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**SHORT-TERM ESTIMATES
OF EURO AREA REAL GDP BY
MEANS OF MONTHLY DATA**

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FRANCK SÉDILLOT**

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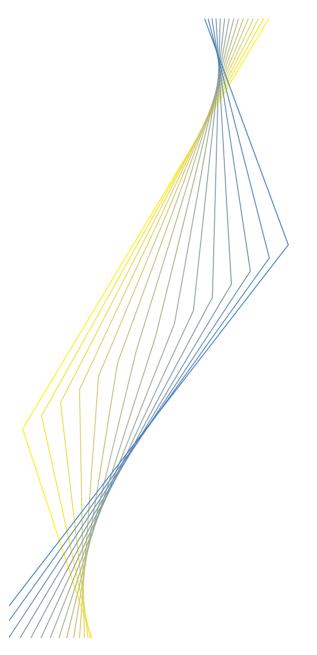**SHORT-TERM ESTIMATES
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**GERHARD RÜNSTLER[2],
FRANCK SÉDILLOT[3]**

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Abstract

The first official data releases of quarterly real GDP for the euro area are published about eight weeks after the end of the reference quarters. Meanwhile, ongoing economic developments must be assessed from various, more readily available, monthly indicators. We examine in the context of univariate forecasting equations to what extent monthly indicators provide useful information for predicting euro area real GDP growth over the current and the next quarter.

In particular, we investigate the performance of the equations under the case that the monthly indicators are only partially available within the quarter. For this purpose, we use time series models to forecast the missing observations of monthly indicators. We then examine GDP forecasts under different amounts of monthly information. We find that already a limited amount of monthly information improves the predictions for current-quarter GDP growth to a considerable extent, compared with ARIMA forecasts. Equations based on either quantitative activity indicators or the CEPR EuroCOIN composite indicator perform best.

JEL classification: C22, C53

Key words: Conjunctural analysis, bridge equations, incomplete monthly information

NON-TECHNICAL SUMMARY

First official releases of quarterly national accounts are published with some delay. Eurostat publishes the first official estimate of euro area real GDP about 8 weeks after the end of the respective quarter. In order to assess the most recent developments in economic activity, economic forecasters thus pay high attention to various monthly indicators, which are more readily available. Examples of such indicators include quantitative activity indicators (such as industrial production and retail trade data), business surveys, financial variables and composite indicators.

A number of studies have used univariate forecasting ("bridge") equations to obtain short-term predictions of GDP from monthly indicators. These studies unambiguously conclude that the monthly information improves the predictions of GDP growth to a considerable extent. The majority of these studies, however, do not provide particularly timely predictions, because they are based on quarterly aggregates of monthly indicators and therefore require that the indicators are known for the entire quarter. For the euro area, the complete set of indicators is available only two weeks in advance of the first official release of real GDP. Hence, using bridge equations under full monthly information adds very little to the timeliness of conjunctural analysis.

In this paper we therefore investigate the forecasting performance of the equations under the case that the monthly indicators are only partially available within the quarter. For this purpose, we combine the quarterly bridge equations for GDP growth with monthly time series models to forecast the missing observations of monthly indicators. This approach allows us to obtain predictions for GDP growth based on incomplete monthly information.

We find that bridge equations based on either quantitative indicators or the CEPR EuroCOIN indicator provide useful information for assessing the current state of the euro area economy, even when based on a limited coverage of monthly data. GDP forecasts for the current quarter improve substantially upon forecasts from standard time series model for GDP. This improvement also extends to forecasts for next-quarter GDP growth.

1 INTRODUCTION

First official releases of quarterly national accounts are published with some delay. Eurostat publishes the first official estimate of euro area real GDP about 8 weeks after the end of the respective quarter.[4] For economic policy purposes, this delay stands in quite some contrast to the need for timely and reliable information on the state of the economy. For instance, such information is essential as a starting point for macroeconomic forecasts.[5]

In order to assess the most recent developments in economic activity, economic forecasters and market participants thus pay high attention to conjunctural information from indicators, which are available more promptly at monthly frequency. Examples of such indicators include quantitative activity indicators (such as industrial production and retail trade data), business surveys, financial variables and composite indicators. Usually, this information is used in a purely qualitative manner. A number of attempts have yet been made to investigate the benefits of incorporating monthly indicators into statistical forecasting models. Studies unambiguously conclude that this results in considerable improvements in predictions of current-quarter GDP growth. There is also some evidence that the improvement extends beyond the current quarter, although the gains decrease very fast with the projection horizon.

Typically, studies use univariate forecasting ("bridge") equations to obtain short-term predictions of GDP and other national account aggregates from monthly indicators. Such methodology has been implemented for US data (Trehan, 1992; Ingenito and Trehan, 1996) and, to lesser extent, for individual euro area countries, as e.g. by Parigi and Schlitzer (1995) and Bovi et al. (2000) for Italy, Irac and Sédillot (2002) for France and Camba-Mendez et al. (2001), Mourougane and Roma (2002) and van Rooij and Stokman (2001) for various European countries. Baffigi et al. (2002) and Grasmann and Keereman (2002) have undertaken two recent studies for aggregate euro area data. Several studies have also examined the benefits of including monthly data into quarterly simultaneous equation models (e.g. Corrado and Green, 1988; Miller and Chin, 1996; Stark, 2000).

The majority of these studies, however, do not provide particularly timely predictions of GDP growth, because they are based on quarterly aggregates of monthly indicators and therefore require that the indicators are known for the entire quarter. For the euro area, the complete set of indicators is available only two weeks in advance of the first official release of real GDP. Hence, using bridge equations under full monthly information in fact adds very little to the timeliness of conjunctural analysis. Several studies (Reynaud and Sherrer, 1996; Camba-Mendez et al., 2001) have attempted to overcome

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[4] Since the 1st quarter of 2003, Eurostat also publishes a flash estimate with a delay of 6 weeks. This estimate is based on a limited set of data releases from official national sources, while the data for the remaining countries are predicted from various sources (Eurostat, 2003).

[5] For example, most international and European institutions publish Spring macroeconomic forecasts for the euro area in April or May. Such forecasts have no official estimates for euro area GDP in the 1st quarter of the respective year available and therefore must rely on monthly information. The same applies to the Eurosystem staff Spring projections, which are published in the June issue of the ECB Monthly Bulletin. The Eurostat flash estimate becomes available at a late stage of the Eurosystem exercise.

this difficulty by forecasting quarterly aggregates of monthly indicators from VAR models. Studies, which deal with the efficient treatment of new monthly information that becomes available within the quarter are yet scarce and are limited to US data (Rathjens and Robins, 1993; Ingenito and Trehan, 1996; Robertson and Tallman, 1999).

In this paper we investigate the forecasting performance of the equations under the case that the monthly indicators are only partially available within the quarter. For this purpose, we combine quarterly univariate bridge equations to predict GDP growth with monthly time series models to forecast the missing observations of monthly indicators. This approach allows us to obtain predictions for GDP growth based on incomplete monthly information. We thereby attempt to treat in an efficient manner the staggered timing of monthly data releases and to obtain rolling predictions for GDP growth based on the most recent set of monthly information.

The structure of the paper is as follows. After presenting the data set in section 2, we set out the bridge equation in section 3 and discuss our model selection strategy. We also show the timing of monthly data releases and implement an updating scheme, which reflects the publication schedule of the particular indicators within the quarter.

The empirical analysis proceeds in two steps. Section 4 starts with the assumption that the monthly indicators are known for all three months within the current quarter. We use standard model selection procedures to derive various versions of bridge equations. Section 5 then examines the forecasting properties of the equations for the case of incomplete monthly information. Based on the publication scheme of monthly data, we inspect GDP forecasts under different amounts of monthly information. We investigate various methods to forecast the missing values of monthly indicators including univariate ARIMA models, a Bayesian VAR (Doan et al., 1984) and multivariate structural time series models (Harvey and Koopman, 1997).

To anticipate our main findings, bridge equations based on either quantitative indicators or composite indicators (notably the CEPR EuroCOIN indicator) provide useful information for assessing the current state of the euro area economy, even when based on a limited coverage of monthly data. GDP forecasts for the current quarter improve substantially upon forecasts from a univariate ARIMA model for GDP, with the root mean squared error being nearly halved. Once missing observations of monthly indicators are forecast from multivariate models, this improvement also extends to GDP predictions for the next quarter.

Section 6 concludes and proposes some avenues for further work. The present study suffers from two caveats related to data limitations. First, due to a lack of historical real-time data, the estimates are based on final data releases. Second, the data used in the study are derived from the aggregation of national sources, which are subject to different seasonal adjustment methods. Given the noisy character of some of the data and the subsequent revisions to initial data releases, these two features may have non-negligible impacts on the findings. A comparison with the results of a disaggregated approach, which is based on real-time data and country-specific equations, may therefore be of interest.

2 THE DATA SET

The data set ranges from 1990 Q1 to 2001 Q4 and comprises available euro area indicators and composite indicators together with some recomputed indicators based on various sources.

- The set of *quantitative real activity indicators* that are available for the euro area is quite limited. We use industrial production excluding construction (IP), new car registrations (CR), a retail sales indicator (RS) and an indicator of industrial production in construction (IPC). The data are used in logs.

  Data on IP are published by Eurostat, whereas data from CR are released by ACEA. RS and IPC are constructed from available country information. The RS indicator comprises Dutch, German and Spanish retail trade data (excluding car sales) and French consumption in manufactured goods excluding cars. The indicator is calculated as a weighted average of these data based on consumption weights. Sédillot (2002) reports that the indicator provides rather accurate early estimates of consumption growth in the euro area. The IPC indicator is calculated as a weighted average of German and French data, based on GDP weights. The limited country coverage of the latter two indicators is due to a lack of timely available data for the remaining euro area countries.

- Among *business surveys* data, we use the main indices from the European Commission' surveys (Commission, 2001), i.e. the business climate index (BCI) and the consumer confidence index (CCI). In addition, we compute a retail climate index (RCI) as the first principal component of the four balances of opinions included in the Commission retail trade survey.

- Among available *composite indicators*, we use the overall Commission's economic sentiment index (TSEN), the CEPR EuroCOIN (ECN) indicator (Forni et al., 2001) and the de-trended OECD (2002) leading indicator (OLI). These indicators are readily available and widely recognised.

  The OECD leading indicator is intended to predict cyclical movements in industrial production. The euro area aggregate is calculated from an aggregation of national indicators. The latter have been constructed in a similar fashion and usually comprise survey data, financial variables (interest rate spreads and stock indexes), the terms of trade, and new passenger car registrations. The EuroCOIN indicator, developed by the CEPR and the Banca d'Italia, is constructed from a dynamic factor analysis of an extensive number of monthly indicators from euro area national sources. It is intended to track the principal common factor in euro area economic activity.

- Finally, we compute two *composite indices* from the above real activity indicators and business survey data. Composite index PCI1 comprises the available monthly real activity data (IP, IPC, CR, and RS), whereas indicator PCI2 also comprises the above listed business survey data. Following the US Conference Board (2000) composite index, the two indices are formed as the weighted sum of month-on-month changes of the particular indicators with the weights being given as the inverse of the standard deviations of first differences.

3 QUARTERLY BRIDGE EQUATIONS FOR EURO AREA GDP GROWTH

To predict quarterly real GDP growth from the above monthly indicators, we aggregate the latter to quarterly frequency and use the Autoregressive Distributed Lag (ADL(p,q)) equation

$$\rho(L)\Delta y_t = \sum_{j=1}^{k} \delta_j(L)\Delta x_{j,t} + \varepsilon_t \qquad (1)$$

where y_t denotes the log of real GDP and $x_{j,t}$ denote monthly indicators. Δ denotes the difference operator, while $\rho(L)$ and $\delta_j(L)$ denote lag polynomials of order p and q_j, respectively. Since indicators $x_{j,t}$ are published in advance of the first estimate of GDP, equation (1) can be used to obtain predictions of the latter from data of the indicators for the same quarter.

As noted in the introduction, we will put special emphasis on the case of monthly indicators being only partially observed within the quarter. However, we do not intend to develop forecasting equations, which are specific to the available monthly information. Such approach would result in revisions to the predictions for GDP growth, which partially reflect different specifications of the forecasting equations, and thereby in application blur the information contained in new monthly information. The analysis of the sources of revisions to earlier predictions is yet an important element in application. In addition, the rather short sample that we have available calls for a robust approach to model selection.

In the case of incomplete monthly information, in turn, missing observations of monthly indicators must be forecast to obtain the quarterly aggregates, which enter equation (1). Clearly, in this case, the GDP predictions then also depend on the properties of the forecasts of monthly indicators.

Our analysis will therefore proceed in two steps. Section 4 starts with the assumption that the monthly indicators are known for all three months within the current quarter. Based on in-sample model selection criteria, we will derive various versions of bridge equation (1). In a second step, section 5 then examines the out-of-sample forecasting properties of the particular equations under different sets of monthly information. We will use a number of methods to forecast the missing data on monthly indicators. Overall, this shall give an indication of the robustness of the findings from step 1 with respect to incomplete monthly information.

In application, the forecasts under incomplete monthly information are dictated by the timing of monthly data releases. Generally, the indicators discussed in section 2 are published with a delay of about two months with the exception of business survey data and CR, which are published with a delay of about one month. Data for industrial production (IP) are published last among the indicators under consideration.

To understand how the sequence of forecasts works in practice, let us examine the example of data releases in early 2002, as shown in Figure 1. A first estimate of real GDP in 2002 Q1 was published on 30 May 2002. On 19 June 2002, after the release of IP data, all indicators were available for April 2002, i.e. the first month of 2002 Q2 (while business surveys and CR were already available for May).

We take this as the starting point to produce the first forecast for GDP in 2002 Q3 and denote this as the 1st *next-quarter* forecast. At the same time, we compute the 1st *current-quarter* forecast for 2002 Q2. The two forecasts rely on one month of information for 2002 Q2 (and two months for business surveys data and CR). Hence, forecasts for monthly indicators must be produced for periods of up to two and five months ahead, for current and next-quarter forecasts, respectively.

On 19 July 2002, the set of monthly information is extended by one month and we compute the *2nd next-quarter* forecast for 2002 Q3 and the *2nd current-quarter forecast* for 2002 Q2. On 19 August 2002 then all monthly data for 2002 Q2 are known. This constitutes the date for the *3rd* set of forecasts for 2002 Q2 and 2002 Q3, respectively.

Going further ahead, on 30 August Eurostat released its first estimate for real GDP for 2002 Q2. Thus the forecasts would no longer cover 2002 Q2 and the updating scheme is shifted one quarter forward. On 19 September 2002, after the release of IP for July 2002, the 1st current-quarter forecast for 2002 Q3 would be computed, together with the 1st next-quarter forecast for 2002 Q4.
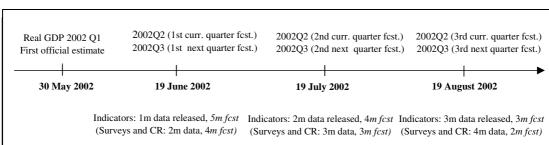
Figure 1: Monthly updating scheme of data releases

Real GDP 2002 Q1 First official estimate	2002Q2 (1st curr. quarter fcst.) 2002Q3 (1st next quarter fcst.)	2002Q2 (2nd curr. quarter fcst.) 2002Q3 (2nd next quarter fcst.)	2002Q2 (3rd curr. quarter fcst.) 2002Q3 (3rd next quarter fcst.)
30 May 2002	**19 June 2002**	**19 July 2002**	**19 August 2002**
	Indicators: 1m data released, *5m fcst* (Surveys and CR: 2m data, *4m fcst)*	Indicators: 2m data released, *4m fcst* (Surveys and CR: 3m data, 3*m fcst)*	Indicators: 3m data released, *3m fcst* (Surveys and CR: 4m data, 2*m fcst)*

Overall, a sequence of six forecasts for quarterly GDP growth in a given quarter is produced, based on different sets of monthly information. The first three (next-quarter) forecasts are solely based on monthly information from the previous quarter (whereas previous-quarter GDP growth is not yet known). The subsequent current-quarter forecasts, in turn, are based on a partial set of within-quarter information of monthly indicators (and previous quarter GDP growth is already known). In particular, the final (3rd) current quarter is based on complete monthly information. This forecast is conducted about two weeks in advance of the first official release of GDP.

4 MODEL SELECTION UNDER COMPLETE MONTHLY INFORMATION

We start our empirical analysis under the assumption that monthly indicators are known for all three months within the quarter. After inspection of the forecasting properties of the individual indicators in section 4.1, we will form combined bridge equations in section 4.2 by means of stepwise regressions. We will further compare the latter with bridge equations based on the composite indicators.

4.1 The information content of individual indicators

As a first step, and in order to obtain preliminary insights into the information content of individual indicators, we follow Blake et al. (2000) and estimate equation (1) for the individual indicators introduced in section 2. We restrict the analysis to real activity indicators and business survey data and will turn to the composite indicators later on.

Table 1 reports the sum of squared residuals (SSR), the root mean squared errors (RMSE) of GDP predictions for the current quarter and F-tests for the significance of the indicators (i.e. against the hypothesis of $\delta_j(L) = 0$). Quantitative indicators are used in first differences, whereas survey data enter the equations in levels.[6]

Table 1
Predictive capability of individual euro area indicators
(Sample period: 1990 Q2 to 2001 Q4)

		SSR (*100)	RMSE (*100)	F Test $\delta_j(L)=0$	P val	Encompassing regression	
Quantitative indicators							
Industrial production	IP	0.036	0.28	37.50	(0.00)	----	----
Car registrations	CR	0.076	0.39	12.80	(0.00)	.78	(.12)
Retail sales indicator	RS	0.078	0.41	11.5	(0.00)	.79	(.12)
Industrial prod. construction	IPC	0.092	0.47	2.04	(0.15)	.94	(.13)
Business surveys							
Business climate	BCI	0.061	0.38	11.21	(0.00)	1.15	(.18)
Consumer confidence	CCI	0.075	0.42	6.57	(0.00)	1.07	(.16)
Retail trade climate	RCI	0.081	0.44	4.51	(0.02)	1.04	(.16)

All indicators, with the exception of IPC, are significant. Industrial production excl. construction (IP) is yet far ahead of the other series in terms of predictive content. The RMSE of GDP predictions from IP amounts to 0.28 pp, compared with RMSEs in a range of 0.38 to 0.47 pp for the other variables. Given the superior performance of IP, it is of interest to see whether the remaining indicators add information to the GDP predictions based on IP. We therefore run the encompassing regressions

$$y_t = \lambda \hat{y}_t^{(IP)} + (1 - \lambda) \hat{y}_t^{(j)}$$

where $\hat{y}_t^{(IP)}$ and $\hat{y}_t^{(j)}$ denote GDP predictions from IP and the alternative indicator, respectively. The estimates of λ are reported in Table 1 together with their standard errors. A value of λ of lower than one implies that the alternative indicator adds information to GDP predictions from IP. Indicators CR and RS appear to contain some additional information to IP with λ being significantly smaller than one in both cases. In contrast, and quite interestingly, λ is estimated to be larger than one for business

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[6] Diebold and Kilian (2000) argue that differencing in order to render the series stationary, according to unit root pre-testing, improves the forecasting performance. Unit root tests largely confirm the conventional wisdom about the stationarity properties of the individual indicators, i.e. nonstationarity of quantitative indicators and stationarity of survey data. For GDP, tests do not reject the presence of a unit root. The augmented Dickey-Fuller statistics (with 4 lag) is -2.07, while the Phillips-Perron statistics (with a truncation lag of 3) gives –1.60, below the 5% critical values.

surveys indicators BCI, CCI and RCI. Hence, the latter do not add information to IP for predicting current-quarter GDP growth.

4.2 Combined bridge equations and composite indicators

In this section, we combine the individual indicators to obtain various versions of equation (1) and examine the predictive content of the composite indicators and indices introduced in section 2.

Overall, we investigate eight models, which may be grouped as follows.

- Model AR is a univariate autoregressive model for GDP and is used as a benchmark;

- Equations SW1 and SW2 are derived from stepwise regressions of the indicators shown in Table 1. We used the significance of F-tests (at the 5% level) as the criterion for inclusion of an indicator. This criterion selected the four indicators IP, CR, IPC and RS. Equation SW1 represents an intermediate step of the stepwise regressions. This equation contains IP and CR. Equation SW2 contains the four indicators IP, CR, IPC and RS. The purpose of maintaining the intermediate step SW1 is to examine the robustness of the findings from the stepwise regressions against out-of-sample forecasting performance and, later on, against forecasts based on incomplete information sets.

- Models TSEN, ECN, OLI, PCI1 and PCI2 are based on the respective composite indicators and composite indices as described in section 2. The indicators are stationary by construction and, hence, enter equation (1) in levels.

The detailed specifications of the equations are described in Annex A. All equations include two dummies in 1992 Q1 and 1992 Q2 to account for sharp residual outliers. In the equations not including CR, a further dummy is added for 1993 Q1.[7]

The main results for these equations are reported in Table 2, along with various diagnostic tests. Figures A.1 to A.7 in Annex A show the fitted values of the equations. Residual mis-specification tests indicate that the equations are well specified. In particular, the results of the Chow predictive failure test suggest that the equations are fairly stable.

The goodness-of-fit statistics of the best-performing bridge equations improve sharply upon the benchmark AR. The RMSE of the best-performing models improves by some 50% to 60% on the benchmark AR. Model SW2 performs best followed by model PCI1. The root mean squared errors (RSMEs) of residuals from these equations amount to 0.14 pp and 0.17 pp, respectively, compared to 0.31 pp for the benchmark AR and a standard deviation of GDP growth of 0.46 pp over the sample. Model ECN falls somewhat short of models SW2 and PC1, whereas the improvement of models TSEN and OLI on the AR is quite limited.

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[7] These unusually large fluctuations in euro area GDP growth are largely accounted for by Germany.

Table 2
Summary statistics of the seven bridge equations for euro area
(Sample period: 1990 Q2 to 2001 Q4)

	AR	SW1	SW2	TSEN	PCI1	PCI2	ECN	OLI
Main statistics								
Adjusted R^2	0.53	0.78	0.90	0.59	0.85	0.68	0.74	0.63
RMSE (in pp)	0.31	0.22	0.14	0.29	0.17	0.26	0.23	0.28
Diagnostic tests								
Durbin Watson	2.16	1.97	2.15	1.97	2.09	1.87	2.38	2.31
LM (1)	0.62 (0.44)	0.00 (0.97)	0.29 (0.59)	0.01 (0.94)	0.39 (0.53)	0.15 (0.70)	1.87 (0.18)	0.16 (0.68)
LM (4)	1.21 (0.32)	0.47 (0.75)	0.18 (0.95)	0.31 (0.86)	0.36 (0.83)	0.19 (94)	0.96 (0.44)	0.14 (0.96)
ARCH(1)	1.37 (0.25)	0.05 (0.83)	0.11 (0.74)	0.28 (0.60)	0.46 (0.50)	0.52 (0.48)	0.01 (0.93)	0.49 (0.49)
WHITE	0.37 (0.77)	0.78 (0.61)	0.40 (0.95)	1.33 (0.26)	0.39 (0.81)	0.85 (0.57)	1.30 (0.27)	1.05 (0.41)
Normality	1.59 (0.45)	0.36 (0.84)	3.87 (0.14)	3.10 (0.21)	0.50 (0.78)	0.40 (0.82)	1.34 (0.51)	0.87 (0.65)
RESET(2)	0.85 (0.43)	1.06 (0.36)	0.03 (0.97)	0.75 (0.48)	1.03 (0.36)	2.40 (0.11)	1.38 (0.26)	1.76 (0.18)
CHOW[1]	0.49 (0.93)	0.64 (0.82)	0.93 (0.55)	0.63 (0.83)	0.93 (0.55)	0.34 (0.98)	0.48 (0.93)	0.66 (0.80)

(1) Predictive failure test over the period 1998-2001.

Despite the sharp improvement on the benchmark, the RMSE of 0.14 from model SW1 still implies forecast confidence bounds of considerable size. The 90% confidence bound, for instance, amounts to ± 0.23 percentage point. Hence, a forecast of, say, 0.30% for GDP growth would give rise to 90% upper and lower forecast confidence bounds of 0.07 to 0.53 pp, respectively, with obviously very different implications for conjunctural analysis. On the other hand, Figures A.1 to A.7 show the better-performing models to track turning points in GDP growth relatively closely.

Various features of the results deserve some discussion.

First, indicators IP, CR, IPC and RS, which have been selected from the stepwise regressions, happen to correspond exactly to the set of quantitative real activity indicators. This result parallels those reported in Table 1 and is also in line with the findings of various related studies for the US. The quantitative indicators are generally used by national statistical agencies in the compilation of quarterly national accounts. Industrial production, in particular, not only accounts for about one third of real GDP, but is also among its more volatile components. Its high predictive content is therefore a direct outcome of its high importance in producing national accounts data. Similar considerations apply to CR and RS.

Second, the direct statistical link of quantitative indicators with national accounts perhaps also explains why the quantitative indicators wipe out business survey data. This should however not be taken as indication that the latter are generally of limited relevance. For instance, the survey data may be more useful when it comes to signalling turning points in the business cycle (e.g., Baffigi et al., 2003).

Third, the predictive performance of model PCI1 comes close to the one of SW2 and the ex-ante aggregation of quantitative indicators does not considerably worsen the results. Again, the inclusion of survey data yet worsens the performance of the composite index, as from the higher RMSE from equation PCI2 compared to PCI1.

Fourth, the above findings indicate that a selection procedure based on the information content of the individual indicators, as used e.g. by Blake et al. (2000), can give sub-optimal results, notably when indicators are highly correlated. Blake et al. (2000) form composite indices as weighted averages of the individual indicators, with the weights determined from the predictive content of the individual indicators, as from the RMSE reported in Table 1. The Blake et al. (2000) procedure would have implied, for instance, to attach a larger weight to the BCI than to CR and RS (see Table 1). However, from the stepwise regressions, BCI does not add to the forecasting performance, whereas the inclusion of RS and CR improve the goodness of fit to a considerable extent. The reason is that IP and BCI are highly correlated and IP encompasses the BCI, but not CR and RS.

While a purely statistical approach would have suggested to combine the indicators of Table 1 also with the composite indicators from stepwise regressions, we did not attempt to do so. The reason is that the composite indicators are largely based on the same indicators as we have examined in the stepwise regressions. One purpose of inspecting the composite indicators is to learn about the potential gains from data reduction techniques against stepwise regressions. Combining individual and composite indicators would have blurred this intention. It has been argued that, in view of the substantial noise component in monthly real activity indicators, data reduction techniques might result in improved forecasting performance.

4.3 Out-of-sample results

We turn to the out-of-sample forecasting performance of the various equations based on recursive parameter estimates.[8] For now, we maintain the assumption that monthly indicators are observed for all three months of the respective quarter. We follow a rule of thumb in using one third of the available sample for conducting the out-of-sample forecasts. This leaves an out-of-sample period from 1998 Q1 to 2001 Q4.

Table 3 reports the root mean squared errors (RMSEs) of the recursive out-of-sample forecasts together with those of the in-sample forecasts, which were already reported in Table 2. Further, Table 3 shows

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[8] This is, at each point in time the equations are estimated from the data, which are available prior to the prediction period. To obtain the GDP prediction for period t, equation (1) is estimated from data up to period t-1.

the ratios of the RMSEs of forecasts from the various equations against the benchmark AR model and the best performing model, SW2.

Table 3
Recursive out-of-sample forecasts (1998 Q1 to 2001 Q4)

	AR	SW1	SW2	TSEN	PCI1	PCI2	ECN	OLI
RMSE (in pp)	.31	.18	.14	.26	.17	.19	.19	.27
Ratio to AR	1.00	***.58	***.45	*.84	***.54	***.61	***.61	.87
Ratio to SW2	***2.21	*1.29	1.00	***1.86	1.21	**1.35	**1.35	***1.93

*HLN test significant at 10% level; ** at the 5% level; *** at the 1% level.

The RMSEs of out-of-sample forecasts turn out to be very close to those of in-sample forecasts, although they are in some cases slightly higher. This confirms the stability of the equations. In addition, the relative performances of the particular equations remain broadly unchanged compared with the in-sample results, although the relative performances of PCI2 and ECN improve somewhat for out-of-sample forecasts.

Table 3 also shows the results from Diebold-Mariano (1995) tests for the significance of the differences between RMSEs. As discussed by Clark (1999), the finite sample behaviour of the test suffers from some size distortions. We thus use the Harvey, Leybourne and Newbold (HLN, 1997) modification of the test to correct for small sample distortions. We find that forecasts from SW2 improve upon the remaining models at the 10% significance level with the exception of PCI1, for which the significance value is slightly above 10%. Compared with the benchmark AR model, all bridge equations provide an improved forecast accuracy at the 1% threshold with the exception of models OLI and TSEN.

5   OUT-OF-SAMPLE FORECASTS UNDER INCOMPLETE MONTHLY INFORMATION

We now turn to the forecasting properties of the above bridge equations under incomplete monthly information. Clearly, in such case the properties of the resulting predictions for GDP depend not only on equation (1), but also on the properties of the models to predict the missing monthly data. The situation is complicated by the fact that monthly indicators are published with different delays. Hence, the relative forecasting performance of different versions of equation (1) may depend on the amount of available monthly information and the optimal set of indicators may vary.

To examine these issues, we conduct an out-of-sample forecasting exercise along the lines of the updating scheme described in section 3. We produce rolling forecasts for both current and next-quarter GDP growth based on different amounts of monthly information as from the updating scheme.

Section 5.1 derives forecasts for the missing monthly data from various univariate and multivariate time series models. In section 5.2, we then insert the resulting forecasts for quarterly aggregates of

monthly indicators into the various bridge equations and investigate the forecasting performance of the latter under incomplete monthly information. To simplify the exercise, we limit this exercise to models to SW1, SW2, PCI1, ECN and OLI.

5.1 Forecasting monthly indicators: out-of-sample results

We examine six models to generate forecasts for monthly indicators.

- As a benchmark, we employ a simple naïve projection, which consists of assuming a constant level at the last known value for the monthly indicators.

- We further use two univariate time series models, i.e. ARIMA and structural time series (STS) models (Harvey, 1989). The latter is designed to decompose a series into a trend and an irregular component (see Annex B). As regards ARIMA models, lag length selection was based on the Schwartz information criterion (SIC).

- In addition, we estimate three multivariate models, i.e. a VAR, a Bayesian VAR, and a multivariate STS model. These models include indicators BCI, IP, RS, CR, ECN and OLI. Lag length selection in the VAR and the BVAR was based on the SIC. The BVAR model was set up with a standard Minnesota prior as proposed by Doan et al (1984). The multivariate STSM has been proposed by Harvey and Koopman (1997).

The STS and BVAR models are discussed in more detail in Annex B.[9] Their usage is motivated from earlier findings on their potentially better forecasting performance compared to the ARIMA and VAR models (Doan et al. 1984; Rick, 1994). We did not investigate error corrections (VEC) models. As pointed out by Hoffman and Rashe (1996), forecasts from VEC models do not necessarily improve upon VAR models over short forecast horizons.

Contrary to Rathjens and Robins (1993), we have preferred to specify the forecasting equations directly in terms of monthly data, and to aggregate the predictions to quarterly frequency thereafter. This enables us to easily carry out multi-step ahead projections. Rathjens and Robins (1993) use quarterly aggregates of monthly indicators, but include information on the within-quarter dynamics of the indicators by defining a further variable as the difference between the third month of the quarter and the average of the quarter. However, this approach precludes any multi-step ahead projections, unless an auxiliary equation is used to predict the additional variable. Indeed, Rathjens and Robins (1993) do not find any improvements in multi-step ahead forecasts from the inclusion of the within-quarter variable.

In the multivariate models, we attempt to make efficient use of the available information set. As noted in section 3, BCI and CR are known one month in advance of other indicators. We use standard procedures to condition the one-step ahead forecasts for IP, RS, OLI and ECN on the additional

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[9] The predictions for composite indicator PCI1 are derived from the forecasts of the individual indicators.

observations for CR and BCI. As regards VAR and BVAR forecasts, we use conditional forecasts as proposed by Doan et al. (1984), generated from a block triangular factorisation of the residual covariance matrix. In the multivariate STSM, conditioning is simply performed by the Kalman filter (see Harvey, 1989:463f). Using such conditional forecasts resulted in some, albeit small improvements in forecasts for IP.

The models were recursively estimated over the period of 1998:1 to 2001:12. Table 4 reports the RMSEs of the recursive forecasts for the quarter-on-quarter growth rates of selected indicators. The numbering of the forecasts in Table 4 refers to the updating scheme for GDP predictions, as described in section 3. For instance, the 3rd current-quarter forecast is trivial, as monthly indicators are available over the entire quarter and the RMSE is, hence, identical to zero. For CR and BCI, which are published one month earlier, the same applies already to the 2nd current-quarter forecast.

Table 4
Quarter-on-quarter growth rate of selected indicators
(Out-of-sample RMSE from 1998 Q1 to 2001 Q4)

| | Model for projecting monthly indicators | | | | | |
| | Univariate models | | | Multivariate models | | |
Within quarter information	Naïve	ARIMA	STS	MSTS	VAR	BVAR
Industrial production (1.110)						
Next quarter						
1st forecast	1.18	1.11	1.12	1.05	0.85	0.84
2nd forecast	1.23	1.03	1.12	0.97	0.84	0.76
3rd forecast	1.12	0.97	1.03	0.74	0.74	0.66
Current quarter						
1st forecast	0.54	0.51	0.51	0.44	0.55	0.52
2nd forecast	0.23	0.20	0.26	0.24	0.29	0.23
3rd forecast	0.00	0.00	0.00	0.00	0.00	0.00
Retail sales indicator (0.701)						
Next quarter						
1st forecast	0.91	0.70	0.70	0.74	0.97	0.92
2nd forecast	0.94	0.70	0.77	0.71	0.94	0.94
3rd forecast	1.24	0.74	0.79	0.79	1.06	0.99
Current quarter						
1st forecast	0.54	0.33	0.41	0.38	0.49	0.46
2nd forecast	0.36	0.31	0.32	0.32	0.31	0.30
3rd forecast	0.00	0.00	0.00	0.00	0.00	0.00
Car registrations (2.821)						
Next quarter						
1st forecast	2.90	3.07	2.74	2.90	4.39	3.43
2nd forecast	3.73	3.20	2.85	3.73	4.82	3.26
3rd forecast	2.33	1.73	1.64	2.34	2.62	1.89
Current quarter						
1st forecast	0.88	0.97	0.94	0.88	1.36	1.02
2nd forecast	0.00	0.00	0.00	0.00	0.00	0.00
3rd forecast	0.00	0.00	0.00	0.00	0.00	0.00

Note: The numbers in brackets in the first column show the standard deviations of quarterly growth rates of the indicators through 1998 Q1 2001 Q4.

Overall, for current-quarter predictions, the improvement in forecast accuracy from the various models upon the naïve forecast is rather limited, although some improvement occurs for the 1st forecast, which

uses one month of observations within the quarter. As regards the next-quarter forecasts, however, multivariate models provide somewhat better forecasts for most indicators. This holds in particular for IP and composite indicator PCI1, as OLI and, to a lesser extent BCI and ECN, appear to contain important predictive content for IP. Overall, the BVAR appears to perform best. For CR and RS, in turn, none of the methods performs well and the best univariate model outperforms the multivariate methods.

Table 4 (contd.)
Quarter-on-quarter growth rate of selected indicators
(Out-of-sample RMSE from 1998 Q1 to 2001 Q4)

	Model for projecting monthly indicators					
	Univariate models			Multivariate models		
	Naïve	ARIMA	STS	MSTS	VAR	BVAR
Composite indicator PCI1 (0.660)						
Next quarter						
1st forecast	0.78	0.65	0.60	0.63	0.55	0.46
2nd forecast	0.85	0.67	0.78	0.69	0.55	0.38
3rd forecast	0.79	0.54	0.53	0.45	0.53	0.42
Current quarter						
1st forecast	0.43	0.36	0.34	0.31	0.37	0.37
2nd forecast	0.23	0.21	0.23	0.24	0.21	0.20
3rd forecast	0.00	0.00	0.00	0.00	0.00	0.00
ECN (level) (0.194)						
Next quarter						
1st forecast	0.27	0.16	0.23	0.23	0.18	0.17
2nd forecast	0.21	0.18	0.17	0.19	0.14	0.11
3rd forecast	0.14	0.13	0.14	0.14	0.11	0.09
Current quarter						
1st forecast	0.07	0.05	0.05	0.05	0.05	0.04
2nd forecast	0.04	0.03	0.42	0.05	0.04	0.04
3rd forecast	0.00	0.00	0.00	0.00	0.00	0.00
OLI (1.107)						
Next quarter						
1st forecast	1.05	0.70	0.80	0.70	0.50	0.54
2nd forecast	0.94	0.64	0.60	0.76	0.54	0.46
3rd forecast	0.73	0.59	0.64	0.70	0.53	0.49
Current quarter						
1st forecast	0.45	0.34	0.42	0.36	0.34	0.35
2nd forecast	0.16	0.05	0.08	0.04	0.01	0.07
3rd forecast	0.00	0.00	0.00	0.00	0.00	0.00

Note: The numbers in brackets in the first column show the standard deviations of the indicators through 1998 Q1 2001 Q4.

Generally, knowledge of one month of information already substantially reduces the RMSE of the predictions. This also holds for the naïve forecast. As regards industrial production for instance, the RMSE of the forecast based on data for the previous quarter only (i.e. the 3rd next-quarter forecast) amounts to 1.12 pp. Adding one month of data for the current quarter (the 1st current-quarter forecast) more than halves the RMSE to 0.54 pp. Two months of information reduce the RMSE of the naïve forecast further to 0.23 pp. These improvements are a direct result of the aggregation properties of

growth rates. As discussed in Annex B, quarter-on-quarter growth rates can be approximated from a weighted average of month-on-month growth rates. The inspection of the weights shows that, for instance, one month of information already explains 66% of the quarterly growth rate of the indicators. Hence, the low forecast errors and the similar performance of the various methods should not come as a surprise.

5.2 GDP forecasts under incomplete information: out-of-sample results

We now examine the performance of the various versions of equation (1) under different amounts of monthly information. For this purpose, we insert the forecasts of q-o-q rates of monthly indicators as obtained in section 5.1 into various versions of the bridge equations developed in section 4. The results of this exercise are given in Table 5 for forecasts of GDP growth in the current and next quarter.

The main finding is that the bridge equations continue to outperform naïve and ARIMA forecasts also when based on limited amounts of monthly information. For current-quarter forecasts this result holds irrespective of the method used for predicting missing monthly observations. For next-quarter forecasts, however, we find a noticeable improvement only if monthly indicators are predicted from multivariate models. The extrapolation of monthly indicators from univariate models, in turn, hardly improves upon a naive forecast for next-quarter GDP. Among the multivariate models, the BVAR performs slightly better than the VAR, whereas the multivariate STSM falls somewhat short of both the VAR and the BVAR. We thus focus the discussion on GDP forecasts based on VAR and BVAR models.

For current-quarter GDP forecasts, the use of only one month of within-quarter information (the 1st current-quarter forecast) provides already a considerably better forecast for GDP than the naïve and ARIMA models. The RMSE from the quarterly ARIMA model amounts to 0.31 pp, compared with values of around or even below 0.2 pp for the bridge equations. For the 2nd current-quarter forecast, based on two months of information, the RMSEs are then generally very close to the final forecast. These findings are largely a direct consequence of the small current-quarter forecast errors for monthly indicators. It also worth mentioning that, although the relative performance of the various bridge equations, as discussed in section 4, is largely maintained, ECN and OLI improve somewhat in case of incomplete monthly information. ECN, in particular, performs about equally well compared to SW2.

Turning to forecasts for the next quarter, the GDP forecasts based on multivariate monthly models still improve considerably upon those based on the univariate naïve and ARIMA models. For all models, the RMSE of the 1st next-quarter forecast, based on only one month of within-quarter information (and two months of data for BCI and CR) remains below 0.3 pp, still by some 25% lower compared to the naïve forecast. This forecast is carried out around six months in advance of the official data release.

Table 5

Out-of-sample GDP projection

(Out-of-sample RMSE from 1998 Q1 to 2001 Q4)

| | Model for projecting monthly indicators | | | | | |
| | Univariate models | | | Multivariate models | | |
	Naïve	ARIMA	STS	MSTS	VAR	BVAR
SW1						
Next quarter						
1st forecast	0.43	0.34	0.39	0.36	0.28	0.28
2nd forecast	0.38	0.33	0.34	0.30	0.24	0.23
3rd forecast	0.37	0.31	0.33	0.24	0.23	0.21
Current quarter						
1st forecast	0.25	0.24	0.24	0.21	0.22	0.21
2nd forecast	0.21	0.20	0.20	0.20	0.20	0.20
3rd forecast	0.20	0.19	0.19	0.19	0.19	0.19
SW2						
Next quarter						
1st forecast	0.43	0.34	0.34	0.36	0.29	0.28
2nd forecast	0.41	0.32	0.39	0.33	0.27	0.25
3rd forecast	0.42	0.32	0.32	0.27	0.28	0.24
Current quarter						
1st forecast	0.24	0.21	0.22	0.19	0.22	0.20
2nd forecast	0.20	0.17	0.20	0.19	0.18	0.18
3rd forecast	0.14	0.14	0.14	0.14	0.14	0.14
PCI1						
Next quarter						
1st forecast	0.42	0.36	0.34	0.36	0.31	0.29
2nd forecast	0.43	0.36	0.41	0.38	0.30	0.27
3rd forecast	0.40	0.33	0.32	0.28	0.30	0.25
Current quarter						
1st forecast	0.24	0.23	0.22	0.21	0.20	0.21
2nd forecast	0.21	0.19	0.20	0.20	0.19	0.20
3rd forecast	0.17	0.17	0.17	0.17	0.17	0.17
ECN						
Next quarter						
1st forecast	0.34	0.26	0.29	0.29	0.26	0.29
2nd forecast	0.31	0.28	0.26	0.29	0.20	0.23
3rd forecast	0.26	0.24	0.20	0.19	0.18	0.19
Current quarter						
1st forecast	0.21	0.18	0.19	0.19	0.18	0.19
2nd forecast	0.19	0.18	0.18	0.18	0.18	0.18
3rd forecast	0.19	0.19	0.19	0.19	0.19	0.19
OLI						
Next quarter						
1st forecast	0.35	0.30	0.31	0.30	0.29	0.29
2nd forecast	0.33	0.25	0.26	0.25	0.26	0.26
3rd forecast	0.30	0.24	0.24	0.23	0.24	0.24
Current quarter						
1st forecast	0.26	0.24	0.24	0.24	0.24	0.24
2nd forecast	0.26	0.26	0.26	0.25	0.25	0.25
3rd forecast	0.25	0.25	0.25	0.25	0.25	0.25
Memorandum items						
GDP growth standard deviation	0.37					
GDP quarterly naïve forecast						
Next quarter	0.37					
Current quarter	0.35					
GDP quarterly ARIMA forecast						
Next quarter	0.41					
Current quarter	0.31					

There arise some shifts in the relative performance of the various equations compared with the results of Table 3. In general, the RSMEs from the particular equations tend to be closer together and the relative performance of composite indicators OLI and ECN improves. Further, SW1 is slightly better than SW2, contrary to what is observed for current-quarter forecasts. Overall, ECN tends to perform best. Although this result should be viewed with some caution, given the relatively short out-of-sample forecasting period, it suggests that the higher parsimony of equations based on composite indicators and the smoother evolution of those indicators may improve the accuracy of next-quarter GDP forecasts. In particular, the rather uninformative forecasts for CR and RS appear to hamper the performance of SW2.

The OECD leading indicator (OLI) falls somewhat short of other indicators, especially at shorter horizons. However, we had found in section 5.1 that the inclusion of OLI into the VAR and BVAR improved the forecasts for industrial production to a considerable extent. In fact, OLI has been developed as a leading indicator for industrial production.

The next-quarter forecasts based on univariate models, in turn, hardly improve upon the naïve forecast. The potential gains from using monthly indicators for next-quarter forecasts thus depend heavily on the predictability of the indicators.

6 CONCLUSIONS AND REMAINING ISSUES

In this paper, we have examined the performance of bridge equations to obtain short-term forecasts for euro area GDP growth from monthly indicators. We find that bridge equations based on quantitative activity indicators (i.e. industrial production, retail sales and car registrations) and, to a lesser extent, equations based on composite indicators result in considerable improvements in predictions for current-quarter GDP growth compared with naïve or ARIMA projections. The equations provide informative forecasts also in case of incomplete monthly information. For instance, when based on only one month of observations, the root mean squared error of the predictions amounts to about 0.2 percentage point, which compares to a value of 0.31 for the ARIMA forecast. The related monthly information becomes available during the last month of the respective quarter, some 2 ½ months in advance of the first official release of GDP.

Once unavailable monthly data are forecast from multivariate models, this improvement also extends to predictions for next-quarter GDP growth. In the latter case, EuroCOIN (Forni et al., 2001) and OLI indicator (OECD, 2002) perform equally well as the equations based on quantitative indicators. Somewhat surprisingly, business survey data however add no information to the above indicators in forecasting GDP growth.

Three important issues are left for further research. First, the coverage of the above quantitative indicators is largely limited to the industrial and retail trade sectors of the economy. The estimates

presented in this paper could perhaps be significantly improved from the inclusion of monthly data covering other services sectors as well. Second, we restricted the investigation to single bridge equations. There might yet be further benefits in combining these predictions with projections from quarterly simultaneous equation models.

Third, there arise a number of data issues, related to the relative performance of aggregate versus disaggregated forecasts and to data revisions. Our study focused on aggregate euro area data. The potential benefits of a disaggregated approach based on the aggregation of individual country forecasts have not been assessed in this paper. The evidence for such benefits is quite mixed. Marcellino et al. (2003) report that forecasts for key macroeconomic variables based on aggregate equations are in general outperformed by the aggregation of individual country forecasts. In contrast, Bodo *et al.* (2000) find that an area-wide model for industrial production improves on the aggregation of individual country models. Clearly, as argued in Baffigi et al. (2002) and Hubrich (2003), while there might be gains from the disaggregated approach, such gains depend on the properties of the single country specifications and might vary over the forecast horizon.

The performance of the aggregate relative to the disaggregated approach also might depend on the way the data are constructed. Eurostat publishes seasonally and working-day adjusted data for GDP, which are aggregated from already adjusted country data. Raw data are not available at the euro area level. In contrast, for monthly indicators, the adjustment is directly undertaken at the aggregate level from raw country data. Maravall (1995) highlights the possible distortive impacts of such differences in seasonal adjustment procedures on the estimated relationships among series.

Related to this, we have not investigated the issue of subsequent revisions to initial data releases and its potential implications for real-time forecasting performance either. The above forecasting exercises were carried out with data series as currently estimated by statistical offices. In real time, practitioners use data, which would eventually be subsequently revised. For aggregate euro area data, due to a lack of backdata on initial data releases, an assessment on the role of data revisions is practically impossible. However, we are fully aware that the results of this study may be altered with the use of initial data releases. Indeed, for US data, Croushore and Stark (2000) conclude that findings on the relative forecasting performance based on final data releases do not necessarily carry over to real time data. Koenig, Dolmas and Piger (2001) go further in this direction and argue that forecasting equations should be rather estimated from real-time data than from final data releases.

Taking these caveats into account, the above estimates nevertheless indicate that early predictions of GDP based on an incomplete amount of monthly information are a useful input into real-time conjunctural analysis.

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This Annex presents coefficient estimates of the seven quarterly bridge equationss used for predicting euro area real GDP growth. Charts A1 to A8 show euro area GDP growth together with the fitted values from the particular equations.

<u>**AR**</u> :

$$\Delta y_t = \underset{(5.01)}{.002} + \underset{(5.58)}{.54}\ \Delta y_{t-1} - \underset{(-6.72)}{.017}\ d922 + \varepsilon_t + 0.92\varepsilon_{t-4}$$

<u>**SW1**</u>:

$$\Delta y_t = \underset{(10.76)}{.004} + \underset{}{.25}\Delta IP_t + \underset{(3.33)}{.025}\ \Delta CR_t + \underset{(2.12)}{.005}\ d914 + \underset{(3.67)}{.008}\ d921 - \underset{(-4.10)}{.009}\ d922 + \varepsilon_t$$

<u>**SW2**</u>:

$$\Delta y_t = \underset{(13.68)}{.003} + \underset{(12.05)}{.25}\ \Delta IP_t + \underset{(3.33)}{.017}\ \Delta CR_t + \underset{(4.74)}{.030}\ \Delta IPC_t + \underset{(5.85)}{.12}\ \Delta RS_t + \underset{(2.64)}{.004}\ d914 + \underset{(5.95)}{.009}\ d921 - \underset{(-5.10)}{.008}\ d922 + \varepsilon_t$$

<u>**TSEN**</u>:

$$\Delta y_t = \underset{(-2.49)}{-.04} + \underset{(5.01)}{.002}\ TSEN_t - \underset{(-4.17)}{.0018}\ TSEN_{t-1} + \underset{(3.32)}{.010}\ d921 - \underset{(-3.39)}{.010}\ d922 - \underset{(-2.57)}{.008}\ d931 + \varepsilon_t$$

<u>**ECN**</u>:

$$\Delta y_t = \underset{(4.32)}{.002} + \underset{(5.58)}{.01}\ ECN_t - \underset{(2.15)}{.004}\ ECN_{t-1} + \underset{(3.91)}{.009}\ d921 - \underset{(-3.05)}{.008}\ d922 - \underset{(-2.29)}{.005}\ d931 + \varepsilon_t$$

<u>**PCI1**</u>:

$$\Delta y_t = \underset{(13.34)}{.004} + \underset{(14.28)}{.38}\ PCI1_t + \underset{(4.51)}{.008}\ d921 - \underset{(-4.73)}{.008}\ d922 + \varepsilon_t$$

<u>**PCI2**</u>:

$$\Delta y_t = \underset{(4.47)}{.003} + \underset{(5.63)}{.577}\ PCI2_t - \underset{(-2.23)}{.253}\ PCI2_{t-1} + \underset{(2.53)}{.337}\ \Delta y_{t-1} + \underset{(2.62)}{.007}\ d921 - \underset{(-4.23)}{.012}\ d922 + \varepsilon_t$$

<u>**OLI**</u> :

$$\Delta y_t = \underset{(11.87)}{.005} + \underset{(4.47)}{.20}\ OLI_t - \underset{(-2.37)}{.10}\ OLI_{t-1} + \underset{(2.68)}{.008}\ d921 - \underset{(-3.98)}{.012}\ d922 - \underset{(-2.63)}{.008}\ d931 + \varepsilon_t$$

Figure A1: AR

Actual --- Fitted

Figure A2: SW1

Actual --- Fitted

Figure A3: SW2

Actual --- Fitted

Figure A4: TSEN

Actual --- Fitted

Figure A5: PCI1

Actual --- Fitted

Figure A6: PCI2

Actual --- Fitted

Figure A7: ECN

Figure A8: OLI

Actual --- Fitted

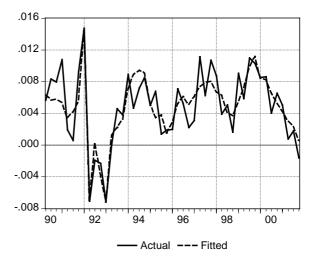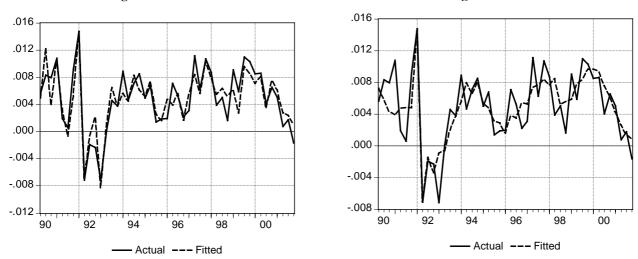Actual --- Fitted

ANNEX B
MULTIVARIATE MODELS TO FORECAST MONTHLY INDICATORS

The univariate STSM is discussed in detail by Harvey (1989). The model decomposes a series y_t into a local linear trend μ_t plus white noise ε_t. The local linear trend is defined as a random walk plus drift, where the drift term is again specified as a random walk.

$$y_t = y_t^{tr} + \varepsilon_t$$
$$\Delta y_t^{tr} = \mu_t + \eta_t$$
$$\Delta \mu_t = \xi_t$$

where ε_t, η_t and ξ_t are mutually uncorrelated white noise. Harvey and Koopman (1997) have proposed a multivariate version of the STSM for an n x 1 vector of series y_t. The model is specified as above, but with ε_t, η_t and ξ_t representing n x 1 vectors of multivariate white noise with

$$\mathrm{cov}(\varepsilon_t', \eta_t', \xi_t') = diag(\Sigma_\varepsilon, \Sigma_\eta, \Sigma_\xi).$$

Covariance matrices $\Sigma_\varepsilon, \Sigma_\eta, \Sigma_\xi$ have been estimated using the Diffuse Kalman Filter (deJong, 1991) in GAUSS. As discussed, e.g., in Harvey (1989:463) the Kalman filter can be easily adapted to handle missing observations. This feature can be used to account for the different timing of data releases of individual monthly indicators.

The Bayesian VAR is set up from a Minnesota prior (Doan et. al, 1984) as implemented in the software package RATS. The prior is specified as an independent normal distribution on each coefficient of the

VAR. The mean of the prior is given from a random walk assumption, whereas the standard deviation for the coefficient related to series i in equation j at lag L is specified as

$$S(i, j, L) = \frac{s_i}{s_j} \gamma L^{-d} f(i, j)$$

where s_i is the standard deviation of the residual of a univariate autoregression in series i and $f(i, j) = 1$ for $i = j$ and ω otherwise. We use values of $\gamma = \omega = d = 0.5$. To handle the different timing of data releases, we use conditional forecasts as proposed by Doan et al. (1984) from the procedure CONDITION implemented in RATS.

We finally show that quarterly growth rates can be approximated from a weighted average of month-on-month (m-o-m) growth rates in a series. Denote with $y_{t\delta}$ the value of the series in month δ of quarter t and with $\overline{y}_t = \sum_{\delta=1}^{3} y_{t\delta}$ the quarterly aggregate. From $\ln(y_{t\delta} / \overline{y}_t) + 1 \approx y_{t\delta} / \overline{y}_t$ we obtain

$$\sum_{\delta=1}^{3} \{\ln(y_{t\delta} / \overline{y}_t) + 1\} \approx 1.$$

Subtracting the equation for quarter t-1 from quarter t gives

$$3(\ln \overline{y}_t - \ln \overline{y}_{t-1}) \approx \sum_{\delta=1}^{3} (\ln \overline{y}_{t\delta} - \ln \overline{y}_{t-1, \delta}) .$$

The quarterly growth rate thus approximately emerges as the average of the growth rates with respect to the corresponding month of the previous quarter. The latter can be transformed into a weighted moving average of m-o-m growth rates $\hat{y}_{t\delta}$.

$$\ln \overline{y}_t - \ln \overline{y}_{t-1} = \frac{1}{3} \left[\hat{y}_{t3} + 2\hat{y}_{t2} + 3\hat{y}_{t1} + 2\hat{y}_{t-1,3} + \hat{y}_{t-1,2} \right].$$

This shows that that the weights in m-o-m rates of up to month 1 in quarter t account already for two thirds of the q-o-q growth rate.

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