeared flat in all directions so that no further moves were made, even though convergence was not achieved), we restarted them at the last parameter values. Sometimes we restarted the iterations several times before achieving convergence. Thus, the MLE was not automatic and needed intervention.

5 Evaluation of GDP Forecasts

For the GDP forecasts, we define normalized root mean squared forecast error for h–period–ahead forecasts as $\mathrm{NRMSFE}_h = \sqrt{\left(\sum_{t=1}^{T} e^2_{t/h-h}\right)/T} \div$ out–of–sample standard deviation of GDP, where $e_{t|t-h} = \mathrm{GDP}_t - \mathrm{GDP}_{t|t-h} =$ error of forecasting GDP_t in period $t-h$, for out–of–sample periods $t = 1, \ldots T$, missing values of $e_{t|t-h}$ are dropped from the summation, and T is reduced correspondingly. For every variable, we define estimation R–squared as the usual $\mathrm{R}^2_e = 1 -$ in–sample variance of a variable's residual in an estimated model $\div$ in–sample variance of the variable and define forecasting R–squared as $R^2_{f,h} = 1 - \mathrm{NRMSFE}^2_h$, for $h \geq 1$. First, generally, $\mathrm{R}^2_{f,h} \leq \mathrm{R}^2_e$ and, equivalently, $\mathrm{NRMSFE}_h \geq \sqrt{1 - \mathrm{R}^2_e}$, for $h \geq 1$. $\mathrm{R}^2_{f,h} \cong \mathrm{R}^2_e$ and $\mathrm{NRMSFE}_h \cong \sqrt{1 - \mathrm{R}^2_e}$, for $h \geq 1$, suggest that the data generating process has changed not at all or insignificantly between the in– and out–of–sample periods, so that out–of–sample forecasts should be maximally accurate. Alternately, $\mathrm{R}^2_{f,h} << \mathrm{R}^2_e$ and $\mathrm{NRMSFE}_h >> \sqrt{1 - \mathrm{R}^2_e}$, for $h \geq$1, suggest that the data generating process has changed significantly between in– and out–of–sample periods, where $<<$ and $>>$ denote "much less than" and "much greater than". Second, an efficient forecast, which fully exploits available information, is orthogonal to its forecast error, so that $\mathrm{R}^2_{f,h} > 0$ and $\mathrm{NRMSFE}_h < 1$, for $h \geq 1$. Because the last conditions are necessary, but not sufficient, for efficiency, $\mathrm{R}^2_{f,h} \leq 0$ and $\mathrm{NRMSFE}_h \geq 1$, for $h \geq 1$, imply that a forecast is inefficient, but $\mathrm{R}^2_{f,h} > 0$ and $\mathrm{NRMSFE}_h < 1$, for $h \geq 1$, do not imply that the forecast is efficient.

Tables 1–7 show that R^2_e is significantly greater than any $\mathrm{R}^2_{f,h}$, which suggests that the data generating process of the German economy changed significantly after 1993. This is what we expect as a result of the immediate political and evolving economic unification of Germany in 1990. We produced nonrecursive forecasts based on fixed models estimated using fixed in-sample data. Recursive forecasts based on models reestimated using recursively updated in–sample data should reduce the differences between R_e^2 and $R_{f,h}^2$. Table 8 shows that monthly–long–term GDP forecasts are inefficient, certainly relative to quarterly–long–term GDP forecasts. Thus, we disregard these forecasts and further evaluate only the remaining three cases.

We can compare forecasts "internally" by comparing in–sample R_e^2 and out–of–sample $R_{f,h}^2$ based on the same estimated model of interest, or, we can compare forecasts "externally" by comparing out–of–sample $R_{f,h}^2$ and NRMSFE_h for the model of interest and competing "external" models. External comparisons are costly to the extent that competing models must be developed, although both comparisons should be made. For simplicity, we focus on internal comparisons and report external comparisons only in terms of Theil U statistics for essentially costless "naive" forecasts. By definition, Theil U = NRMSFE_h of the forecast of interest $\div$ NRMSFE_h of the naive forecast, where the naive forecast is the last observed value of the variable of interest at least h periods ago Doan [3]. A Theil U value < 1 implies that the forecasts of interest are better than the naive forecasts. As hoped, this occurs in almost all cases in tables 2–7. Although we focus on NRMSFE_h and $R_{f,h}^2$, conclusions based on Theil U would be the same.

We used the following test to determine whether using the Ifo variables, CUR and EXP, results in better monthly or quarterly GDP forecasts. In the undiscarded, monthly–short–term and quarterly, cases in table 8, we let ρ denote the total number of variables in the 50%–best–forecasting models divided by the total number of variables in the 50%–worst–forecasting models. Thus, $.636 \leq \rho \leq 1.571$; because using 2, 3, or 4 variables means using 0, 1, or 2 Ifo variables, higher values of ρ imply that using Ifo variables produces better GDP forecasts; and, if ρ is uniformly distributed, its bottom quartile spans $[.636, .870]$, its middle quartiles span $[.870, 1.338]$, and its top quartile spans $[1.338, 1.571]$. Thus, if ρ is in the lowest quartile, the middle quartiles, or the highest quartile, we conclude, respectively, that using Ifo variables significantly reduces, insignificantly changes, or significantly improves GDP–forecast accuracy.

We used analogous tests to determine which filtering and aggregation methods produced better GDP forecasts. We assigned 0 to AD filtering, 1 to AD/AMA filtering, 0 to stock aggregation, and 1 to flow aggregation (analogous tests follow from reverse assignments). For each classification, we let φ denote the sum of the numerical values in the 50%–best–forecasting models divided by 3 in monthly cases or divided by 6 in quarterly cases. Then, $0 \leq \varphi \leq 1$ and, if φ is uniformly distributed, its bottom quartile spans $[0.0, .25]$, its middle quartiles span [.25, ,75], and its top quartile spans $[.75, 1.0]$. Thus, for a particular classification, if φ is in the lowest quartile, the middle quartile, or the highest quartile, we conclude, respectively, that choosing the zero option significantly improves GDP forecasting accuracy, choosing either option insignificantly affects GDP forecasting accuracy, and choosing the unit option significantly improves GDP forecasting accuracy.

Recall that we are forecasting AD–filtered GDP. We could transform the forecasts of filtered GDP back to the original form of GDP by unnormalizing the forecasts using the standard deviation and mean of filtered GDP and undifferencing the result. Frequently, the backtransformed original-form forecasts are more accurate, because the restored trends and seasonalities are purely deterministic, hence, perfectly predictable.

6 Conclusions

NRMSFE_h and $\mathrm{R}^2_{f,h}$ of the filtered GDP forecasts in tables 2–7 are summarized in table 8 and imply the following six general conclusions.

1. Monthly GDP forecasts are feasible. Estimating a monthly VAR model of quarterly-observed German GDP and monthly–observed indicators of the German economy, using Kalman–filtering–based MLE to produce monthly GDP forecasts, is feasible only if the variables are in compatible cyclical form and not too many parameters are estimated. We estimated unrestricted VAR(2) models of 2–4 variables, with 15–42 parameters, using 408 monthly and 96 quarterly in–sample periods. Estimating monthly models using monthly–quarterly data seems essential for producing accurate monthly GDP forecasts, especially short–term forecasts, because, even though we can transform quarterly models estimated with purely–quarterly data into monthly models, generally, such transformed models are not expected to produce accurate monthly forecasts.

2. Monthly models produce better short-term GDP forecasts. Monthly models 1–3 produce better short–term GDP forecasts (1–3 months ahead) than the best quarterly–short–term GDP forecasts (1 quarter ahead) produced by model 14. Both monthly– and quarterly–short–term GDP forecasts are not inefficient ($\mathrm{NRMSFE}_h < 1$). The greater accuracy of the monthly–short–term GDP forecasts should provide sufficient motivation for estimating monthly models, using quarterly–observed GDP and monthly–observed indicators, for producing monthly–short–term GDP forecasts.

3. Quarterly models produce better long–term GDP forecasts. Every monthly model produced inefficient monthly–long–term GDP forecasts (average NRMSFE_h of 1–24 months ahead > 1) which should be disregarded. Every quarterly model produced not inefficient, hence, at least tentatively acceptable, quarterly long–term GDP forecasts (average NRMSFE_h of 1–8 quarters ahead < 1).

4. Ifo variables improve long-term GDP forecasts. After disregarding monthly–long–term GDP forecasts, we have monthly–short–term, quarterly–short–term, and quarterly–long–term cases in table 8. In these cases, ρ is, respectively, 1.125, 1.400, and 1.118, which implies that using the Ifo variables insignificantly improves monthly–short–term or quarterly–long–term GDP forecasts, but significantly improves quarterly–short–term GDP forecasts (use of ρ is explained in section 5).

5. Aggregation and filtering choices insignificantly affect GDP forecasts. In the monthly–short–term case in table 8, the filtering $\varphi = 0$, which implies that AD filtering produces significantly better GDP forecasts, and the aggregation φ is irrelevant. In the quarterly cases, the aggregation $\varphi = .500$ and .667, and the filtering $\varphi = .500$ and .333, which implies that how we aggregate or filter has no significant effect on GDP forecasts (use of φ is explained in

section 5). Thus, choosing AD filtering makes a difference — improves GDP forecasts — only in the monthly–short–term case.

6. Extensions to mixed-frequency forecasting with larger models. We might want to estimate larger models, with more variables and more parameters, but the present experience suggests that the present models are at the limit of what MLE can handle, especially with mixed–frequency data. To estimate larger models with mixed–frequency data, we should not use MLE, but should use a noniterative finite–step estimation method. For example, Chen and Zadrozny [2] developed and illustrated the extended Yule–Walker (XYW) method, a linear 2–step GMM method (Hansen [5]) for estimating a VAR model with mixed–frequency data. Being linear and 2–step, the XYW method can be implemented automatically and should be able to handle much larger models than MLE can handle. Mittnik [7], [8], [9] developed and illustrated a linear 2–step method for estimating a state–space model with single–frequency data and using the estimated model for forecasting. Extending this method to mixed–frequency data could be more attractive, because, although the two methods have comparable numerical properties, state–space models are more general. Often, a low–dimensional state–space model can fit data well, which even a many–lag VAR model cannot.

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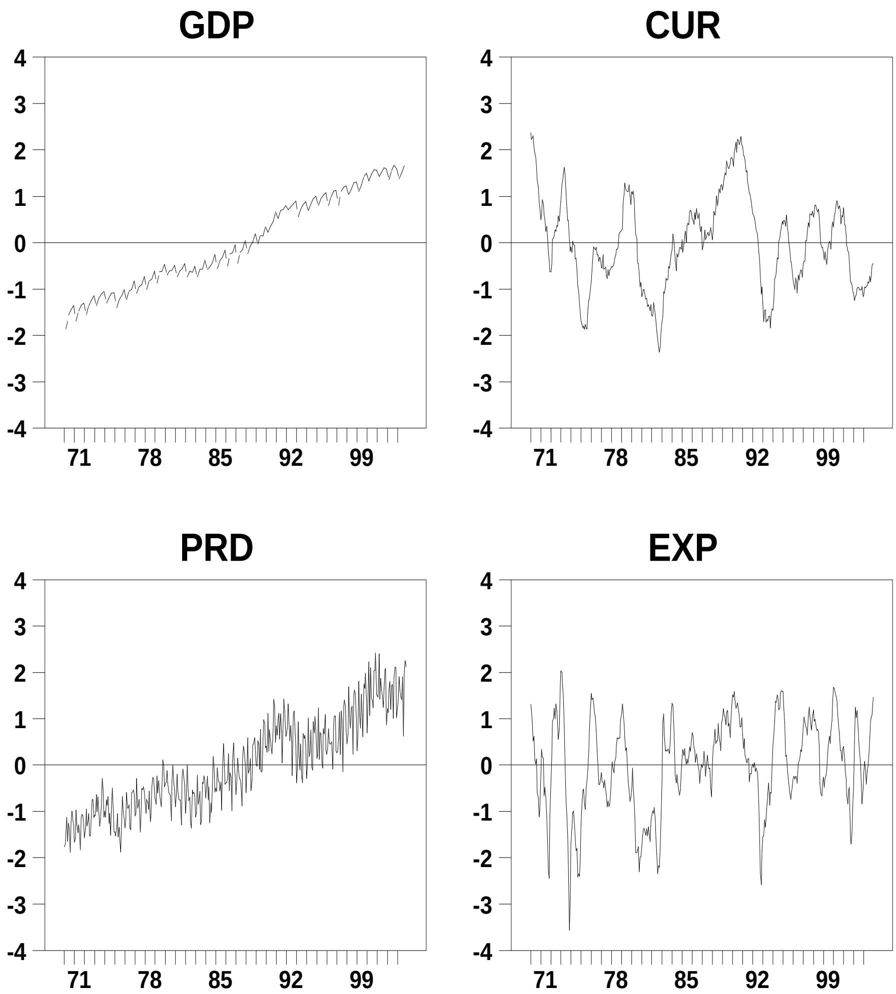

Fig. 1. Monthly, Original Variables

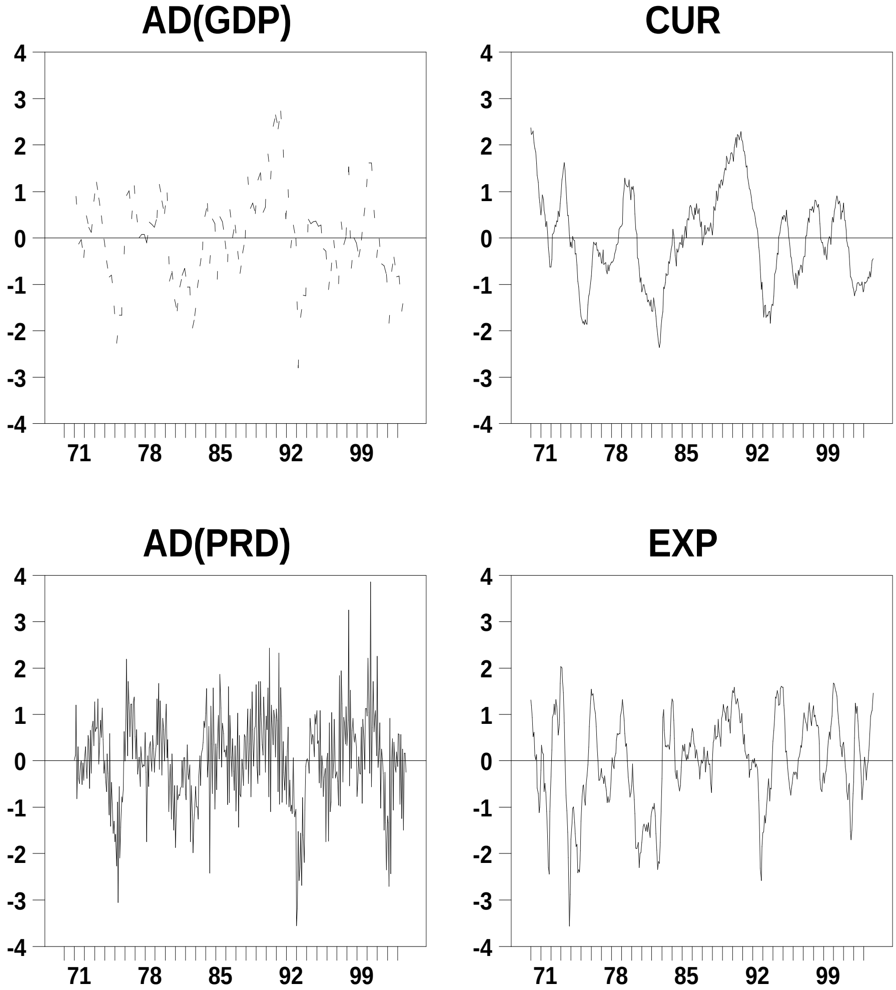

Fig. 2. Monthly, AD Filtered

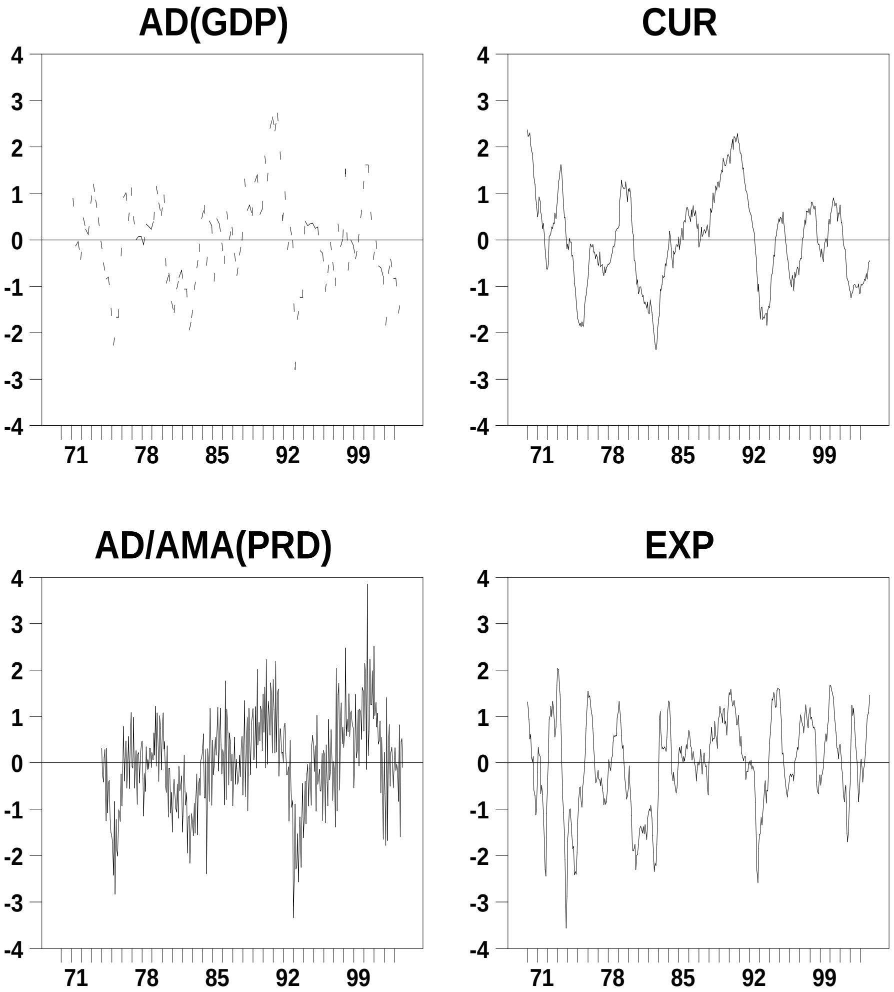

Fig. 3. Monthly, AD/AMA Filtered

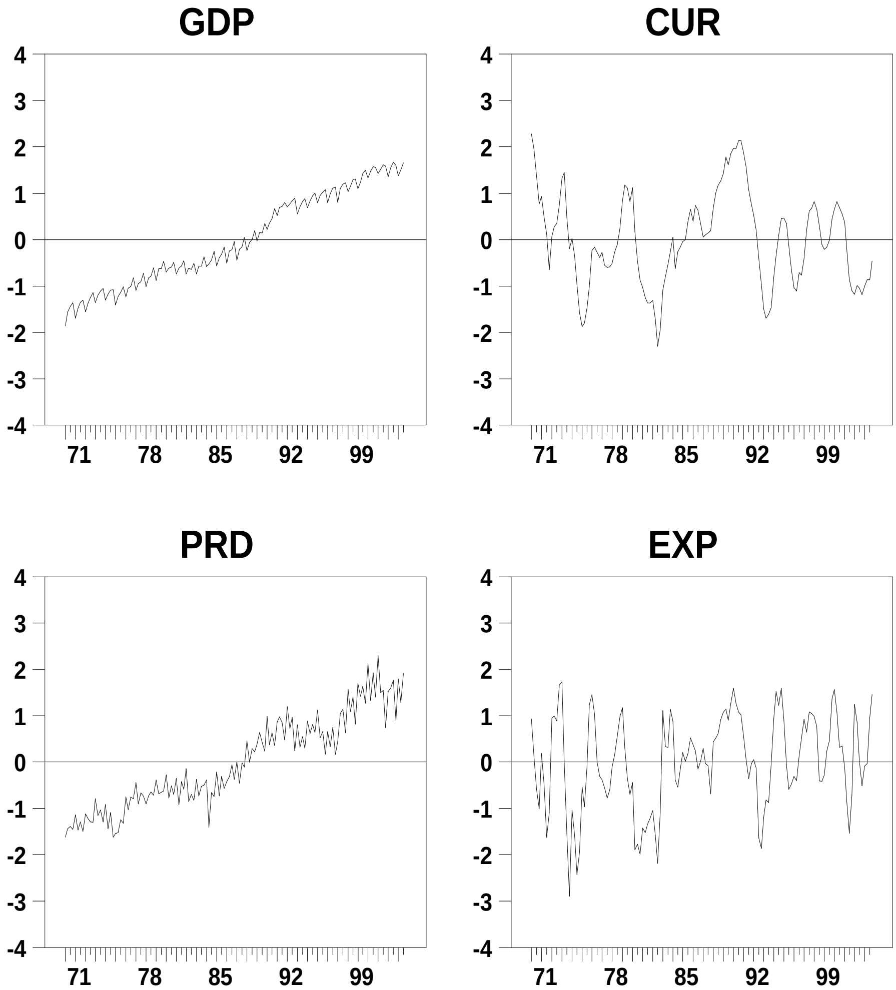

Fig. 4. Quarterly, Stocks, Original Variables

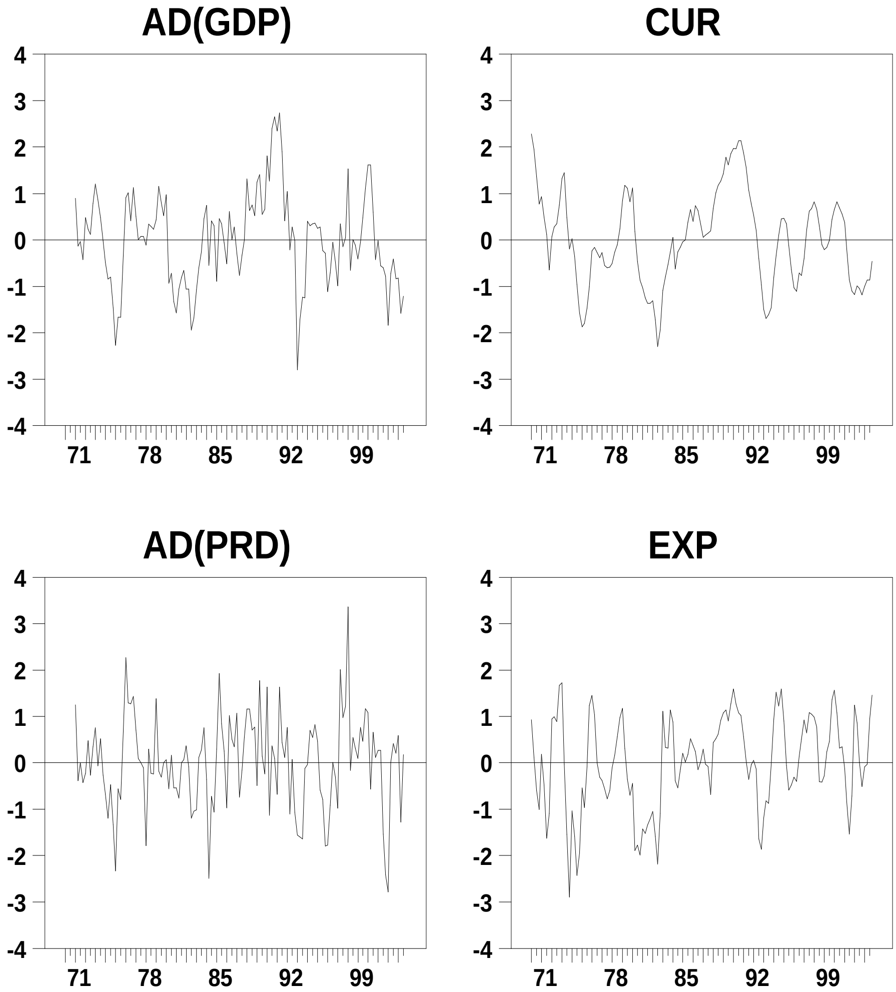

Fig. 5. Quarterly, Stocks, AD Filtered

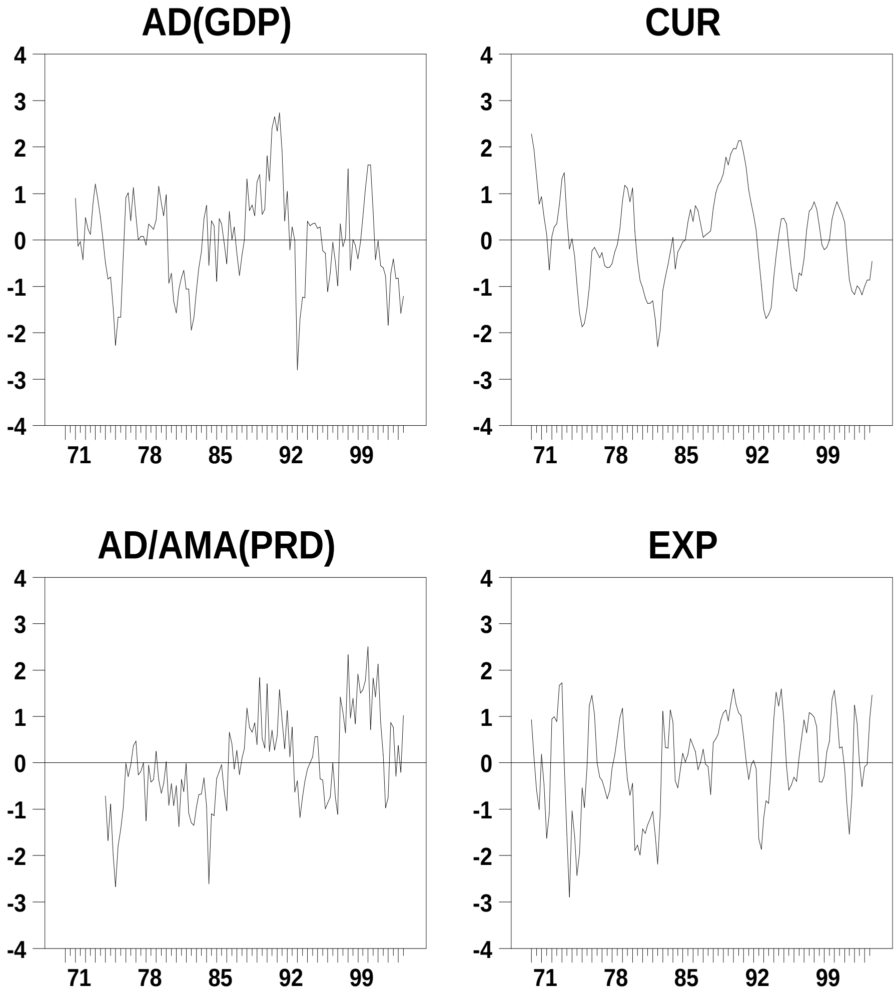

Fig. 6. Quarterly, Stocks, AD/AMA Filtered

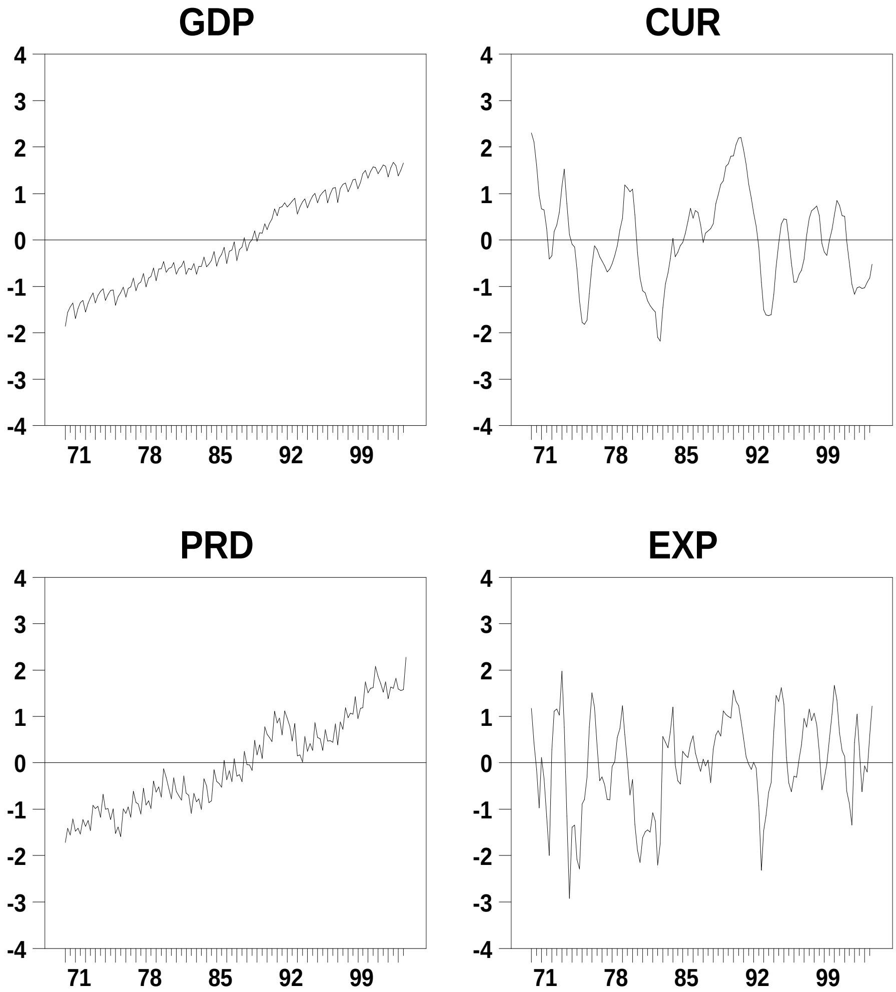

Fig. 7. Quarterly, Flows, Original Variables

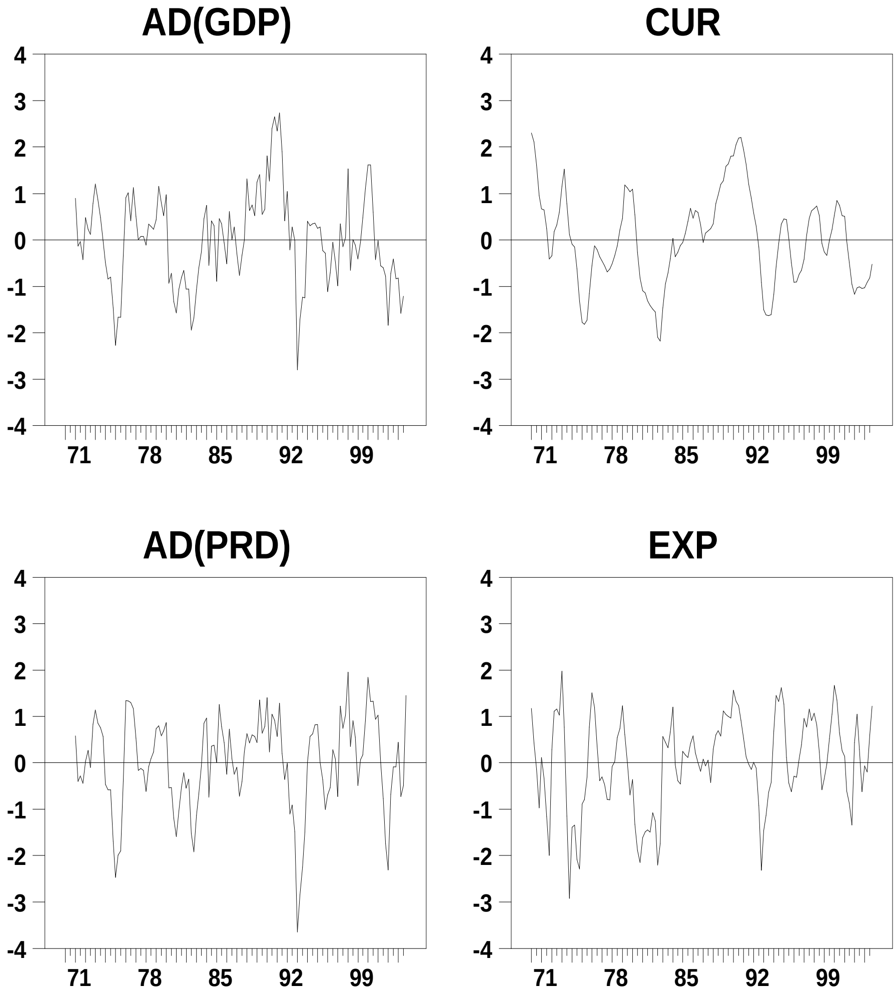

Fig. 8. Quarterly, Flows, AD Filtered

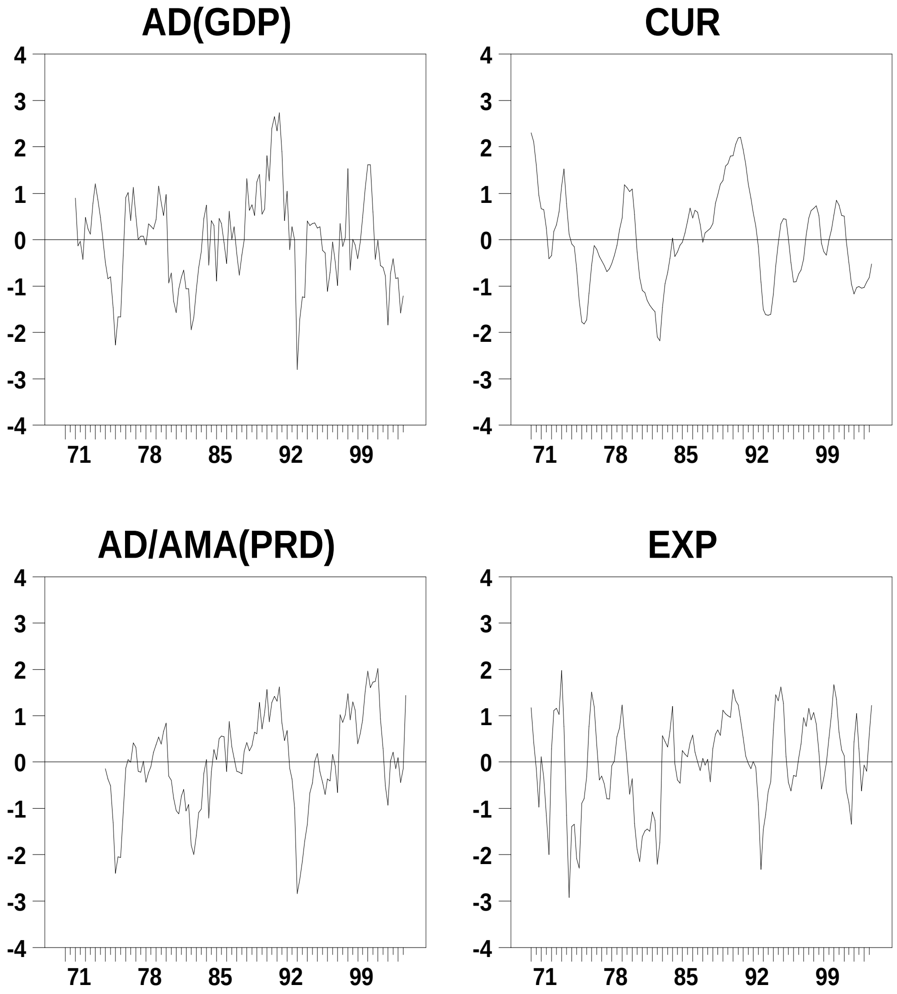

Fig. 9. Quarterly, Flows, AD/AMA Filtered

Table 1. R_e^2 of Estimated VAR(2) Models

	Model	GDP	PRD	CUR	EXP
1	mon, 4 vars, AD	.804	.522	.966	.904
2	mon, 3 vars, AD	.812	.478	.958	—
3	mon, 2 vars, AD	.850	.488	—	—
4	mon, 4 vars, AD/AMA	.783	.608	.966	.903
5	mon, 3 vars, AD/AMA	.780	.592	.959	—
6	mon, 2 vars, AD/AMA	.516	.567	—	—
7	qrt, 4 vars, stocks, AD	.735	.239	.882	.606
8	qrt, 3 vars, stocks, AD	.663	.201	.867	—
9	qrt, 2 vars, stocks, AD	.592	.145	—	—
10	qrt, 4 vars, stocks, AD/AMA	.734	.553	.882	.606
11	qrt, 3 vars, stocks, AD/AMA	.663	.530	.867	—
12	qrt, 2 vars, stocks, AD/AMA	.592	.499	—	—
13	qrt, 4 vars, flows, AD	.725	.715	.912	.626
14	qrt, 3 vars, flows, AD	.685	.682	.900	—
15	qrt, 2 vars, flows, AD	.606	.600	—	—
16	qrt, 4 vars, flows, AD/AMA	.721	.822	.911	.632
17	qrt, 3 vars, flows, AD/AMA	.690	.802	.901	—
18	qrt, 2 vars, flows, AD/AMA	.597	.739	—	—

Tables 1–8 display estimation R–squared $\left(R_e^2\right)$, forecasting R–squared $\left(R_{f,h}^2\right)$, normalized root mean squared forecast error (NRMSFE_h), and Theil U statistics, for $h \geq 1$ forecast periods ahead, all defined in section 5.

Table 2. GDP Forecast Accuracy, Monthly, AD Filtered

Model 1: VAR(2) of 4 variables AD(GDP), AD(PRD), CUR, EXP

months ahead	$NRMSFE_h$	$R^2_{f,h}$	Theil U
1	.723	.477	.724
2	.802	.357	.796
3	.852	.274	.846
4	.947	.103	.787
5	.993	.014	.824
6	1.02	-.404	.846
9	1.22	-.488	.900
12	1.36	-.850	.795
18	1.30	-.690	.756
24	1.16	-.346	.671
average 1-24 months	1.18	-.392	.781

Model 2: VAR(2) of 3 variables AD(GDP), AD(PRD), CUR

months ahead	$NRMSFE_h$	$R^2_{f,h}$	Theil U
1	.731	.466	.725
2	.846	.284	.839
3	.917	.159	.910
4	1.02	-.040	.847
5	1.12	-.254	.934
6	1.15	-.323	.958
9	1.39	-.932	1.02
12	1.54	-1.37	.896
18	1.46	-1.13	.852
24	1.33	-.769	.771
average 1-24 months	1.32	-.742	.872

Model 3: VAR(2) of 2 variables AD(GDP), AD(PRD)

months ahead	$NRMSFE_h$	$R^2_{f,h}$	Theil U
1	.711	.494	.705
2	.799	.362	.792
3	.920	.154	.913
4	.959	.080	.797
5	.962	.075	.799
6	1.02	-.040	.846
9	1.07	-.144	.785
12	1.17	-.369	.684
18	1.25	-.563	.656
24	1.11	-.232	.644
average 1-24 months	1.08	-.166	.719

Table 3. GDP Forecast Accuracy, Monthly, AD/AMA Filtered

Model 4: VAR(2) of 4 variables AD(GDP), AD/AMA(PRD), CUR, EXP			
months ahead	NRMSFE$_h$	$R^2_{f,h}$	Theil U
1	.820	.328	.813
2	.816	.334	.810
3	.821	.326	.814
4	.932	.131	.774
5	.993	.014	.792
6	.981	.038	.815
9	1.18	-.392	.873
12	1.31	-.716	.763
18	1.27	-.613	.740
24	1.12	-.254	.649
average 1-24 months	1.15	-.323	.761

Model 5: VAR(2) of 3 variables AD(GDP), AD/AMA(PRD), CUR			
months ahead	NRMSFE$_h$	$R^2_{f,h}$	Theil U
1	.814	.337	.808
2	.870	.243	.863
3	.882	.222	.875
4	.966	.067	.802
5	1.07	-.145	.888
6	1.06	-.124	.882
9	1.23	-.513	.906
12	1.34	-.796	.783
18	1.33	-.769	.774
24	1.19	-.416	.691
average 1-24 months	1.21	-.464	.804

Model 6: VAR(2) of 2 variables AD(GDP), AD/AMA(PRD)			
months ahead	NRMSFE$_h$	$R^2_{f,h}$	Theil U
1	.935	.126	.927
2	1.02	-.040	1.01
3	.997	.006	.989
4	1.11	-.232	.923
5	1.23	-.513	.936
6	1.13	-.277	.939
9	1.10	-.210	.808
12	1.06	-.124	.617
18	1.09	-.188	.634
24	1.07	-.145	.623
average 1-24 months	1.07	-.145	.729

Table 4. GDP Forecast Accuracy, Quarterly, Stocks, AD Filtered

Model 7: VAR(2) of 4 variables AD(GDP), AD(PRD), CUR, EXP			
quarters ahead	NRMSFE_h	$R^2_{f,h}$	Theil U
1	.812	.341	.872
2	.822	.324	.730
3	.846	.284	.648
4	.876	.233	.512
6	.928	.139	.512
8	.977	.045	.510
average 1-8 quarters	.889	.210	.600

Model 8: VAR(2) of 3 variables AD(GDP), AD(PRD), CUR			
quarters ahead	NRMSFE_h	$R^2_{f,h}$	Theil U
1	.765	.415	.821
2	.751	.436	.687
3	.764	.416	.610
4	.788	.379	.482
6	.837	.299	.482
8	.877	.231	.480
average 1-8 quarters	.807	.349	.565

Model 9: VAR(2) of 2 variables AD(GDP), AD(PRD))			
quarters ahead	NRMSFE_h	$R^2_{f,h}$	Theil U
1	.845	.286	.907
2	.837	.299	.759
3	.842	.291	.674
4	.856	.267	.533
6	.889	.210	.533
8	.919	.155	.530
average 1-8 quarters	.871	.241	.625

Table 5. GDP Forecast Accuracy, Quarterly, Stocks, AD/AMA Filtered

Model 10: VAR(2) of 4 variables AD(GDP), AD/AMA(PRD), CUR, EXP			
quarters ahead	NRMSFE_h	$\mathrm{R}^2_{f,h}$	Theil U
1	.811	.342	.870
2	.790	.376	.729
3	.823	.323	.647
4	.858	.264	.512
6	.931	.133	.511
8	.991	.018	.509
average 1-8 quarters	.883	.220	.599

Model 11: VAR(2) of 3 variables AD(GDP), AD/AMA(PRD), CUR			
quarters ahead	NRMSFE_h	$\mathrm{R}^2_{f,h}$	Theil U
1	.780	.392	.837
2	.760	.422	.700
3	.768	.410	.622
4	.786	.382	.492
6	.838	.298	.492
8	.888	.211	.489
average 1-8 quarters	.812	.341	.576

Model 12: VAR(2) of 2 variables AD(GDP), AD/AMA(PRD)			
quarters ahead	NRMSFE_h	$\mathrm{R}^2_{f,h}$	Theil U
1	.844	.288	.906
2	.825	.319	.758
3	.828	.314	.673
4	.842	.291	.532
6	.881	.224	.532
8	.918	.157	.530
average 1-8 quarters	.863	.255	.624

Table 6. GDP Forecast Accuracy, Quarterly, Flows, AD Filtered

Model 13: VAR(2) of 4 variables AD(GDP), AD(PRD), CUR, EXP

quarters ahead	$NRMSFE_h$	$R^2_{f,h}$	Theil U
1	.786	.382	.844
2	.752	.434	.706
3	.752	.434	.627
4	.769	.409	.496
6	.848	.281	.496
8	.913	.166	.493
average 1-8 quarters	.814	.337	.581

Model 14: VAR(2) of 3 variables AD(GDP), AD(PRD), CUR

quarters ahead	$NRMSFE_h$	$R^2_{f,h}$	Theil U
1	.734	.461	.787
2	.709	.497	.659
3	.712	.493	.585
4	.748	.440	.463
6	.842	.291	.463
8	.918	.157	.460
average 1-8 quarters	.793	.371	.542

Model 15: VAR(2) of 2 variables AD(GDP), AD(PRD)

quarters ahead	$NRMSFE_h$	$R^2_{f,h}$	Theil U
1	.825	.319	.885
2	.800	.360	.741
3	.805	.352	.658
4	.827	.316	.520
6	.874	.236	.520
8	.912	.168	.517
average 1-8 quarters	.849	.279	.609

Table 7. GDP Forecast Accuracy, Quarterly, Flows, AD/AMA Filtered

Model 16: VAR(2) of 4 variables AD(GDP), AD/AMA(PRD), CUR, EXP

quarters ahead	NRMSFE_h	$\text{R}^2_{f,h}$	Theil U
1	.762	.419	.818
2	.736	.458	.685
3	.767	.412	.608
4	.823	.323	.481
6	.901	.188	.481
8	.905	.181	.478
average 1-8 quarters	.834	.304	.563

Model 17: VAR(2) of 3 variables AD(GDP), AD/AMA(PRD), CUR

quarters ahead	NRMSFE_h	$\text{R}^2_{f,h}$	Theil U
1	.819	.329	.879
2	.850	.278	.736
3	.869	.245	.653
4	.872	.240	.517
6	.882	.222	.516
8	.923	.148	.514
average 1-8 quarters	.874	.236	.605

Model 18: VAR(2) of 2 variables AD(GDP), AD/AMA(PRD)

quarters ahead	NRMSFE_h	$\text{R}^2_{f,h}$	Theil U
1	.818	.331	.877
2	.803	.355	.734
3	.809	.346	.652
4	.828	.314	.516
6	.877	.231	.516
8	.920	.154	.513
average 1-8 quarters	.851	.276	.604

Table 8. GDP Forecast Accuracy, Rankings of All Models

Monthly short term: NRMSFE$_h$ and R$^2_{f,h}$ of GDP forecasts 1 month ahead

rank	NRMSFE$_h$	R$^2_{f,h}$	variables	model
1	.711	.494	2 vars, AD	3
2	.723	.477	4 vars, AD	1
3	.731	.466	3 vars, AD	2
4	.814	.337	3 vars, AD/AMA	5
5	.820	.328	4 vars, AD/AMA	4
6	.935	.126	2 vars, AD/AMA	6

Monthly long term: average NRMSFE$_h$ and R$^2_{f,h}$ of GDP forecasts 1–24 mons. ahead

rank	NRMSFE$_h$	R$^2_{f,h}$	variables	model
1	1.07	-.145	2 vars, AD/AMA	6
2	1.08	-.166	2 vars, AD	3
3	1.15	-.323	4 vars, AD/AMA	4
4	1.18	-.392	4 vars, AD	1
5	1.21	-.464	3 vars, AD/AMA	5
6	1.32	-.742	3 vars, AD	2

Quarterly short term: NRMSFE$_h$ and R$^2_{f,h}$ of GDP forecasts 1 quarter ahead

rank	NRMSFE$_h$	R$^2_{f,h}$	variables	model
1	.734	.461	3 vars, flows, AD	14
2	.762	.419	4 vars, flows, AD/AMA	16
3	.765	.415	3 vars, stocks, AD	8
4	.780	.392	3 vars, stocks, AD/AMA	11
5	.786	.382	4 vars, flows, AD	13
6	.811	.342	4 vars, stocks, AD/AMA	10
7	.812	.341	4 vars, stocks, AD	7
8	.818	.331	2 vars, flows, AD/AMA	18
9	.819	.329	3 vars, flows, AD/AMA	17
10	.825	.319	2 vars, flows, AD	15
11	.844	.288	2 vars, stocks, AD/AMA	12
12	.845	.286	2 vars, stocks, AD	9

Quarterly long term: average NRMSFE$_h$ and R$^2_{f,h}$ of GDP forecasts 1-8 qrts. ahead

rank	NRMSFE$_h$	R$^2_{f,h}$	variables	model
1	.793	.371	3 vars, flows, AD	14
2	.807	.349	3 vars, stocks, AD	8
3	.812	.341	3 vars, stocks, AD/AMA	11
4	.814	.337	4 vars, flows, AD	13
5	.834	.304	4 vars, flows, AD/AMA	16
6	.849	.279	2 vars, flows, AD	15
7	.851	.276	2 vars, flows, AD/AMA	18
8	.863	.255	2 vars, stocks, AD/AMA	12
9	.871	.241	2 vars, stocks, AD	9
10	.874	.236	3 vars, flows, AD/AMA	17
11	.883	.220	4 vars, stocks, AD/AMA	10
12	.889	.210	4 vars, stocks, AD	7

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