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Working Paper

Forecasting Quarter-on-Quarter Changes of German GDP with Monthly Business Tendency Survey Results

ifo Working Paper, No. 40

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Abberger, Klaus (2007) : Forecasting Quarter-on-Quarter Changes of German GDP with Monthly Business Tendency Survey Results, ifo Working Paper, No. 40, ifo Institute - Leibniz Institute for Economic Research at the University of Munich, Munich

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Working Papers

Forecasting Quarter-on-Quarter Changes of German GDP with Monthly Business Tendency Survey Results

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Ifo Working Paper No. 40

January 2007

An electronic version of the paper may be downloaded from the Ifo website www.ifo.de.

Forecasting Quarter-on-Quarter Changes of German GDP with Monthly Business Tendency Survey Results

Abstract

Results from business tendency surveys are often used to construct leading indicators. The indicators are then, for example, employed to forecast GDP growth. In this article more detailed results of business tendency surveys are used to forecast quarter-on-quarter GDP growth. The target series is very challenging because this type of growth rate leads to quite volatile time series. The present study focuses on German GDP data and survey results provided by the Ifo Institute. Since numerous time series of possible indicators result from the surveys, methods that can handle this setting are applied. One candidate method is principal component analysis, which is used to reduce dimensionality. On the other hand, subset selection procedures are applied. For the present setting the latter method seems more successful than principal components. But this is not a statement about the two types of procedures in general. Which method should be favoured depends very much on the aims of the specific study.

JEL Code: C42, C22, E32.

Keywords: Business tendency surveys, business cycle analysis, principal component regression, subset selection.

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1 Introduction

First official releases of quarterly national accounts are published with some delay. In Germany the Federal Statistical Office publishes the first official estimate of real GDP about 45 days after the respective quarter. To obtain a more timely forecast of GDP growth, high attention is paid to various monthly indicators. These include, for example, quantitative indicators like industrial production, stock of orders or retail trade volume, financial indicators and also qualitative business survey results. A quite common procedure for forecasting quarterly GDP growth, with the help of these monthly time series, is the use of so-called bridge models. Usually these models are based on quarterly aggregates of monthly indicators and therefore require that the indicators are known for the entire quarter. This is irritating, because the timeliness of the forecast is not so large. To overcome this problem one can try to forecast the indicators so that the models work even when the monthly indicators are not available for all months within the quarter; see Rünstler, Sedillot (2003) for such an attempt to forecast euro zone GDP growth.

The basic idea of this article is to use the monthly business tendency survey results for Germany more extensively. Usually different kinds of questions are contained in the questionnaire, some which focus on the the last months (How has the stock of orders changed in the last month?) some about the present situation (How do you assess the present stock of orders?) and some about the coming months (How will production develop in the coming three months?). But not only the time horizons of the questions are different, also the asked items may have different leading behaviours. There are, on the one side, for example, questions about the stock of orders, and, on the other, questions about production, which usually have different lead times. Thus we analyze whether quarter-on-quarter changes in real GDP can be forecasted

with the help of these extensive survey results. The indicators are not aggregated to obtain quarterly indicators; instead the survey results are used as they are to see whether the different leading behaviour of the indicators can be used to obtain improved forecasts.

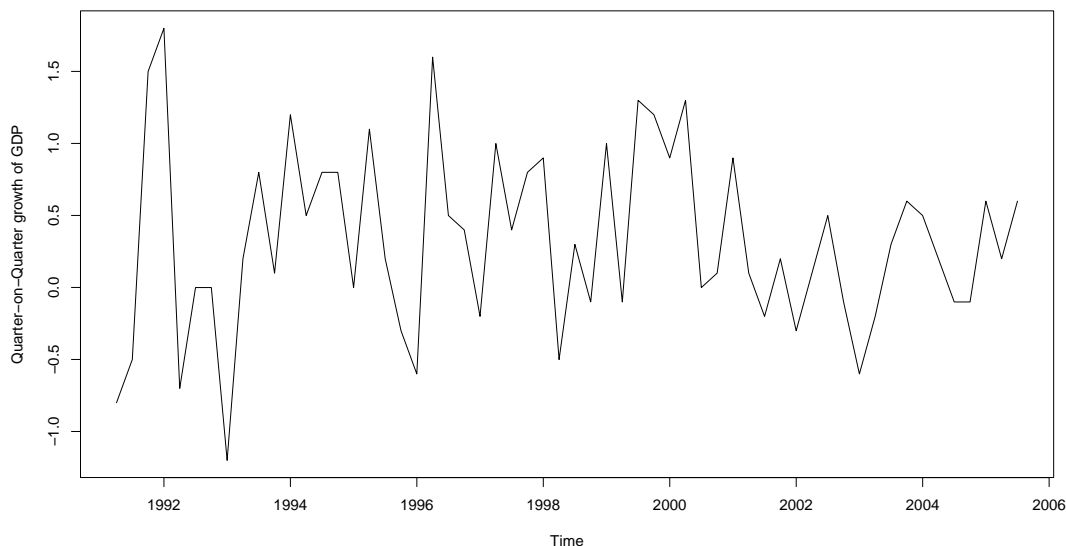


Figure 1: Quarter-on-quarter growth of real GDP in Germany (from II 1991 until III 2005)

A novelty in this study is that detailed survey results are used to forecast quarterly GDP growth. Usually only one business confidence indicator, constructed from some survey results, is added to a forecast equation, e.g. an autoregressive time series model. The monthly indicator can be aggregated to quarterly series, or quarterly GDP growth is estimated at monthly frequency with the help of the indicator; see e.g. Mittnik and Zadrozny (2005) for a recent study using Ifo data and the latter approach. Models which use monthly indicators to forecast quarterly target series are, for example, the above mentioned bridge models, because they bridge the gap between the indicators and the target variables. See Baffigi et al. (2004) for a study

about euro area GDP and some country GDPs including Germany's with bridge models.

Figure 1 shows German quarter-on-quarter real GDP growth rates for the time span ranging from the second quarter of 1991 to the third quarter of 2005. To avoid problems with the structural break caused by German unification, only data after the year 1990 are used. The time series are published by the German Federal Statistical Office. The published series is seasonally adjusted with the X12-ARIMA method. The depicted time series is quite volatile and shows no clear structural pattern. The auto-correlation function and the partial auto-correlation function, which are not figured here, show no remarkable correlations. This pattern is common knowledge and indicates that univariate ARIMA modeling is not suitable. Thus, in the following various regression models with GDP growth as dependent variable and monthly indicator series as independent variables are estimated.

The used business tendency survey results are generated by the Ifo Institute, which conducts such surveys in Germany. The covered sectors are manufacturing, construction, wholesaling and retailing. There is also a survey covering the service sector, but the results are not included in the present study because they are only available back to 2001. Ifo publishes a monthly indicator called the Ifo Business Climate, which receives great attention from the public but is also an object of many scientific studies. (See Abberger and Wohlrabe (2006) for an overview about recent scientific articles studying the forecast performance of this indicator.)

In the literature there is some discussion about how to quantify qualitative survey data. This point will not be considered here, though. A common way to publish such data is the calculation of net balances. This means that from the fraction of positive answers, the fraction of negative answers is subtracted. Nardo (2003) provides a survey about quantification of qualitative expectations. Öller (1990) finds balance statistics useful as a means for cyclical turning points, whereas Entorf (1993) and Cunningham et al. (1998) find that the use of balance statistics results in a loss of

information. Since the publication of balances is a well-established procedure, we use them in the following. We are also aware that there might be room for improvements, by using more elaborate quantification strategies.

Since the focus in this article is on forecasting, the considered model estimations are assessed according to their prediction errors. These prediction errors have to be estimated. Ideally, if there were enough data available, one could set aside a validation set of data not used for estimating the model. This validation set would be used to assess the performance of the prediction model. But data are too scarce in our application to have some put aside. All the data are needed for model choice; and estimating the prediction error with only a few data is also not suitable. A possible way out is the use of the cross-validation technique. Cross-validation means that a small part of the data, in this article only one case, is set aside and is predicted from the rest of the data. This is done repeatedly, setting aside a different part of the data and predicting it from the remainder. Cross-validation of regression models is discussed, for example, in Picard and Cook (1984). The aim of this method is to provide an estimation of the mean square prediction error, that is the average squared error in predicting a new observation using the fitted model. Quite popular is cross-validation, also in the field known as statistical learning, which deals with situations where large numbers of variables are analyzed (see Hastie et al. ,2001).

The organization of this article is as follows: in the next section relatively small regression models are estimated, using aggregated results for two questions only. In Section 3 detailed survey results are used for forecasting. Because of the large number of indicators, dimension reduction techniques are applied. Alternatively subsection selection methods are used. Section 4 summarizes the findings.

2 Regressions with Business Situation Assessments

In Germany the Ifo Business Climate is regarded as a very important indicator for the business cycle. Although the survey questionnaire contains various questions, for the Ifo Business Climate only two of them are used. These are the more vague questions about the present business situation and the expected change in the business situation. One advantage of these questions is that they can be asked in all sectors and branches. The respondents can interpret the business situation in a way that is meaningful in their kind of business. The answers can be simply aggregated to form an overall indicator.

For the business climate the results of both questions in one month are averaged. To forecast quarter-on-quarter GDP growth, this need not be the best way to proceed, though. It could be a better strategy to use either only one of the questions or to combine results from different months. To analyze the forecasting performance of the two questions, a simple linear regression approach is used. The pool of possible predictors contains the survey results of the months in the quarter under consideration and the previous quarter. So there are two variables for six months summing up to twelve possible predictors when all data of the quarter under consideration are available. Model choice is carried out automatically by selecting the model that minimizes Akaike's Information Criteria (AIC). The model is estimated with least squares.

The results of this procedure are shown in Table 1. Data available up to month 0 means that only the data for the previous quarter are known. Availability up to month 1 means that the data for the first month in the quarter under consideration are available, and so on. In sum, the calculations indicate that the most important variable for the prediction of the quartely GDP growth rates is the business expectations three months ago. A simple regression model with only this variable as predictor reduces the cross-validation value (CV) by a remarkable 14.6%. All of the other variables seem to have only a minimal impact on forecasting performance.

Data availability up to month in resp. quarter	Variables chosen by AIC	CV
0	ex_{-3}	0.3418520
1	si_{-3}, si_{-5} ex_{-3}, ex_{-5}	0.3614828
2	si_{-1}, si_{-3} $ex_{-1}, ex_{-3}, ex_{-5}$	0.3380533
3	si_{-1}, si_{-3} $ex_{-1}, ex_{-3}, ex_{-5}$	0.3380533

Table 1: Results for models based on predictors Business Situation and Business Expectations. ex_{-t} means expectations with time lag t months, si_{-t} stands for current situation. (model choice by AIC, CV without any covariate 0.4002615)

When more timely data than the ones three months before the end of the quarter are available, AIC chooses larger models that do not improve forecast performance. In the case where data are available up to the first month of the quarter under consideration, the cross-validation criteria points to an overfitting problem.

In this context one should bear in mind that the Ifo Business Climate and its components are not designed with the aim of giving quantified forecasts of real GDP growth rates. It is an indicator of the business cycle and the business condition on its own right, but clearly its evolvement should be linked to GDP growth. With the aim in mind of calculating optimal numeric GDP growth forecasts, one would probably use an adapted weighting scheme for aggregation and/or a more refined quantification method for the three response categories than net balances. But in practice this also means that probably different strategies are optimal depending on whether one tries to forecasts real or nominal GDP growth, quarter-on-quarter or year-on-year growth or instead growth rate cycles or growth cycles and so on. So for a institution like Ifo, which publishes the survey results, it is reasonable to use a simple and easy-to-interpret quantification method like net balances, which is also very effective for the analysis of the business cycle.

3 Forecasting with Extensive Results of Business Surveys

In the above calculations only the two questions about the assessment of the current business situation and the expected situation are used. Now the list of survey results employed for forecasting is enlarged.

The following questions are included into the analysis using extensive survey results:

- Manufacturing: current business situation, expected change of business situation, assessment of stock of orders, stock of orders compared to last month, assessment of stock of finished goods, demand situation compared to last month, production compared to last month, production plans
- Construction: current business situation, expected change of business situation, development of construction activity, expected construction activity, stock of orders compared to last month, assessment of stock of orders
- Wholesaling: current business situation, expected change of business situation, turnover against same month last year, assessment of stock of orders, order activity
- Retailing: current business situation, expected change of business situation, turnover against same month last year, assessment of stock of orders, order activity.

Every month there are results of 24 questions and with three months in a quarter 72 indicators result within the respective quarter. Since some series could have longer leads than three months the survey results of the previous quarter are also included into the set of possible indicators, which results in at last 144 candidate predictors. Because of this extended number, either a method which condenses the information included in these variables is required or a method which selects a suitable subset has to be applied. Both routes are pursued in the following.

3.1 Principal Component Regression

Since the number of possible predictors is quite large when all the questions for the four sectors are included, one can try to extract the contained information in a few principal components. Principal components is a classical method of multivariate statistical analysis. For an extensive treatment, see e.g. Jolliffe (2002). Stock and Watson (2002) established principal components as a tool for forecasting with a large number of predictors. The method is embedded in the field of dynamic factor analysis which is summarized by Stock and Watson (2006).

To be more specific, let y_t be again the scalar time series of quarterly GDP growth rates to be forecasted and let Z_t be a N -dimensional multiple time series of candidate predictors. It is assumed that (Z_t, y_{t+1}) admit a factor model representation with r common latent factors F_t ,

$$Z_t = \Lambda F_t + e_t \quad (1)$$

and

$$y_{t+1} = \beta' F_t + \epsilon_{t+1} \quad (2)$$

where e_t is a $N \times 1$ vector of idiosyncratic disturbances and ϵ_{t+1} the resulting forecast error. Estimation of F_t is done by classical principal components, which means that $\hat{\Lambda}$ is set equal to the eigenvectors of $Z'Z$ corresponding to its r largest eigenvalues. Asymptotic results for this method are given in Stock and Watson (2002).

Cross-validation is used as cut-off criterion for the number of principal components used for forecasting. The first principal components are successively added into the forecast equation until there is no further improvement in the cross-validation criterion. The results of this procedure are shown in Table 2. In all cases the first four principal components are chosen by the procedure. But even compared with the simple model of Section 2 with the predictor business expectations three months ago only, there is no improvement in forecasting quality.

The disappointing results of the above principal component regression may be due to

Data availability up to month in resp. quarter	No. of components	CV
0	4	0.42263
1	4	0.4129348
2	4	0.4015757
3	4	0.3984134

Table 2: Cross-validation results for principal component regression using the largest eigenvalues

the fact that the principal components are successively added to the model depending on the size of the corresponding eigenvalues. The components with the largest eigenvalues need not be the components with the best prediction performance. This is a well-known feature in principal component regression (see Jolliffe, 2002). Also components with relatively small eigenvalues could be very important for the aim of forecasting, although they may be not so important for the task of dimension reduction of a multivariate data set. Therefore, in another attempt the principal components are selected according to their ability to reduce the cross-validation criterion. Table 3 contains the results of this approach.

Data availability up to month in resp. quarter	Chosen components	CV
0	3, 4, 9, 12, 13, 14, 15, 34, 44	0.2553280
1	3, 4, 9, 13, 17, 28, 32, 35, 45	0.2584474
2	3, 4, 8, 11, 17, 18, 21, 27, 38, 43	0.2874074
3	3, 4, 9, 13, 16, 28, 34, 37, 47	0.2594100

Table 3: Cross-validation results for principal component regression using the reported components

These results seem to be very promising. But in practice, the estimation of the smaller principal components is very unstable when new observations are added. So it could be that when a new observation is available, the position of the components might change. This is not a problem for the first components, which have large eigen-

values. But the eigenvectors of components with very small eigenvalues can change substantially when new data points are included. So for the purpose of forecasting, only the principal components with large eigenvalues are sensible. Therefore in the procedure behind the results in Table 4 those principal components are considered that reduce the cross-validation criteria and in addition have eigenvalues larger than one. The later criterion is similar to the Kaiser criterion, which is well known in principal component analysis. Here it guarantees a certain stability of the forecast model.

Overall, this realistic view reveals that the use of principal component regression does not outperform the simple regression model with one aggregated business expectation variable used in the previous section. This conclusion depends very much on the concrete aim of the study, though. This article focuses on forecasting the exact quarter-on-quarter changes of GDP. This is a very volatile series. A different one would be, for example, to predict some kind of growth rate that better reveals the underlying business cycle. For this task usually smoother target series are appropriate. For example the popular EuroCOIN indicator from the Centre of Economic Policy Research is constructed with smoothed GDP growth rates as target series. (Details of this indicator and a description of its construction can be found on the Web page www.cepr.org/Data/eurocoin.) It is thus important to notice that there are different targets for forecasting. If one is interested in some kind of underlying growth, then factor models using only the first factors are very suitable. But in some circumstances it is also very important to obtain forecasts for the actual growth rate. Then the short term fluctuations are also important and these can only be captured by principal components with smaller eigenvalues.

3.2 Supervised Principal Components

When principal components of the indicator variables are calculated, the relationships of the latter with the target variable to be predicted are not directly taken into

Data availability up to month in resp. quarter	Chosen components	CV
0	3, 4, 9	0.3598757
1	3, 4, 9	0.3537094
2	3, 4, 8	0.3457005
3	3, 4, 9	0.3453838

Table 4: Cross-validation results for principal component regression using the reported components (selected PC with eigenvalue greater than 1)

account. Supervised Principal Components is a recent method suggested by Bair et al. (2006) which is meant to overcome this problem. It is similar to conventional principal components analysis except that it uses a subset of the predictors selected based on their association with the outcome. The procedure the authors suggest consists of the following steps:

1. Compute (univariate) standard regression coefficients for each feature.
2. Form a reduced data matrix consisting of only those features whose univariate coefficient exceeds a threshold θ in absolute value (θ is estimated by cross-validation).
3. Compute the first (or first few) principal components of the reduced data matrix.
4. Use these principal component(s) in a regression model to predict outcome.

Mathematical details of the procedure can be found in the original paper. When the algorithm is applied to the data set used in this article the figures contained in Table 5 result.

The cross-validation values are better than for the above model using the first four principal components. This is remarkable because the supervised model is a much simpler one. But the results are also not really satisfying, compared to the simple

Data availability up to month in resp. quarter	No of components	<i>Threshold</i>	CV
0	1	1.19	0.3850772
1	1	0.34	0.3904911
2	1	1.48	0.3345838
3	1	1.50	0.3352639

Table 5: Cross-validation results for regressions with supervised principal components

model in Section 2. Again, this is not a general assessment of this method, but it seems unsuitable for the task in this paper. The principal component approach and also the idea of supervised principal components is very interesting and indeed very useful for various purposes.

3.3 Subset Selection

Since we have many indicators that can be used as independent variables in a linear regression, the strategy of dimension reduction with the help of principal components was used in the above section. The results with these approaches are not fully satisfactory in the present application. Therefore we step back and try to find subsets of the original variables that help to predict GPD growth rates. Since there are too many possible regressor variables to choose a model by hand, a systematic variable selection procedure is needed. Miller (2002) has presented an exhaustive monograph about subset selection in regression with a special focus on forecasting. *Best subset selection* tries to find for each model size the subset of variables that gives the smallest residual sum of squares. The so-called leaps and bounds algorithm makes it feasible to search through all possible subsets even when 30 or 40 variables are analyzed. Since more than 40 variables are used in the present analysis, this kind of exhaustive search is not applicable here. Rather than search through all possible subsets, one can seek a good path through them. *Forward stepwise selection* starts with the intercept, and then sequentially adds into the model the predictor that most improves the fit. *Backward stepwise selection* starts with the full model and

sequentially deletes predictors, but can only be used when more observations than independent variables are available. Another method that is used in this section is *sequential replacement*. The basic idea here is that once two or more variables have been selected, it is tried whether any of those variables can be replaced with another variable that gives a smaller residual sum of squares. Unfortunately, also this algorithm does not guarantee convergence upon the best-fitting subset of the size being considered. Nevertheless, we follow Miller’s conclusions that sequential replacement is the more successful method than forward or backward stepwise selection.

When subsets of various sizes are determined by the algorithm, an appropriate model size has to be selected. Since the focus in this article is on forecasting, a suitable selection criteria is again cross-validation. A maximum number of 15 variables are included into the model and the favored model size is chosen with the help of the cross-validation criteria. Table 6 shows the size and the resulting cross-validation value of the preferred models.

Data availability up to month in resp. quarter	No. of variables	CV
0	15	0.1788432
1	13	0.1606736
2	13	0.1405883
3	14	0.1268022

Table 6: Cross-validation results for regressions with subset selection

The calculations reveal that this approach, compared to the other approaches used in this article, leads to relatively low cross-validation values. Thus the strategy of subset selection is the most sensible for forecasting GPD changes. The selected variables are tabulated in the Appendix.

So for the present aim of forecasting quarter-on-quarter changes in GPD, the sensible selection of a suitable subset of results from the business tendency survey seems more appropriate than extracting the information from all variables in principal components.

A further interesting aspect is that whenever the variable "assessment of the demand situation against the month before" in manufacturing from the second month of the respective quarter is available, this predictor is selected in the model with only one regressor and is included in almost all subsets of the other sizes. So this predictor seems to be very important. One can estimate a simple regression model with only this regressor and can obtain a cross-validation value of 0.3173451. So there is a very simple model with a quite low cross-validation value which is even lower than the values for the much more complicated models analyzed in the previous sections. Further experiments with the *lasso*, which is a common shrinkage method in regression (see Tibshirani, 1996), reveal that always this variable is selected as the important one. The detailed results of these experiments are not presented in this article, because, apart from the fact that always a small model with only this assessment variable is chosen, no further insights can be obtained.

4 Conclusions

The aim of this study was to analyze whether the extensive use of business tendency survey results is helpful for forecasting quarter-on-quarter growth rates of GDP. This target series is only one possible choice out of various series. Sometimes year-on-year growth rates or some kind of smoothed growth rate is chosen as target series. The quarter-on-quarter changes are of interest because they show the current business cycle dynamics very early and because forecasts of yearly GDP growth rates are usually based on these. On the other hand quarter-on-quarter changes is the most demanding target series to predict because it is quite volatile. Therefore especially for this target of forecasting, useful indicators are sought after.

Since the pool of possible indicators for forecasting with detailed survey results is quite large, two streamlines of methods are pursued: dimension reduction and subset selection. For the aim of this article - forecasting quarter-on-quarter changes in GDP -

the sensible selection of a suitable subset of results from the business tendency survey seems more appropriate than extracting the information from all variables in principal components. These results cannot be generalized, though. It is possible that the conclusion is different when other target series are used. For example year-on-year changes in GPD is a much smother time series than quarter-on-quarter changes, and it is possible that methods based on principal components are the better choice in this case.

5 Appendix

Variable	Time lag
Construction stock of orders against month before	-5
Retailing assessment of stock of goods	-5
Manufacturing business expectations	-4
Manufacturing stock of orders against month before	-4
Construction business situation	-4
Construction expected construction activity	-4
Construction expected construction activity	-3
Manufacturing stock of orders against month before	-2
Retailing turnover against year before	-2
Manufacturing business expectations	-1
Manufacturing demand situation against month before	-1
Construction stock of orders against month before	-1
Manufacturing production plans	-0
Wholesaling business expectations	-0

Table 7: Variables selected when data are available up to the third month of the quarter under consideration

Variable	Time lag
Construction stock of orders against month before	-5
Retailing assessment of stock of goods	-5
Manufacturing stock of orders against month before	-4
Manufacturing production plans	-4
Construction expected construction activity	-4
Wholesaling turnover against year before	-4
Construction expected construction activity	-3
Wholesaling business expectations	-3
Manufacturing production plans	-2
Retailing turnover against year before	-2
Manufacturing demand situation against month before	-1
Manufacturing production against month before	-1
Construction assessment of stock of orders	-1

Table 8: Variables selected when data are available up to the second month of the quarter under consideration

Variable	Time lag
Manufacturing production plans	-5
Construction business expectations	-4
Construction expected construction activity	-4
Retailing turnover against year before	-4
Manufacturing business situation	-3
Construction business situation	-3
Construction expected construction activity	-3
Construction assessment of stock of orders	-3
Wholesaling business expectations	-3
Wholesaling assessment stock of goods	-3
Construction business expectations	-2
Retailing business situation	-2
Retailing business expectations	-2

Table 9: Variables selected when data are available up to the first month of the quarter under consideration

Variable	Time lag
Manufacturing business situation	-5
Manufacturing production plans	-5
Construction stock of orders against month before	-5
Wholesaling orders	-5
Retailing assessment of stock of goods	-5
Manufacturing stock of orders against month before	-4
Construction business expectations	-4
Construction expected construction activity	-4
Wholesaling turnover against year before	-4
Retailing business situation	-4
Retailing turnover against year before	-4
Construction business situation	-3
Construction expected construction activity	-3
Wholesaling assessment of stock of goods	-3
Wholesaling business expectations	-3

Table 10: Variables selected when data are available up to the third month of the previous quarter

6 Literature

Abberger, K., Wohlrabe, K. (2006): Einige Prognoseeigenschaften des ifo Geschäftsklimas - Ein Überblick über die neuere wissenschaftliche Literatur. ifo Schnelldienst, 59/22, 19-26.

Baffigi, A., Golinelli, R., Parigi, G. (2004): Bridge models to forecast the euro area GPD. *International Journal of Forecasting*, 20, 447-460.

Bair, E., Hastie, T., Paul, D., Tibshirani R. (2006): Prediction by Supervised Principal Components. *Journal of the American Statistical Association*, 101, 119-137.

Cunningham, A., Smith, R., Weale, M. (1998): Measurement Errors and Data Estimation: the Quantification of Survey Data, in I.G. Begg and S.G. B. Henry, ed., *Applied Economics and Public Policy*, Cambridge University Press, Cambridge.

Entorf H. (1993): Constructing Leading Indicators from Non-balanced Sectoral Business Survey Series. *International Journal of Forecasting*, 9, 211-225.

Hastie, T., Tibshirani, R., Friedman, J. (2001): *Elements of Statistical Learning*. Springer, Heidelberg.

Jolliffe, I.T. (2002): *Principal Component Analysis*. Springer, Heidelberg.

Miller, A. (2002): *Subset Selection in Regression*. Chapman & Hall, London.

Picard, R.R., Cook, R.D. (1984): Cross-Validation of Regression Models. *Journal of the American Statistical Association*, 79, 575-583.

Mitnik, S., Zadrozny, P. (2005): Forecasting Quarterly German GDP at Monthly Intervals Using Monthly Ifo Business Conditions Data, in: Sturm, J.-E., Wollmershäuser, T. (ed.): *Ifo Survey Data in Business Cycle Analysis and Monetary Policy Analysis*. Physica-Verlag, Heidelberg.

Nardo, M. (2003): The Quantification of Qualitative Business Surveys: a critical Assessment. *Journal of Economic Surveys*, 17, 645-668.

Öller, L. (1990): Forecasting the business cycle using survey data. *International Journal of Forecasting*, 6, 453-461.

Rünstler, G., Sedillot, F. (2003): Short-Term Estimates of Euro Area Real GDP by Means of Monthly Data. ECB Working Paper No. 276.

Stock, J.H, Watson, M. (2002): Forecasting Using Principal Components From a Large Number of Predictors. *Journal of the American Statistical Association*, 97, 1167-1179.

Stock, J.H, Watson, M. (2006): Forecasting with Many Predictors. In: Elliott, Granger, Timmermann (eds.): *Handbook of Economic Forecasting*. Elsevier, Amsterdam.

Tibshirani, R. (1996): Regression shrinkage and selection via the lasso. *J. Royal. Statist. Soc. B*, 58, 267-288.

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