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Business Tendency Surveys and Macroeconomic Fluctuations*

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Abstract

We investigate the information content of business tendency surveys for key macroeconomic variables in Switzerland. To summarise the information of a large data set of sectoral business tendency surveys we extract a small number of common factors by a principal components estimator. The estimator is able to deal with mixed-frequency data and missing observations at the beginning and end of the sample period. We show that these survey-based factors explain a relevant share of the movements of key macroeconomic variables, i.e., CPI inflation, GDP, employment, and an output gap. In particular, questions about the current and future expected situation are informative. However, backward-looking questions, for example questions about the situation compared to the previous year, do not contain additional information. We then examine the economic dimension of the data set. Questions about prices, real activity and capacity constraints contain important information for the corresponding macroeconomic variables. Finally, we estimate a dynamic relationship to produce forecasts for our factors and these key macroeconomic variables. It turns out that the predictive ability of our survey-based factor approach is quite encouraging. In a pseudo out-of-sample exercise, our approach beats relevant benchmarks for forecasting CPI inflation and an output gap and adds information to the benchmark forecasts for GDP and employment.

JEL classification: E32, E37, C53

Keywords: Business tendency surveys, dynamic factor models, mixed frequencies, missing observations, nowcasting, forecasting

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1 Introduction

This paper investigates the information content of business tendency surveys for key macroeconomic variables in Switzerland. Therefore, we consider a large survey conducted by KOF – a business cycle research institute in Switzerland. The main advantage of business tendency surveys is their prompt availability and that they are almost not subject to revisions and measurement errors. We relate the qualitative response survey data to key macroeconomic variables. Our aim is to learn which dimensions of the business tendency survey contain information on the current state of the economy. Moreover, we conduct an out-of-sample exercise to examine the predictive content of business tendency surveys.

To summarise the information content of the business tendency surveys we apply a dynamic factor model. When estimating the factors we are confronted with several issues. First, we have to take into account quarterly and monthly time series. Second, some surveys are conducted quarterly at the beginning of the sample period but monthly later on. Third, not all sectors and questions are available from the beginning of the sample period which implies that a relevant fraction of observations is missing. Fourth, the survey data do not all refer to the same time period which implies missing observations at the end of the sample (“ragged-edge” problem). This will be especially relevant in our pseudo out-of-sample forecasting exercise. All these issues are tackled applying a two-step approach, where initial estimates are obtained by an expectation-maximisation (EM) algorithm accounting for mixed sampling frequencies and missing observations (Stock and Watson 2002) and the final factors are estimated by the Kalman-smoother as suggested by Doz et al. (2012).

Our results may be summarised as follows. A small number of factors extracted from the data set of business tendency surveys is able to explain a relevant share of the movements of key macroeconomic variables. We further investigate which dimensions of the data set help to explain the macro variables. This is shown by the in-sample explanatory power of the factors. The dimensions investigated are the sectors, the time reference of the questions, the sample frequency of the questions and the economic concept associated with the questions. According to this analysis, the most important sectors explaining economic fluctuations are manufacturing, retail trade and construction. With respect to

the time reference, we find that questions about the current and expected future situation contain most additional information, whereas, backward-looking questions are more or less redundant. This is also reflected in our finding that quarterly questions do not contain additional information to monthly questions, except for employment. In terms of economic concepts, we find an intuitive match between the survey dimensions and the macroeconomic aggregates. Questions about capacity constraints and real economic activity contain most information about GDP growth and the output gap and questions about prices and capacity constraints contain most information about CPI inflation.

A further advantage of the factor model is that it can be easily applied for forecasting (Schumacher and Breitung 2008). Because the survey data are usually not subject to revisions only revisions of the variable to be forecasted have to be considered. This implies that the real time performance of our approach can be easily assessed. It turns out that the predictive ability of our survey-based factor approach is quite encouraging. In particular, the forecast accuracy improves upon two relevant benchmarks which implies that the survey data should be considered for now- and forecasting. We find that the factors extracted from the survey data improve forecast performance, especially at horizons of four to eight quarters ahead and for CPI inflation and an output gap. For GDP growth and employment encompassing tests show that our survey approach adds information for forecasting relative to our benchmarks, while in absolute terms, it does not significantly perform better. Taking into account the idiosyncratic component of the macroeconomic variables further improves the accuracy of the nowcast and the one-quarter ahead forecast.

This paper contributes to a growing literature which uses factor models for now- and forecasting (e.g. Stock and Watson 2002, Banbura et al. 2010). In particular, recent studies emphasised that business survey data may be especially useful because they are readily available (Hansson et al. 2005, Frale et al. 2010, Carriero and Marcellino 2011) and because they can help to predict final releases of macroeconomic variables that are often heavily revised (Graff and Sturm 2011). Our paper is probably most closely related to Hansson et al. (2005), Schumacher and Breitung (2008), Kholodilin and Siliverstovs (2012) and Martinsen et al. (2014). The main difference to Hansson et al. (2005), Kholodilin and Siliverstovs (2012) and Martinsen et al. (2014) is that we use a monthly factor model which is able to deal with a large, mixed-frequency data set. We

expect that exploiting both, monthly and quarterly information may be important, in particular for nowcasting macroeconomic variables that are published with some delay. Moreover, Schumacher and Breitung (2008) focus on forecasting GDP based mostly on macroeconomic variables while we focus on the information content of business tendency survey for a range of macroeconomic variables. More generally, we are interested also in the in-sample explanatory power of the surveys. This may give us an indication whether what we measure as macroeconomic variables is indeed related to the views of economic agents.

The paper proceeds by presenting the data and the methodology to summarise the information content of the survey data set. Afterwards, we document the in-sample explanatory power of the survey data for current macroeconomic fluctuations as well as the out-of-sample predictive content. Finally, we offer some conclusions.

2 Data

The KOF business tendency survey polls around 11,000 firms from eight sectors of the Swiss economy. The surveys are conducted on a monthly or quarterly basis. However, the available observations have increased considerably since the survey was first established, but also, during our sample period, because some questions or sectors were added, and some questions changed to a monthly survey frequency. Therefore, taking into account missing data and mixed collection frequencies will be key when relating the information content of the surveys to macroeconomic fluctuations.

We group the survey questions along different dimensions (see Table 10 in the Appendix for a complete list of the questions). First, the questionnaires are distributed to firms in eight different sectors, namely manufacturing, project engineering, construction, retail, wholesale, services, financial services, and restaurants and hotels (some example questions are given in Table 1). Second, we group the questions asked according to economic concepts. We may expect that some economic dimensions of the survey will be more relevant for particular macroeconomic variables.¹ Third, we group the questions according to time reference of the specific question asked. I.e., there are questions about the past,

¹In a similar vein, Lein and Köberl (2009) show, based on micro survey data, that price increases are triggered mainly in response to labour shortages.

current and expected future situation of the firm. Finally, we group the questions into monthly and quarterly survey frequency.

Table 1 — Survey question examples

<i>Sector</i>	<i>Example question</i>	<i>Possible answers</i>		
Manufacturing	We judge our stock of final products as	too high	sufficient	too low
Construction	Over the last 3 months, our competitive position has	improved	remained unchanged	deteriorated
<i>Economic concept</i>	<i>Example question</i>	<i>Possible answers</i>		
Real economic activity	Over the last 3 months, the demand for our services has	increased	remained unchanged	decreased
Capacity constraints	We judge our technical capacities as	too high	sufficient	too low
Labour market	We judge our employment as	too high	sufficient	too low
Prices	Over the next 3 months, our prices will	increase	remain unchanged	decrease
<i>Time reference</i>	<i>Example question</i>	<i>Possible answers</i>		
Change last twelve months	Over the last 12 months, our production activity has	increased	remained unchanged	decreased
Current situation	We judge our order books actually as	high	sufficient	too low
Expected situation	Over the next 3 months, our prices will	increase	remain unchanged	decrease

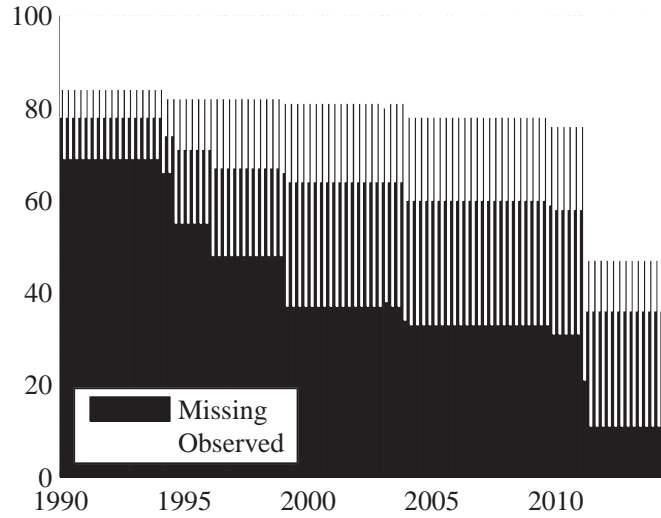
A large share of the data set is based on qualitative response data. For these data, we obtained a sectoral aggregate of the share of negative answers subtracted from the share of positive answers (balance statistic). There are two exceptions. For questions with more than three possible responses, we use the percentage share of the corresponding answer category. Moreover, the survey contains quantitative questions, e.g., on capacity utilisation rates.

In all cases, we use the sectoral aggregate of the corresponding series provided by KOF. To construct these sectoral aggregates, individual firm answers are first aggregated to various groups, separately for three firm-size classes (small, medium, large), where each individual answer is weighted by the firm size approximated by the number of employees in the sample. For each group, the firm-size classes are then aggregated using the corresponding share of employees in the population, which may differ from the share of employees in the survey sample. Finally, the group levels are aggregated to the overall

sector using the share of value added or the share of employees in the population.²

We shifted the sectoral series in time in such a way, that they are saved in those periods we think the question most likely refers to. For example, for quarterly questions, we shift the series in such a way that the value is stored in the last month of the quarter the survey was conducted. However, we do not shift questions about expectations.

Figure 1 — Number of observations



Although we account for missing data and changing sampling frequency, we specify a minimum number of observations that we would like to include in the analysis, discarding all series with less than 36 non-missing observations. Moreover, we drop financial sector data because most series are particularly short. That way we end up with 100 time series at the end of the sample period. Figure 1 shows that the number of observations increases substantially since the beginning of the sample period, reflecting that additional sectors were surveyed over time or the survey frequency has increased. Moreover, the ragged black area illustrates that some questions are in fact asked only on a quarterly basis.

Note that we treat our vintage of the KOF survey as real-time data for two reasons. First, we use non-seasonally adjusted data such that there are no revisions due to end-of-sample instability. Second, the only revisions may stem from the fact that first results of the survey are calculated about five working days before the end of the month. However, in our recursive analysis, we assume a state-of-information based on the definitive

²For more information, see <http://kof.ethz.ch>, Surveys, Meta-information.

results which are available shortly after the end of the reporting month.

We add to this set of business tendency surveys a small set of macroeconomic variables which we would like to explain and forecast in real time (see also Table 11 in the Appendix). These macroeconomic variables include monthly year-on-year CPI inflation, quarterly growth rates for GDP and employment (full-time equivalents) and an output gap measure (production function approach). All growth rates are calculated as annualised log-changes in %. We are not mainly interested in the influence of revisions to the macroeconomic data and therefore we use only the releases available as of October 2014.

Our sample period covers the time span from 01/1990 to 09/2014. To estimate the model, we adjust CPI inflation by a structural break in the mean in 1994 (see e.g. Stulz 2007). This has to be done to relate the stationary survey data without structural break to CPI inflation. However, in our out-of-sample analysis, we evaluate forecasts only starting in 1996 and also, all benchmark models are estimated accounting for this structural break.

3 Methodology

This section discusses the estimation procedure for summarising the survey information. In particular, we present the treatment of data irregularities (e.g. mixed frequencies and missing data). Furthermore, we present our methodology to conduct forecasts based on the estimated factor model and the relevant benchmarks.

3.1 Factor estimation

Our aim is to determine the information content of the business tendency surveys for the macro variables. We do so by summarising the information content of the business tendency survey by extracting common factors using a principal components approach. Let $\bar{X} = [X_m, X_s]$ be a $(T \times N)$ matrix of data containing a set of macro variables and business tendency surveys. The macro variables are denoted by a matrix \bar{X}_m with dimension $(T \times N_m)$ and the business tendency survey are denoted by a matrix \bar{X}_s with dimension $(T \times N_s)$. All data are standardised so that they have mean zero and standard deviation one. If all data was available in monthly frequency over the entire sample period, we could estimate an approximate factor model of the form

$$\bar{X} = F\Lambda + e \quad , \quad (1)$$

where we explain the data set using a small number of common factors F ($T \times r$) mapped to the data via the factor loadings Λ ($r \times N$), and e ($T \times N$) is a matrix of unexplained idiosyncratic components. Following Stock and Watson (2002), the straightforward way to proceed would be to extract the common factors via principal components from the data set and examine how much of the variance of the macro variables we can explain.

The general use of factor models in analysing survey data for is not completely new. Hansson et al. (2005), Carriero and Marcellino (2011) and Martinsen et al. (2014) apply a similar procedure than we do. In analysing the KOF surveys, we are faced with an important complication: the business tendency surveys may have monthly or quarterly frequency and the data set is unbalanced because of missing data at the beginning and the end of the sample. Therefore, we have to take into account the mixed frequencies and missing data when estimating the factors. Additionally, we want to examine the information content of the business survey data for the macro variables but not vice versa. In what follows, we present our strategy to deal with these two issues.

To account for mixed survey frequency and missing data, we follow Stock and Watson (2002) and specify for each variable $n = 1, \dots, N_m + N_s$ a matrix A_n linking the observed normalised data to the unobserved underlying monthly data $\bar{X}_n = A_n X_n$. In what follows, \bar{X}_n will be the n^{th} data series where entries with missing values have been removed. Specifying A_n appropriately, we can take into account mixed frequencies of the data, temporal aggregation and missing data. Based on this relationship we can derive an EM-algorithm to estimate the factors, assuming that $X_{nt} \sim i.i.d. N(\lambda_n F_t, 1)$. Based on this assumption, the best prediction of the unobserved monthly data conditional on the observed mixed frequency data is given by

$$E[X_n | \bar{X}_n] = F\lambda_n + A_n' (A_n A_n')^{-1} (\bar{X}_n - A_n F\lambda_n) \quad , \quad (2)$$

where F is a $(T \times r)$ matrix of factors, λ_n is a $r \times 1$ vector of factor loadings for variable n , and $-$ is a generalised inverse. Based on this expression, we can use the EM-algorithm to estimate the model. j^{th} iteration of the EM-algorithm proceeds as follows:

1. Calculate $E[X_n|\bar{X}_n]$ for each n based on $F^{(j-1)}$ and $\lambda_n^{(j-1)}$.
2. Estimate $F^{(j)}$ and $\lambda^{(j)}$ using the principal components estimator on $E[X|\bar{X}]$, which is the full panel of the estimated monthly frequency data.
3. Calculate the average sum of squared residuals $1/(NT) \sum_n \sum_t (E[X_{nt}|\bar{X}_n] - A_n F^{(j)} \lambda_n^{(j)})^2$ and check convergence.

To obtain starting values, $F^{(0)}$, we estimate factors using the principal component estimator on a small subset of the data that is available monthly over the entire sample period. We then obtain starting values for the loadings, $\lambda_n^{(0)}$, for each variable n by regressing non-missing values of $A_n^- \bar{X}_n$ on the corresponding values of $F^{(0)}$.

The presented model can be seen as an approximate dynamic factor model (Bai and Ng 2002). The estimator based on principal components is simple to apply and relatively robust (e.g. it allows for some autocorrelation in the factors and the idiosyncratic component). Alternatively, we could estimate a dynamic factor model proposed by Forni et al. (2000) based on dynamic principal components and the parametric dynamic factor model in state space form proposed by Doz et al. (2012). A drawback of the static representation might be that it does not account for dynamics among the factors, if they exist. However, dynamic effects can be present directly in the factors. On the other hand, the alternative methods are sensitive to the exact specification, since different choices have to be made (more parameters to specify and estimate). Generally, the literature documents the simpler approach of Stock and Watson (2002) is not inferior relative to competitive methods (see Boivin and Ng 2005, Carriero and Marcellino 2011, for similar applications). In our analysis, we still opted for the two-step approach proposed by Doz et al. (2012). It turned out that first accounting for missing data and mixed-frequency using the EM-algorithm and then re-estimating the factors using the Kalman-smoother provided more stable estimates of the factors, when more data becomes available over time.

To address the issue that we want to examine the explanatory power of the business tendency surveys for the macro data but not vice versa, we estimate the factors only for

the business tendency survey data. This ensures that the estimation of the factors is not affected by the specific macro data we include. Therefore, the algorithm yields estimates of F_s and Λ_s . We then estimate loadings for the macro data, Λ_m , by regressing for each macro variable $n = 1, \dots, N_m$ the non-missing values of $A_n^- \bar{X}_n$ on F_s .

Having estimated the factors and the factor loadings, we can derive the common components of the macro data which is driven by the survey data. For each variable $n = 1, \dots, N_m + N_s$, the monthly frequency common component is given by $C_n = F_s \lambda_n$, which is an estimate of the unobserved monthly data. We denote the low-frequency common component by $\bar{C}_n = A_n F_s \lambda_n$, which is just the estimated common component in the frequency of the original data. From this, we can derive the share of variance explained by the factors by the R^2 of a regression of \bar{X}_n on the low-frequency common component non-missing values.

3.2 Forecasting macro variables using monthly factors

To form forecasts based on our estimated factor model we rely on an iterative multi-step forecasting procedure (see Boivin and Ng 2005, Schumacher and Breitung 2008, for a detailed discussion). Notice that in the second step of the two-step approach by Doz et al. (2012), we estimated a VAR in companion form for the factors according to

$$\hat{F}_t = \Phi \hat{F}_{t-1} + u_t, \quad (3)$$

where with \hat{F}_t includes the estimated factors (and corresponding lags to set up the companion form). Φ is of dimension $(rp \times rp)$ where we set $p = 1$. Using this dynamic equation in the factors, we can obtain forecasts by iterating forward according to

$$\hat{F}_{t+h|t} = \hat{\Phi}^h \hat{F}_t \quad (4)$$

$$\bar{C}_{t+h|t,n} = A_n \hat{F}_{t+h|t} \hat{\lambda}_n, \quad (5)$$

where $\bar{C}_{t+h|t,n}$ denotes the h -step ahead prediction of the (low frequency) common

component with respect to variable n . In other words, we produce a forecast for the factors and map this forecast into a forecast for the common component of the corresponding macroeconomic variable.

Note that these forecasts are based on the recursive estimates of the factors and therefore they ignore the information content contained in the macroeconomic variables themselves. Therefore, the forecast should track the common component of the macroeconomic variables but ignores the idiosyncratic component. For nowcasting, however, the idiosyncratic may play an important role as the idiosyncratic component may be autocorrelated. Therefore, we would expect our forecast to perform well for the medium term rather than for the short term.

To improve the short-term forecasting performance, we may allow for serial correlation of the idiosyncratic component. We follow Boivin and Ng (2005) and estimate an AR(p) model on the monthly frequency component $\hat{e}_{n,t}$ by regressing it on p_e lags, where the idiosyncratic component, distributed to the underlying monthly frequency, is given by $A'_n(A_n A'_n)^-(\bar{X}_n - A_n \hat{F} \hat{\lambda}_n)$. In companion form the process is given by

$$\hat{E}_{t,n} = P \hat{E}_{t-1,n} + u_t, \quad (6)$$

where P is of dimension $p_e \times p_e$ and $\hat{E}_{t,n} = (e_{t,n}, e_{t-1,n}, \dots, e_{t-p_e,n})'$. The corresponding forecasts for the idiosyncratic component of variable n is obtained by iterating h -steps ahead given

$$\hat{E}_{t+h|t,n} = \hat{P}^h \hat{E}_t. \quad (7)$$

In our application, we set the lag length to $p_e = 1$. To arrive at the final forecast $\bar{X}_{t+h|t,n}$, one can then combine the common component forecast and with the idiosyncratic forecast

$$\bar{X}_{t+h|t,n} = A_n(\hat{F}_{t+h|t} \hat{\lambda}_n + \hat{e}_{t+h|t,n}). \quad (8)$$

Obviously the inclusion of the autocorrelation structure of the idiosyncratic component may improve the forecasting accuracy only in cases where the error term shows any signs of serial correlation. However, there might be a drawback to include the information content in the idiosyncratic component. Namely, for macro series that undergo substantial revisions the inclusion of the idiosyncratic component might cause problems in real time. Forecasts based exclusively on the common component are mostly immune to data revision of the macro economic variable as long as the revisions are unsystematic (and unbiased). Because we can assume that our vintage of the KOF survey was available in this form in real time, the factor-based forecasts are consistent, while unsystematic measurement error in the target variable is captured by a residual term. The results obtained by Schumacher and Breitung (2008) – which used only the common component – confirm this result. They found no quantitative differences between real time and final released data in their out-of sample study.

In terms of model out-of-sample model comparison based on latest available data it is natural to use the additional information in the idiosyncratic component. In practice, however, there is clearly a trade-off of employing the idiosyncratic component in cases for macro variables (e.g. GDP, employment and the output gap) that are revised over time.³

3.3 Benchmark models

We compare the survey-factor VAR forecasts with two benchmarks. First, we estimate recursively simple AR processes for the macroeconomic variables. Second, we add to these AR processes exogenously given leading indicators. We take into account four different leading indicators: PMI composite manufacturing index, the balance statistic of the KOF survey on manufacturing production (compared to previous month), PMI subindex on price expectations and the KOF economic barometer (see Table 12 in the Appendix). Among these variables the KOF economic barometer and the PMI manufacturing index can be regarded as the most prominent early available indicators in Switzerland and have received some attention in the literature (see e.g. Maurer and Zeller 2009, Siliverstovs

³Because our information set is based solely on survey data that is almost never revised, our approach, at least when ignoring the idiosyncratic component, is likely to prove robust also in the presence of revisions to the independent variables. Evaluating the real time performance of our approach in the presence of data revisions is beyond the scope of this paper.

2011). The remaining two indicators are motivated by other considerations. The PMI subindex of expected price changes is seen as a monthly price indicator which might contain useful information on future inflation rates. Additionally, we pick out one particular survey from the KOF data set which we think is conventionally closest to GDP, namely the change in actual production in the manufacturing sector.

To obtain h -step ahead forecasts from the leading indicator models we follow Stock and Watson (2003) and set up an autoregressive distributed lag model (ARDL) of the form

$$\bar{X}_{t,n} = \sum_{i=1}^{p^x} \alpha_i \bar{X}_{t-i,n} + \sum_{j=0}^q \beta_j y_{t-j} + u_t, \quad (9)$$

$$y_t = \sum_{i=1}^{p^y} \phi_i y_{t-i} + e_t \quad (10)$$

We select p^x , p^y and q by BIC and use an iterated forecast procedure (motivated by Marcellino et al. 2006) to obtain h -step ahead forecasts $\bar{X}_{t+h,n|t}$ for the macroeconomic variables of interest. Note that the AR model is a special case where $q = 0$. In most cases $\bar{X}_{t,n}$ and y_t are of different frequencies (all indicators are available at monthly frequency while most macro series are only available at quarterly frequencies). Therefore we have to transform the monthly variable to quarterly frequency. We employ a moving average definition proposed by Koenig (2002) and Lahiri and Monokroussos (2013) for the PMI to map monthly observation to quarterly variables. This approach simply assumes $y_t = 1/9y_{t-1,2}^m + 2/9y_{t-1,3}^m + 3/9y_{t,1}^m + 2/9y_{t,2}^m + 1/9y_{t,3}^m$.⁴

4 Results

4.1 Is survey data informative for macroeconomic fluctuations?

First, we ask how many factors capture the information content of the business tendency data set sufficiently well. Table 2 shows the share of variance that is explained by various numbers of factors extracted from the survey data. The first column contains the average

⁴An alternative would be to estimate MIDAS models which allow for a more flexible weighting scheme.

R^2 explaining the low-frequency component of the survey data. The remaining columns contain the R^2 of our variables of main interest. We see that there is a lot of co-movement in the survey data. A modest number of three factors explains almost 70% of the variation among our 100 survey series. However, ultimately we are interested in the information content of these factors for macroeconomic fluctuations. We see that the factors explain relatively well current fluctuations of real variables. Focusing on three factors, we see that they explain more than 80% of output gap fluctuations, almost 60% of employment fluctuations and still 35% of GDP fluctuations. An even smaller number of two factors explains 36% of CPI inflation. Note that adding another factor does actually lower the R^2 in some cases. This is because we have a mixed-frequency data set with missing data. Therefore, estimating one factor more leads to changes in the other factors and may actually worsen the explanatory power.

The R^2 may help us to decide, how many factors we should use for every macro variable in the subsequent analysis.⁵ However, because more factors imply that we have to estimate more parameters in our forecasting exercise, we only increase the number of factors if the rise in the R^2 is substantial. For CPI inflation and employment, two factors seem to be sufficient. For the output gap, we find that increasing the number of factors to three increases the R^2 considerably. For GDP growth, it even seems worthwhile to include four factors in the analysis.

Table 2 — In-sample fit (R^2)

	Survey data	CPI inflation	GDP growth	Employment	Output gap
$r = 1$	0.45	0.13	0.15	0.51	0.64
$r = 2$	0.56	0.36	0.23	0.57	0.75
$r = 3$	0.67	0.30	0.35	0.57	0.83
$r = 4$	0.72	0.37	0.39	0.58	0.85
$r = 5$	0.76	0.38	0.41	0.58	0.87
$r = 6$	0.79	0.38	0.41	0.60	0.88

To confirm this choice of the number of factors, we rely on the BIC calculated from the regression of the variables of interest on the factors (Table 3). In doing so, we ignore that the factors are estimated and, therefore, we should choose the number of factors rather smaller than what the criterion suggests. For CPI inflation, the BIC confirms our choice

⁵Note that because of the mixed-frequency and missing data set, standard information criteria for the number of factors are not appropriate (Bai and Ng 2002).

based on the R^2 as the criterion is minimised with two factors. For GDP growth and employment, the BIC would actually be minimised at $r = 6$. However, the differences in the R^2 and the BIC compared to our preferred choice of $r = 4$ for GDP and $r = 2$ for employment is very small and therefore we opt for the more parsimonious specifications. Finally, for the output gap, we also find that increasing the number of factors may be beneficial. However, we remain cautious and add only one additional factor to obtain a parsimonious specification with $r = 4$ factors. For the remaining paper, all results are based on the number of factors specifically for every variable as just discussed.

Table 3 — Number of factors (BIC)

	CPI inflation	GDP growth	Employment	Output gap
$r = 1$	-48.66	490.69	169.37	-5.25
$r = 2$	-133.47	466.63	135.29	-99.06
$r = 3$	-103.95	421.99	136.64	-223.17
$r = 4$	-127.00	405.26	137.18	-249.15
$r = 5$	-126.92	401.68	139.93	-283.10
$r = 6$	-122.34	405.01	134.39	-300.84

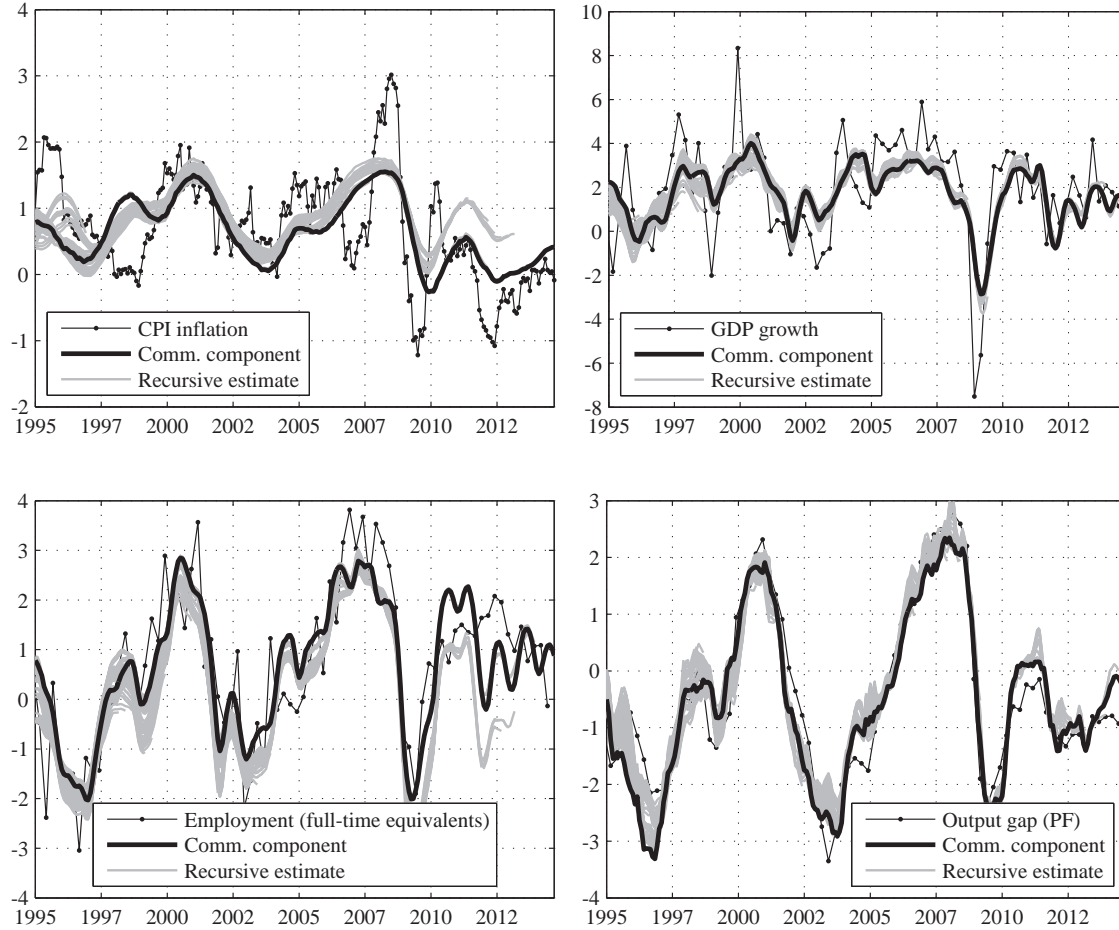
To give a visual impression of the explanatory power of the survey data, Figure 2 shows the macroeconomic variable in original frequency together with the final estimate of the common component based on the survey data and recursive estimates on 75 quarterly vintages. For all macroeconomic variables, the final common component tracks the original series closely. Clearly, this is reflected in a high R^2 in Table 2 between 36% and 85%, four our preferred choice of rank.⁶ By construction, the common component is much smoother than actual CPI inflation. But it tracks the major shifts in CPI inflation very well. For GDP growth, the results look even better. For example, we would have predicted the economic downturn during 2007 and 2008 earlier. In addition, official GDP estimates are available much later than our survey projection and these numbers are usually heavily revised after some years.⁷ The highest correlation we find for employment and the output gap. The survey data seem especially useful to explain these two variables. Given that output gap estimates are even more uncertain than GDP estimates in real-time, and

⁶The explanatory power of the factors may seem low compared to other factor models in the literature (see e.g. Giannone et al. 2005, Kaufmann and Lein 2013, for the US and Switzerland, respectively). However, recall that the explanatory power entirely stems from the survey data and not from the macroeconomic variables. Adding a larger set of macroeconomic variables and incorporating them into the estimation of the factors would likely improve the explanatory power.

⁷Estimates for the demand and supply side of GDP are given in Figures 3 and 4 in the Appendix.

survey data are not, this result indicates that survey are especially useful to obtain an early indication of the state of the business cycle.

Figure 2 — Recursive estimates of the common component



The grey lines give the common component recursively estimated on 75 quarterly vintages where we add one additional quarter of survey data at a time. We see, that the in-sample fit may be overestimated because of some instability in the estimated common components. The instability is most pronounced at the beginning of the sample. This instability stems mainly from the fact that the common component is estimated on a much smaller information set, as many surveys have become more and more available over time. In particular, for CPI inflation and employment there is a one-time shift in the common component when a substantial number of newly available survey data is added to the data set coinciding with a downward shift of CPI inflation in the aftermath of the great recession and during the euro area debt crisis. However, as our out-of-sample forecasting

exercise will show later on, these instabilities do not hamper the forecasting ability of the approach. Another reason for revision is through the re-estimation of factor loadings that change with new data and that the mean and standard deviation of the survey data changes over time. Nevertheless, we think that the instability is small enough so that the common components provide a good signal in real time. In particular, the turning points do not seem to be strongly affected by the instability. Notably before and during the crisis 2008/2009 the revisions remain very small which indicates that the approach is reliable.

4.2 Which dimensions of the survey data are most informative?

In the following, we show tables with the explanatory power of the factors, where we exclude one dimension of the survey at a time. A drop in the R^2 therefore implies that the corresponding dimension helps to explain the macro data. In fact, it shows whether a dimension contains information in addition to the remaining data set. By contrast, an unchanged R^2 implies that the sectors contains no additional information and a rise in the R^2 implies that the corresponding dimension actually worsens the explanatory power.⁸

Table 4 — Sectors

	CPI inflation	GDP growth	Employment	Output gap
Entire data set	0.36	0.39	0.57	0.85
Excl. project engineering	0.34	0.38	0.52	0.86
Excl. construction	0.30	0.41	0.50	0.86
Excl. retail	0.20	0.36	0.44	0.85
Excl. services	0.36	0.39	0.57	0.85
Excl. hotels and restaurants	0.43	0.39	0.56	0.86
Excl. wholesale	0.34	0.40	0.57	0.85
Excl. manufacturing	0.30	0.00	0.62	0.70

Note: The table shows the R^2 computed for our key macroeconomic variables with respect to the common component. Each row corresponds to a removal of one dimension of the data set at a time.

Table 4 shows the share explained of the variance of our key macroeconomic variables for the entire sample (first row) and excluding one sector at a time (remaining rows). The sectors that contain most additional information relative to the entire data set are manufacturing, retail trade, and construction. For CPI inflation, the largest drop of the explanatory power occurs if we exclude the retail sector. This seems intuitive as

⁸This may be the case for dimensions with very few data points, which may introduce instability of our estimation procedure.

the CPI contains a large share of retail goods prices. But also, the construction sector and manufacturing contain additional information. For GDP growth, the single most important sector is manufacturing. The R^2 almost falls to 0, which is also reflected by the fact that no other sector seems to contain much additional information relative to the entire data set. The only exception seems to be the retail sector, for which the R^2 does also fall slightly. For employment questions in the retail sector are containing additional information, closely followed by construction. Finally, for the output gap, most additional information stems from questions in the manufacturing sector. It should be noted that for some sectors, we have only few or relatively short series with many missing observations. If this is the reason for an unchanged R^2 we would not discard these sectors a priori because these sectors may become informative in the future. Not surprisingly, perhaps, manufacturing and construction are two sectors with fewer missing data points than other sectors.

Table 5 — Time reference

	CPI inflation	GDP growth	Employment	Output gap
Entire data set	0.36	0.39	0.57	0.85
Excl. current situation	0.34	0.35	0.52	0.76
Excl. expected situation	0.19	0.40	0.46	0.85
Excl. change last twelve months	0.35	0.39	0.59	0.85
Excl. change last three months	0.36	0.39	0.57	0.86
Excl. last quarter	0.35	0.37	0.57	0.84
Excl. change to last years' quarter	0.40	0.39	0.56	0.85
Excl. change to previous quarter	0.36	0.39	0.56	0.85

Note: See table 4.

Table 5 examines the time reference of the questions asked in the surveys. It turns out that questions about the current and future expected situation are particularly valuable. For CPI inflation, questions about the expected future situation contain most additional information. The R^2 falls substantially from 0.36 to 0.19 when excluding this dimension of the data. To a lesser extent, questions about the current situation contain additional information. Quarterly questions, and questions about the situation relative to the past do not contain additional information. This suggests that, according to the surveys, price changes are explained by expectations of the firms about the future, rather than the current or past situation. A very similar picture emerges for employment, where questions

about the expected future situation contain more additional information than questions about the current situation. For the two other real variables, GDP growth and the output gap, questions about the current situation are more important. Notice that, not even for these quarterly variables, do questions about the last quarter or the change in the past three months contain additional information to the entire data set.

Table 6 — Survey frequency

	CPI inflation	GDP growth	Employment	Output gap
Entire data set	0.36	0.39	0.57	0.85
Excl. quarterly	0.36	0.39	0.44	0.84

Note: See table 4.

This leads us to ask, whether questions asked on a quarterly basis are all that useful in the surveys or whether we could limit our attention to monthly questions only.⁹ Table 6 shows that, for three out of four macroeconomic variables, the monthly survey questions contain the bulk of the relevant information for macroeconomic fluctuations. Only for employment, we find that the quarterly questions contain additional information relative to the remaining data set. Of course, this does not imply that we should abandon the quarterly questions entirely, because, for no macroeconomic variable does the fit improve if we exclude the quarterly questions.

Table 7 — Economic concept

	CPI inflation	GDP growth	Employment	Output gap
Entire data set	0.36	0.39	0.57	0.85
Excl. capacity constraints	0.34	0.33	0.53	0.81
Excl. labour market	0.37	0.39	0.57	0.85
Excl. prices	0.32	0.40	0.56	0.85
Excl. real activity	0.45	0.34	0.58	0.79

Note: See table 4.

Finally, we may examine whether the information content for the macroeconomic variables really correspond to the economic concept asked in the questionnaire (Table 7). The results show that, overall, firms qualitative answers for each economic concept help to explain the corresponding macroeconomic aggregate. For CPI inflation we find that the surveys information is in line with a New Keynesian model of price-setting.

⁹Note that questions that changed from quarterly to monthly frequency during the sample period are treated as monthly questions in this analysis.

Not surprisingly, perhaps, do questions about prices contain useful information about CPI inflation. But also, questions about capacity constraints contain some additional information. For GDP growth and the output gap, questions about real activity and about capacity constraints contain most additional information. But also, employment is mostly explained by questions about capacity constraints. Interestingly, questions about the labour market do not add information, not even for employment.

4.3 Does survey data improve forecast accuracy?

Up to now, we have only examined the in-sample explanatory power of the survey data for macroeconomic fluctuations. This section shows that the recursive estimation of the factors is stable enough so that the explanatory power carries over in pseudo real-time and that the factor model performs well in forecasting the macroeconomic fluctuations.

To evaluate the predictive information of the survey data we produce forecasts and compare them with several benchmark models in a pseudo out-of sample experiment. The benchmarks include recursively estimated autoregressive models as well as leading indicator models for the macro variables (see section 3.3 for details). The predictive ability of our models under consideration is compared in terms of relative root mean squared errors (RMSEs). The forecast experiment is conducted recursively and our first set of forecasts are obtained starting in Q1/1996. In each point in time up to eight-quarters ahead forecasts are obtained. This leaves use with 75 quarterly vintages to make the pseudo out-of-sample model comparisons.¹⁰

We take into account that the quarterly macroeconomic variables are released with a time lag and therefore we produce a nowcast for these variables. However, we assume that the data is available for CPI inflation, for the monthly and quarterly KOF surveys, as well as for all monthly leading indicators. Therefore, we do not produce a nowcast for these variables. The state of information reflects the typical situation in the middle of the first month t of a specific quarter, where CPI inflation, the KOF survey and all leading indicators are available up to $t - 1$, but the quarterly macroeconomic aggregates are only available up to $t - 4$.

¹⁰Due to data limitation we use a slightly smaller data set for the comparison with the PMI series (here we start at Q1/1999).

Table 8 shows relative RMSE for the two versions of the survey-factor VAR and the two benchmarks, i.e., a simple AR model and an AR model augmented by a leading indicator. The results suggest that the survey data are useful for forecasting macroeconomic fluctuations not only for the current quarter, but in particular in the medium term. First, we compare the survey-factor VAR forecast in the first panel, where we ignore the idiosyncratic component with an AR benchmark. A relative RMSE smaller than one implies that the survey-factor VAR forecast improves upon the AR forecast. For forecasting CPI inflation one-quarter ahead, we see that the model performs significantly worse than a simple AR benchmark. However, for four and eight quarters ahead, the RMSE is significantly lower. This suggests that the survey-factor VAR is particularly useful for medium-term forecasting. A similar pattern emerges for the output gap. An AR benchmark forecasts the current quarter output gap better than the survey-factor VAR. However, the relative RMSE are below one for one- and four-quarter ahead horizons. For an eight-quarter ahead horizon, the survey-factor VAR beats the AR benchmark significantly at the 10% level. For GDP growth and employment, the relative differences are often not significant. However, we find relative RMSE below one especially for one- and four-quarter ahead horizons.

So far, we have seen that the survey-factor VAR is successful in predicting medium-term movements in macroeconomic variables but does not significantly improve upon our benchmarks for nowcasting and short-term forecasting. This may stem from the fact that we ignored the idiosyncratic component, which may exhibit some persistence as we ignored the information of the lagged variable to be forecast in the survey-factor VAR. The results based on the survey-factor VAR taking into account the idiosyncratic component shows that this is indeed the case (second panel of Table 8). The relative RMSE is significantly below unity for short- and medium-term forecasting for CPI inflation and GDP growth. Also, the output gap can be forecasted relatively well; only for the nowcast does the survey-factor VAR yield an insignificantly lower RMSE. No significant improvement do we observe for employment, although the relative RMSE fall almost all below unity.

For the leading indicator models we will focus only on the PMI manufacturing index which gave the most promising results for the macro variables under investigation. The survey-factor VAR does also a good job relative to the PMI based forecasts. For GDP

Table 8 — Relative RMSE pseudo out-of-sample

<i>Survey-factor VAR relative to AR(p)</i>				
Horizon (Q)	CPI inflation	GDP growth	Employment	Output gap
0	—	0.92	1.10	1.25*
1	1.43***	0.86	0.91	0.74*
4	0.93***	0.96	0.95	0.71**
8	0.92*	0.99	1.02	0.88
<i>Survey-factor VAR + idiosyncratic component relative to AR(p)</i>				
Horizon (Q)	CPI inflation	GDP growth	Employment	Output gap
0	—	0.85*	0.91	0.93
1	0.77**	0.87	0.82	0.69**
4	0.93**	0.97	0.92	0.72**
8	0.91*	0.99	1.01	0.90*
<i>Survey-factor VAR relative to AR(p) + PMI</i>				
Horizon (Q)	CPI inflation	GDP growth	Employment	Output gap
0	—	1.09	1.36**	1.37**
1	1.24	0.91	1.31*	0.83*
4	0.81**	0.92	1.09	0.66**
8	0.92	0.89	1.03	0.80*
<i>Survey-factor VAR + idiosyncratic component relative to AR(p) + PMI</i>				
Horizon (Q)	CPI inflation	GDP growth	Employment	Output gap
0	—	1.02	1.12	1.05
1	0.54***	0.91	1.19	0.81*
4	0.79**	0.91	1.06	0.68**
8	0.91	0.87	1.02	0.81*

Note: The table shows relative root-mean-squared errors (RMSE) for the quarterly nowcast ($Q = 0$) and forecast ($Q = 1-8$). For CPI inflation, we report the relative RMSE of the corresponding monthly year-on-year rate at the end of the quarter. The results are based on 75 quarterly vintages of recursive forecasts.

growth, the performance of our model is very similar to the PMI as the differences are not statistically significant. For the nowcast the performance is slightly worse, but for longer horizons we find lower RMSE of the survey-factor VAR. For employment the PMI turns out to perform better. Whereas for inflation and the output gap the survey-based VAR shows promising results. Again, the short-term performance seems to improve when the idiosyncratic component is taken into account. Generally, the survey-based VAR does relatively well in terms of forecast accuracy, in particular when the idiosyncratic component is taken into account.

Table 9 — Encompassing tests

(a) Does the survey-factor VAR encompass PMI based forecasts?

Horizon (Q)	CPI inflation	GDP growth	Output gap
0	—	0.000	0.000
1	0.945	0.000	0.000
4	0.826	0.003	0.201
8	0.155	0.001	0.682

(b) Do PMI forecasts encompass those of the survey-factor VAR?

Horizon (Q)	GDP growth	Employment
0	0.000	0.000
1	0.000	0.000
4	0.000	0.000
8	0.000	0.000

Note: The tables show p-values of forecast encompassing tests for different forecast horizons. The test is based on the regression $e_{1t} = \lambda(e_{1t} - e_{2t}) + u_t$, where the null hypothesis is $\lambda = 0$ (conditional efficiency) and $\lambda > 0$ as the alternative (a combination is superior). In table 9a, e_{1t} and e_{2t} are the errors of the survey-factor VAR (including idiosyncratic component) and the PMI leading indicator model, respectively. Whereas in table 9b e_{1t} are the errors of the PMI leading indicator model and e_{2t} the survey-factor VAR errors.

To get a more complete picture of the relative forecasting performance of our survey-factor VAR relative to the PMI leading indicator model, we also consider the notion of conditional efficiency as discussed by Granger and Newbold (1977). This concept is essentially similar to the encompassing principle as considered by Chong and Hendry (1986) in a forecasting context. The main question is whether a forecasting model under consideration does already include all the information relative to a competitor model. Or whether a combined forecast may be superior. In this case, although a model has a higher

RMSE than its competitor, it may contain additional information that improves forecast accuracy.

In our case this may be applied to the following questions. First, in the case of CPI, GDP and output gap forecasts (where the survey-factor VAR performs relatively well), does the PMI contain additional information beyond that already included in the survey-factor VAR based forecasts? Second, in the case of employment and GDP growth (where the PMI does relatively well) does the survey-factor VAR contain useful information to improve the overall forecasting performance relative to the PMI-based forecast?

Tables 9a and 9b show the results using the encompassing test proposed by Harvey et al. (1998). For inflation and the output gap at larger horizons we find evidence that the survey-factor VAR encompasses the PMI leading indicator model. On the contrary, for GDP growth we reject that the survey-factor VAR encompasses the leading indicator model. This indicates that a combined forecast is better and thus the PMI contains additional information that is not fully covered by our survey-factor model. However, for inflation and medium term output gap projections, the leading indicator model does not contribute anything. If we investigate whether the PMI model encompasses the survey-factor based forecasts, we find a rejection for both employment and GDP for all horizons. This implies that even for employment where the average performance for the PMI model tended to perform better, the KOF survey contains additional useful information.

5 Conclusions

Business tendency surveys are informative about macroeconomic fluctuations. We find that the information extracted by a mixed-frequency factor approach from the questionnaire is able to explain a relevant share of the fluctuations of key macroeconomic variables. This is particularly relevant because survey data are almost not subject to revisions or measurement errors and because they are timely available. We find that such data can be readily used for tracking the current state of the economy. Additionally, our results stress the usefulness of such data in particular for medium-term forecasting.

Aside from the usefulness of this data for now- and forecasting, we find that firms'

answers in the questionnaires related to specific economic concepts indeed help explain the corresponding macroeconomic aggregate. This confirms at an aggregate level the result by Lui et al. (2011), who compare the qualitative answers at the firm-level with the corresponding quantitative outcomes and find a strong relationship.

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Appendix

Table 10 — Survey data set

No.	Description	Sector	Frequency	Econ. concept	Time reference	Unit
1	New orders, last 1M	Manufacturing	Monthly	Real activity	Current situation	Balance
2	New orders, last 12M	Manufacturing	Monthly	Real activity	Change last twelve months	Balance
3	Order books, last 1M	Manufacturing	Monthly	Real activity	Current situation	Balance
4	Order books, assessment	Manufacturing	Monthly	Real activity	Current situation	Balance
5	Foreign order books, assessment	Manufacturing	Monthly	Real activity	Current situation	Balance
6	Production, last 1M	Manufacturing	Monthly	Real activity	Current situation	Balance
7	Production, last 12M	Manufacturing	Monthly	Real activity	Change last twelve months	Balance
8	Stock primary products, last 1M	Manufacturing	Monthly	Capacity constraints	Current situation	Balance
9	Stock primary products, assessment	Manufacturing	Monthly	Capacity constraints	Current situation	Balance
10	Stock, last 1M	Manufacturing	Monthly	Capacity constraints	Current situation	Balance
11	Stock, assessment	Manufacturing	Monthly	Capacity constraints	Current situation	Balance
12	Employment, assessment	Manufacturing	Monthly	Labour market	Current situation	Balance
13	Business situation, assessment	Manufacturing	Monthly	Real activity	Current situation	Balance
14	New orders, next 3M	Manufacturing	Monthly	Real activity	Expected situation	Balance
15	Production, next 3M	Manufacturing	Monthly	Real activity	Expected situation	Balance
16	Purchases, next 3M	Manufacturing	Monthly	Real activity	Expected situation	Balance
17	Employment, next 3M	Manufacturing	Monthly	Labour market	Expected situation	Balance
18	Technical capacities, last 3M	Manufacturing	Quarterly	Capacity constraints	Change last three months	Balance
19	Technical capacities, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Balance
20	Capacity utilisation, average last 3M	Manufacturing	Quarterly	Capacity constraints	Last quarter	Percentage share
21	Prices, last 3M	Manufacturing	Quarterly	Prices	Change last three months	Balance
22	Profitability, last 3M	Manufacturing	Quarterly	Real activity	Change last three months	Balance

Continued on next page

TABLE 10 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Time reference	Unit
23	Range of orders in hand, # of months	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
24	Competitive position, last 3M	Manufacturing	Quarterly	Capacity constraints	Change last three months	Balance
25	Competitive position within EU, last 3M	Manufacturing	Quarterly	Capacity constraints	Change last three months	Balance
26	Competitive position outside EU, last 3M	Manufacturing	Quarterly	Capacity constraints	Change last three months	Balance
27	Obstacles - insufficient demand, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
28	Obstacles - shortage of labour force, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
29	Obstacles - insufficient technical capacities, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
30	Obstacles - financial constraints, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
31	Obstacles - other factors, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
32	Obstacles - none, assessment	Manufacturing	Quarterly	Capacity constraints	Current situation	Percentage share
33	Exports, next 3M	Manufacturing	Quarterly	Real activity	Expected situation	Balance
34	Purchase prices, next 3M	Manufacturing	Quarterly	Prices	Expected situation	Balance
35	Prices, next 3M	Manufacturing	Quarterly	Prices	Expected situation	Balance
36	Business situation, next 6M	Manufacturing	Quarterly	Real activity	Expected situation	Balance
37	Business situation, assessment	Construction	Monthly	Real activity	Current situation	Balance
38	Business situation, last 3M	Construction	Monthly	Real activity	Change last three months	Balance
39	Business situation, next 6M	Construction	Monthly	Real activity	Expected situation	Balance
40	Demand, last 3M	Construction	Monthly	Real activity	Change last three months	Balance
41	Demand, next 3M	Construction	Monthly	Real activity	Expected situation	Balance
42	Order books, assessment	Construction	Monthly	Real activity	Current situation	Balance

Continued on next page

TABLE 10 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Time reference	Unit
43	Activity, last 3M	Construction	Monthly	Real activity	Change last three months	Balance
44	Activity, next 3M	Construction	Monthly	Real activity	Expected situation	Balance
45	Obstacles - none, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
46	Obstacles - insufficient demand, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
47	Obstacles - weather conditions, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
48	Obstacles - shortage of labour force, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
49	Obstacles - shortage of space and/or equipment, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
50	Obstacles - financial constraints, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
51	Obstacles - other factors, assessment	Construction	Monthly	Capacity constraints	Current situation	Percentage share
52	Employment, assessment	Construction	Monthly	Labour market	Current situation	Balance
53	Employment, last 3M	Construction	Monthly	Labour market	Change last three months	Balance
54	Employment, next 3M	Construction	Monthly	Labour market	Expected situation	Balance
55	Prices, next 3M	Construction	Monthly	Prices	Expected situation	Balance
56	Range of orders in hand, # of months	Construction	Quarterly	Real activity	Current situation	Percentage share
57	Capacity utilisation, average last 3M	Construction	Quarterly	Capacity constraints	Last quarter	Percentage share
58	Renovation and maintenance, last 1Q	Construction	Quarterly	Capacity constraints	Last quarter	Percentage share
59	Business situation, last 3M	Project engineering	Monthly	Real activity	Change last three months	Balance
60	Business situation, next 6M	Project engineering	Monthly	Real activity	Expected situation	Balance
61	Demand, last 3M	Project engineering	Monthly	Real activity	Change last three months	Balance
62	Demand, next 3M	Project engineering	Monthly	Real activity	Expected situation	Balance
63	Activity, last 3M	Project engineering	Monthly	Real activity	Change last three months	Balance

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TABLE 10 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Time reference	Unit
64	Activity, next 3M	Project engineering	Monthly	Real activity	Expected situation	Balance
65	Employment, assessment	Project engineering	Monthly	Labour market	Current situation	Balance
66	Employment, last 3M	Project engineering	Monthly	Labour market	Change last three months	Balance
67	Employment, next 3M	Project engineering	Monthly	Labour market	Expected situation	Balance
68	Prices, next 3M	Project engineering	Monthly	Prices	Expected situation	Balance
69	Order books, last 3M	Project engineering	Quarterly	Real activity	Change last three months	Balance
70	Renovation and maintenance, last 1Q	Project engineering	Quarterly	Capacity constraints	Last quarter	Percentage share
71	Construction sum - house building, last 1Q	Project engineering	Quarterly	Real activity	Change to previous quarter	Balance
72	Construction sum - industrial construction, last 1Q	Project engineering	Quarterly	Real activity	Change to previous quarter	Balance
73	Construction sum - public construction, last 1Q	Project engineering	Quarterly	Real activity	Change to previous quarter	Balance
74	Construction sum - total, last 1Q	Project engineering	Quarterly	Real activity	Change to previous quarter	Balance
75	Sales, last 4Q	Hotels and restaurants	Quarterly	Real activity	Change to last years' quarter	Balance
76	Turnover, last 4Q	Hotels and restaurants	Quarterly	Real activity	Change to last years' quarter	Balance
77	Turnover, last 4Q in %	Hotels and restaurants	Quarterly	Real activity	Change to last years' quarter	Percentage share
78	Employment, assessment	Hotels and restaurants	Quarterly	Labour market	Current situation	Balance
79	Operational facilities, assessment	Hotels and restaurants	Quarterly	Capacity constraints	Current situation	Balance
80	Profitability, last 3M	Hotels and restaurants	Quarterly	Real activity	Change last three months	Balance
81	Sales, next 1Q	Hotels and restaurants	Quarterly	Real activity	Expected situation	Balance
82	Sales, last 4Q	Wholesale	Quarterly	Real activity	Change to last years' quarter	Balance
83	Stock, last 4Q	Wholesale	Quarterly	Capacity constraints	Change to last years' quarter	Balance
84	Stock, assessment	Wholesale	Quarterly	Capacity constraints	Current situation	Balance
85	Delivery time, last 4Q	Wholesale	Quarterly	Capacity constraints	Change to last years' quarter	Balance

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TABLE 10 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Time reference	Unit
86	Delivery time, next 3M	Wholesale	Quarterly	Capacity constraints	Expected situation	Balance
87	Purchase prices, next 3M	Wholesale	Quarterly	Prices	Expected situation	Balance
88	Sales prices, next 3M	Wholesale	Quarterly	Prices	Expected situation	Balance
89	Turnover, next 3M	Retail	Monthly	Real activity	Expected situation	Balance
90	Business situation, assessment	Retail	Monthly	Real activity	Current situation	Balance
91	Sales, last 3M	Retail	Monthly	Real activity	Change last three months	Balance
92	Customer frequency, last 12M	Retail	Monthly	Real activity	Change last twelve months	Balance
93	Stock, assessment	Retail	Monthly	Capacity constraints	Current situation	Balance
94	Employment, assessment	Retail	Monthly	Labour market	Current situation	Balance
95	Prices, next 3M	Retail	Monthly	Prices	Expected situation	Balance
96	Employment, next 3M	Retail	Quarterly	Labour market	Expected situation	Balance
97	Stock, last 12M	Retail	Quarterly	Capacity constraints	Change last twelve months	Balance
98	Profitability, last 3M	Retail	Quarterly	Real activity	Change last three months	Balance
99	Purchases, next 3M	Retail	Quarterly	Real activity	Expected situation	Balance
100	Business situation, next 6M	Retail	Quarterly	Real activity	Expected situation	Balance

Note: All data are obtained from KOF Swiss Economic Institute.

Table 11 — Macro data set

Description	Source	Comments
CPI inflation	SFSO, SNB	Monthly percentage change compared to previous year. Seasonally adjusted. Clothing and footwear items not collected monthly are interpolated using a Kalman-filter approach (Huwiler and Kaufmann 2013).
GDP	SECO	Quarterly percentage change compared to previous quarter, seasonally adjusted
Output gap	SNB	Quarterly percentage deviation from potential, seasonally adjusted, production function approach
Employment	SFSO	Quarterly percentage change compared to previous quarter, seasonally adjusted, full-time equivalents

Note: Abbreviations used in the table are SFSO (Swiss Federal Statistical Office), SNB (Swiss National Bank), and SECO (State Secretariat for Economic Affairs).

Figure 3 — GDP demand side

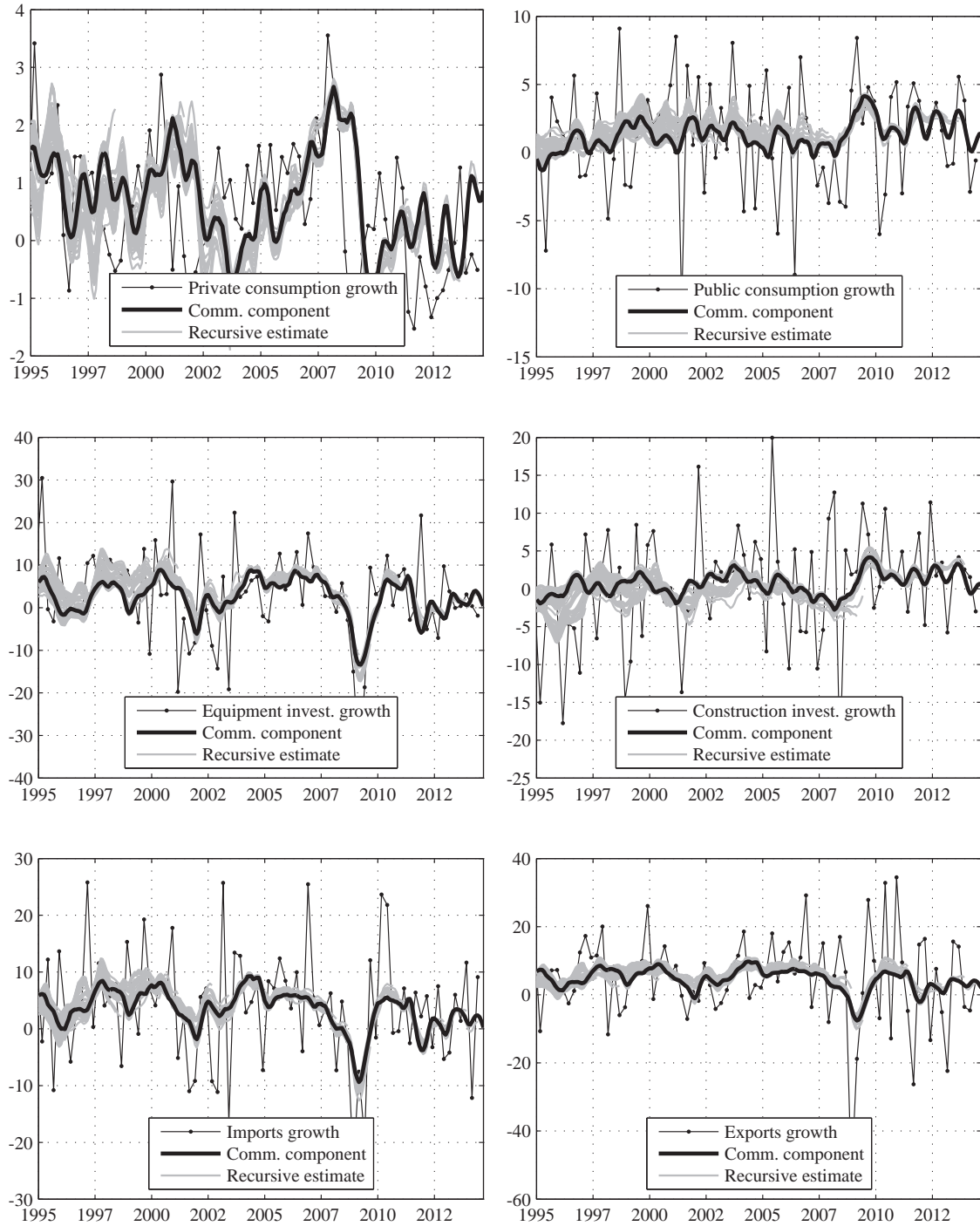


Figure 4 — GDP supply side

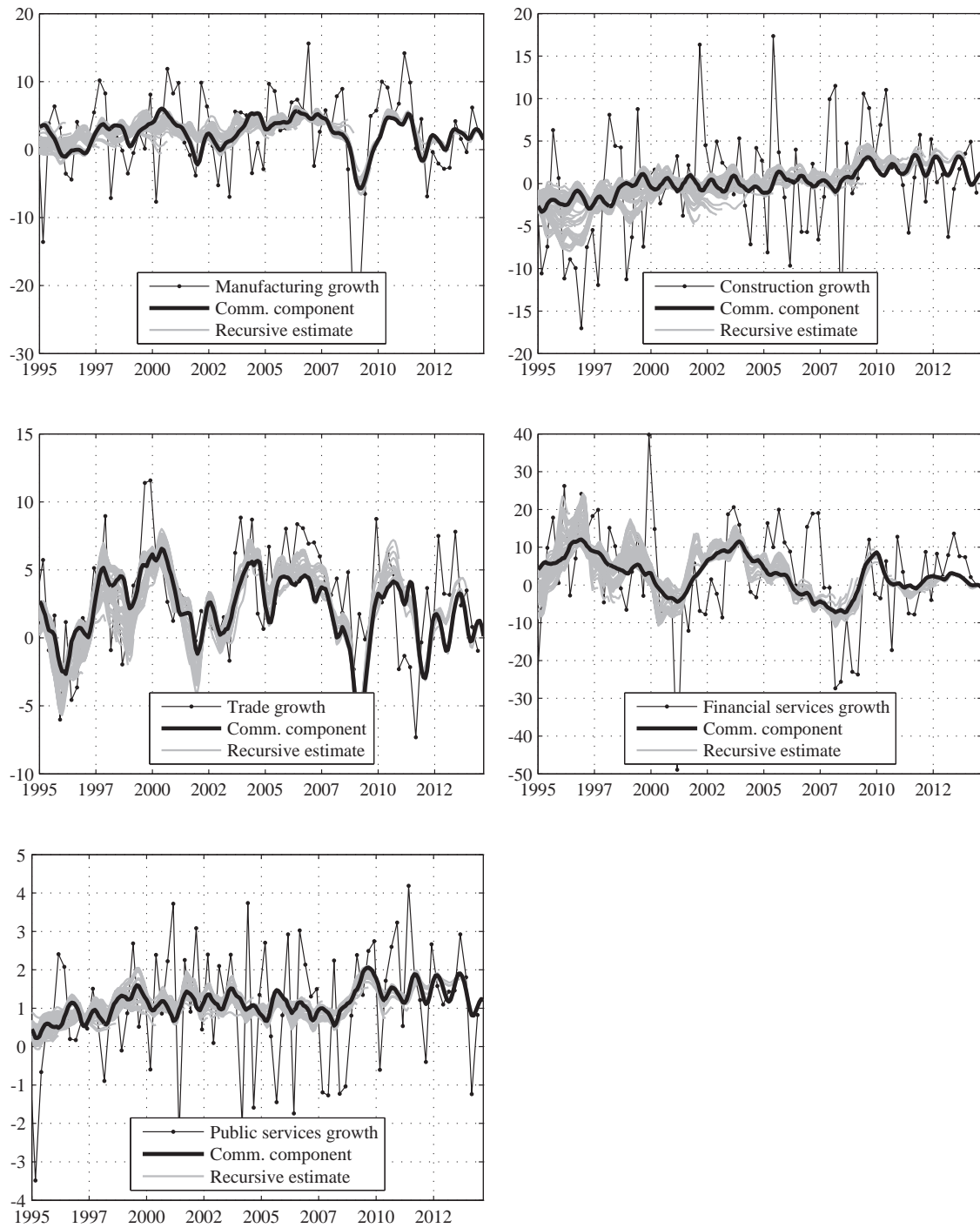


Table 12 — Leading indicators

Description			Source	Comments
PMI	composite	manufacturing	CS/ZEW	Monthly, transformed to quarterly index
KOF	survey	manufacturing	KOF	Situation compared to previous month. Monthly, transformed to quarterly production
PMI subindex price expectations			CS/ZEW	Monthly, transformed to quarterly
KOF economic barometer			KOF	Monthly, transformed to quarterly

Note: Abbreviations used in the table are CS/ZEW (Credit Suisse/Centre for European Economic Research), and KOF (KOF Swiss Economic Institute).