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Abstract

This paper investigates the information content of a large sectoral mixed-frequency business tendency survey for Switzerland relative to competing early available monthly information. Using a factor-augmented regression framework, we find that a broad set of dimensions of the survey adds information for explaining CPI inflation, employment growth and an output gap. For GDP growth, however, the survey contains no additional information. A pseudo out-of-sample forecasting exercise suggests that survey information is particularly useful for forecasting medium-term CPI inflation.

JEL classification: E32, E37, C53

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

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1 Introduction

At least since the 1920s, qualitative business tendency surveys have been used to track the business cycle. Historically, the first business tendency surveys were conducted because official statistics were released infrequently and with a long delay (OECD 2003). Although quantitative hard data has become more readily available over the last decades, business tendency surveys are still regarded as a useful source of information in real-time. In this paper, we examine whether abundantly available sectoral survey information for Switzerland indeed helps to track and forecast macroeconomic dynamics relative to other early available information.

There is ample international evidence that survey data help tracking economy activity. For the European Union and the euro area, many studies report that survey information is useful for forecasting real activity (see Lemmens et al. 2005, Giannone et al. 2009, Frale et al. 2010, Klein and Özmucur 2010, Carriero and Marcellino 2011). Moreover, Banbura and Rünstler (2011) and Keeney et al. (2012) show for the euro area that, even nowadays, publication lags of quantitative hard data are an important reason why survey information is valuable. The usefulness of surveys has been confirmed by Hansson et al. (2005) for Sweden, Matheson (2010) for New Zealand, Lahiri and Monokroussos (2013) for the US, Martinsen et al. (2014), Luciani and Ricci (2014) for Norway, Modugno et al. (2016) for Turkey, Dahlhaus et al. (2015) for several emerging market countries, as well as, Bragoli (2017) for Japan. For Switzerland, Etter and Graff (2003) investigate whether surveys predict production and orders and Siliverstovs (2013) examines a survey-based leading indicator for employment.

The literature agrees that aggregate survey indicators, such as the PMI for example, contain valuable information for nowcasting GDP growth because they are timely available (see Banbura et al. 2013, and references therein). The surveys underlying such indicators are often optimised for nowcasting and associated with a particular economic concept.[1] Indeed, Banbura et al. (2011) and Banbura and Modugno (2014) find that there is little gain using disaggregate information for nowcasting GDP growth. Whether existing aggregate indicators for Switzerland make efficient use of abundantly available

[1]For example, the KOF employment indicator investigated by Siliverstovs (2013) is a weighted average of 19 industry-specific employment-related survey indicators.

sectoral survey information, in particular for medium-term forecasting, remains less clear. To examine this question, we conduct a broad assessment of a large sectoral Swiss business tendency survey covering various sectors and economic concepts and compare its information content to prominent aggregate indicators. In addition, we broaden the analysis by exploring the predictive content for GDP growth, employment growth, CPI inflation, and an output gap.

The qualitative survey data are collected by the KOF Swiss Economic Institute – a business cycle research institute.[2] Today, the survey covers eight sectors of the economy and a broad range of economic concepts such as prices, real activity, the labor market, and capacity utilization. To examine the information content of surveys relative to competing information, we assembled early available monthly hard data as well as a set of prominent aggregate leading and coincident indicators reflecting the typical state of information of an analyst tracking the Swiss economy. The macroeconomic variables are related to the the disaggregate survey and hard data using a factor-augmented regression framework (see Stock and Watson 2002b). The number and combination of factors to include in the model are determined using the consistent information criteria developed by Groen and Kapetanios (2013). Therefore, our approach builds on a large literature summarizing information from large-dimensional data using dynamic factor models (see e.g. Bai and Ng 2008, Stock and Watson 2010, for an overview). Those models have been proved useful for now- and forecasting, for example, by Stock and Watson (2002b), Banbura et al. (2013) Kuzin et al. (2013) and Luciani (2014).

The data set confronts us with a substantial fraction of missing values. First, the surveys are conducted at a quarterly and monthly frequency. Second, many survey questions were added since the survey has first taken place. Third, we restrict the data at the end of the sample to the typical state of information of an analyst tracking the Swiss economy, which implies that a relevant fraction of the hard data is missing.[3] To tackle the mixed survey frequencies and the missing observations, we estimate the factors using the EM-algorithm by Stock and Watson (2002b), which has also been applied

[2]KOF is an abbreviation for *Konjunkturforschungsstelle* which can be translated as business cycle research institute.

[3]As emphasised by Giannone et al. (2008) and Banbura and Rünstler (2011), taking into account missing data at the end of the sample due to publication lags is key for assessing the state of the economy in real time.

by Schumacher and Breitung (2008). The estimator is simple to apply and allows to summarise the information content of the large mixed-frequency data set. However, a shortcoming of this approach is that we do not take into account dynamics in the common factors and the idiosyncratic components. Banbura and Modugno (2014) and Poncela and Ruiz (2016) show that this can hamper forecast performance and inference particularly when a large fraction of data points are missing. Because we focus on comparing the relative information content of various sources of data an additional comparison among alternative approaches to factor estimation is beyond the scope of this paper.

The results may be summarised as follows. In-sample, the surveys contain relevant additional information for CPI inflation, employment growth, and the output gap. The correlation with the output gap may be related to the fact that, unlike similar surveys for the US, many questions ask about the firm's situation relative to a normal level of activity. This is also in line with the finding that for GDP growth, survey data do not improve the model fit relative to hard data. A broad set of dimensions of the survey data are useful. In particular, quarterly survey questions add information supporting the use of a mixed-frequency approach. When examining the survey data with regard to the corresponding economic concepts, the most striking result is that the explanatory power for CPI inflation is not only limited to survey questions about prices, but also, capacity constraints, real activity and the labour market. We then compare the predictive performance of various versions of the factor model to models based on aggregate coincident and leading indicators. It turns out that the business tendency survey improves medium-term forecasts, in particular, for CPI inflation. By contrast, the sectoral survey adds no relevant information for nowcasts and short-term forecasts despite taking into account realistic publication lags of the quantitative hard data.

In what follows, the paper first presents the various data sources. Afterwards, we introduce the methodology used to estimate the factors and select the model. The results section first examines the in-sample explanatory power of various dimensions of the KOF survey and then the out-of-sample predictive content. Finally, we offer some conclusions.

2 Data

The KOF Swiss Economic Institute polls firms from eight sectors of the Swiss economy (manufacturing, project engineering, construction, retail, wholesale, services, financial services, and restaurants and hotels). Most questions are qualitative in nature: Firms are asked, for example, whether their competitive position has improved, deteriorated, or remained unchanged.

Table 1 — Survey question examples

Question	Answer categories			Economic concept
Over the last 3 months, the demand for our services has	increased	remained unchanged	decreased	Real economic activity
We judge our technical capacities as	too high	sufficient	too low	Capacity constraints
We judge our employment as	too high	sufficient	too low	Labour market
Over the next 3 months, our prices will	increase	remain unchanged	decrease	Prices

We obtained the sectoral aggregate of the share of responses in every answer category.[4] The majority of questions has three ordered answer categories (see Table 1 for examples; a complete list of the data set is given in the Appendix). Therefore, we follow Carlson and Parkin (1975) and use a probability approach to transform the data to meaningful quantities.[5] Recent research on the predictive ability of survey data underscores the benefit of this approach especially during the Global Financial Crisis (see Vermeulen 2014).[6] Assume that firms report an increase only if the change of their output prices, for example, exceeds a threshold α and a decrease if the change is smaller than $-\alpha$. If we further assume that the underlying distribution of firms is normal we can calculate

[4]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. For more information, see `http://kof.ethz.ch`, Surveys, Business Tendency Surveys, Metainformation.

[5]There are two exceptions for which we use the untransformed series: Questions with more than three answer categories are included as separate shares; a small number of quantitative questions are included untransformed (e.g., on capacity utilisation).

[6]Stalder (1989) applies the method using the KOF business tendency survey for manufacturing. We have examined alternative transformation schemes such as the balance statistic, that is the share of positive minus the share of negative answers, and including the share of positive and share of negative answers separately. Moreover, we followed Dasgupta and Lahiri (1993) and added a measure of dispersion to the measure of the mean. The results favour the Carlson and Parkin (1975) approach and are available upon request.

the mean of the distribution as

$$\mu_t = \alpha \left[\frac{\Phi^{-1}(P(-)+m) - \Phi^{-1}(P(+)+m)}{\Phi^{-1}(P(-)+m) + \Phi^{-1}(P(+)+m)} \right]_t \qquad (1)$$

where $\Phi(z)$ is the cumulative density function of a standard normal distribution and $P(+)$, $P(-)$ denote the probability of a positive or negative answer. Those probabilities are then replaced with estimates, namely the shares of positive and negative answers from the KOF survey. Moreover, we set α arbitrarily to unity and $m = 0.1$, to make sure that shares close to zero do not have an overly large influence.[7]

After this transformation, the resulting data set is cleaned from excessive missing values and outliers. As a rule, observations that deviate from the median by more than six times the interquartile range are removed as proposed by Stock and Watson (2002b). In addition, we exclude financial services from the analysis because this sector comprises a particularly large share of missing values. Finally, we exclude all series with less than four observations.

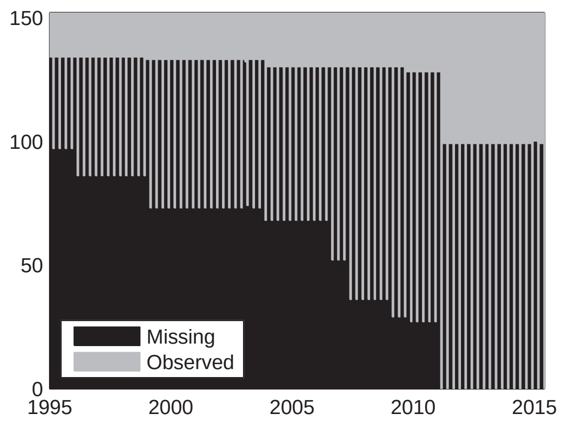
The analysis is performed for a sample covering January 1995 to June 2015. Figure 1 displays the number of observed and missing observations over this period. By 2015, we end up with a sample comprising 150 time series. The shrinking black area reflects that the number of observations increased substantially since the beginning of the sample period because some questions and sectors were added, and some surveys changed to a monthly frequency. Moreover, the black spikes reflect that a relevant share of questions are asked only on a quarterly basis. Therefore, taking into account missing data and mixed survey frequencies will be key when relating the information content of the surveys to macroeconomic variables.

The KOF survey can be regarded as real-time data because we use the non-seasonally adjusted series and there are no revisions.[8] Throughout, we use the state of information at the beginning of the first month of the quarter. By then, all monthly and quarterly

[7] Because we normalise all data in our factor model, the choice of α is inconsequential.

[8] The only revisions possibly stem from the fact that first results of the survey are calculated about five working days before the end of the month. But the state of information we assume throughout the paper implies that the definitive results are already available.

Figure 1 — Number of observations survey data



survey data in the preceding quarter are available.[9]

Table 1 shows that the KOF survey contains information about real economic activity, labour market activity, and price developments. Therefore, we aim to explain and forecast quarterly GDP growth, employment growth, and CPI inflation. In addition, unlike similar business tendency surveys for the US, the Swiss questionnaire not only asks about changes compared to the previous period, but also, about an assessment relative to some normal level of activity. For example, firms are asked whether their technical capacities or employment levels are too high, sufficient, or too low. Those questions are likely to be informative about an output gap concept rather than an output growth concept. Therefore, we additionally include a production function output gap calculated by the Swiss National Bank.[10]

In contrast to the survey data, all macroeconomic data used in the main analysis are releases available as of June 2015 and cannot be regarded as real-time data. The only exception is CPI inflation, which is not revised up to potential instabilities due to seasonal adjustment. To account for revisions in macroeconomic data we therefore perform some robustness tests using the real-time data for GDP growth and employment by Indergand and Leist (2014) and confidential historical output gap data from the Swiss

[9] We shifted the series in time in such a way, that they correspond to the time period the question most likely refers to. This means that we shift the observation becoming available in July 2015, for example, to June 2015 because firms were asked during June about their current situation.

[10] Potential output is calculated as the weighted sum of the trend input factors labour and capital and the residual trend in total factor productivity (see Lüscher and Ruoss 1996) and the output gap is defined as the percentage deviation of GDP from potential.

National Bank.

Publication lags also imply differing states of information for the macroeconomic variables. At the beginning of the first month of the quarter, CPI inflation figures are available for the entire preceding quarter. Meanwhile, quarterly national accounts data for the preceding quarter are published at the beginning of the last month of the current quarter. Our timing convention therefore implies that the GDP numbers for the preceding quarter are not yet available. The same applies to employment growth. Finally, the Swiss National Bank updates its output gap calculations as soon as new GDP figures are available and therefore it has the same state of information as the GDP growth rate.

To show the additional information content of the business tendency surveys relative to other early available hard data, we assembled 52 monthly time series including financial, international, labour market, trade, as well as retail sales data. The number of series is relatively small compared to the data set used by Stock and Watson (2002b) for the US, for example. This reflects that monthly hard information is scarce in Switzerland.

Hard data is often released with some delay, which may matter for a real-time assessment of the information content (see Giannone et al. 2008). We therefore take into account the typical state of information available to an analyst at the Swiss National Bank in the first month of the quarter. The state of information is determined by downloading the data from the Swiss National Bank's internal database in July 2015 and we assume that this is representative for the entire sample. Therefore, we do not take into account that publication lags may have changed over time. This implies that only 43% and 89% of the hard data are available in the two preceding months, whereas, the information for the previous quarter is complete for the surveys. As in other countries, the early availability relative to hard data is a particular advantage of survey data (see Banbura and Rünstler 2011).

Finally, for the forecasting exercise, we assemble a benchmark information set to compare the relative predictive ability of the large-scale survey and hard data sets. The focus stays on variables with the following properties: they are used as coincident or leading indicators; they are closely related to the economic concepts of the macroeconomic variables; the state of information is comparable to the KOF survey; they were potentially available in real time. Those requirements imply that we focus on aggregate indicators from various surveys. A prominent coincident indicator for real activity in Switzerland is the monthly PMI of the manufacturing sector conducted by Credit Suisse (see e.g. Maurer and Zeller 2009, Siliverstovs 2015).[11] Similar indicators proved to contain useful information for GDP growth in other countries (see e.g. Lahiri and Monokroussos 2013, for the US). We add the KOF employment indicator, which is a quarterly composite indicator of business tendency surveys and has proven to comprise useful information for employment growth (see Siliverstovs 2013). The quarterly capacity utilisation rate in the manufacturing sector represents an early available proxy for the output gap (see Graff and Sturm 2012). Finally, for prices, we choose the monthly PMI survey on producer prices as a benchmark indicator.

3 Methodology

For relating the information of the large-scale survey and hard data sets to the macroeconomic variables we use factor-augmented forecasting regressions (see Stock and Watson 2002b). The exact model specification is determined by the modified information criteria proposed by Groen and Kapetanios (2013). This allows us to compare the information content of surveys and hard data relative to prominent benchmark indicators.

3.1 Factor estimation

We summarise the information content of the data set by extracting common factors using a principal components approach. Let $\bar{X} = [\bar{X}_H, \bar{X}_S]$ be a $(T \times N)$ matrix of data. The business tendency survey data are denoted by a matrix $\bar{X}_S$ with dimension $(T \times N_S)$. The hard data are denoted by a matrix $\bar{X}_H$ with dimension $(T \times N_H)$.[12] 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

[11] Another well-known leading indicator for Swiss GDP growth is the KOF economic barometer, which is based on a large-scale factor model and potentially contains similar variables as our procedure (see Abberger et al. 2014). We do not include this indicator as a benchmark variable, however, because it was heavily revised ex post and therefore does not represent the state of information available in real time.

[12] The macroeconomic and benchmark variables are not considered in the factor estimation.

approximate factor model of the form

$$\bar{X} \;=\; F\Lambda + e \quad , \tag{2}$$

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 (2002b), the principal components estimator can be used to estimate the factors and loadings.[13]

To account for mixed survey frequency and missing data, we specify for each variable $n = 1, \ldots, N_H + N_S$ a matrix A_n linking the observed data to the unobserved underlying monthly data $\bar{X}_n = A_n X_n$. $\bar{X}$ represents the untransformed and possibly incomplete data matrix, while X denotes the balanced and complete data matrix that is defined in monthly frequency. Specifying A_n appropriately, we can take into account mixed frequency, temporal aggregation and missing data.[14] Stock and Watson (2002b) derive an EM-algorithm to estimate the factors, assuming that $X_{n,t} \overset{i.i.d.}{\sim} N(\lambda_n' F_t, 1)$, where λ_n is an $(r \times 1)$ vector of factor loadings for variable n. Based on this assumption, the best prediction of the unobserved monthly data conditional on the observed mixed frequency data is given by

$$E[X_n|\bar{X}_n] \;=\; F\lambda_n + A_n'(A_n A_n')^{-}(\bar{X}_n - A_n F\lambda_n) \quad , \tag{3}$$

where $^{-}$ denotes a generalised inverse. Iteration s of the EM-algorithm to estimate the factors and factor loadings proceeds as follows:[15]

1. Calculate $E[X_n^{(s)}|\bar{X}_n]$ from eq. (3) for each variable n based on $F^{(s-1)}$ and $\lambda_n^{(s-1)}$.
2. Estimate $F^{(s)}$ and $\lambda^{(s)}$ using the principal components estimator on $E[X^{(s)}|\bar{X}]$,

[13] In principle, it would be possible to estimate the factors individually for survey and hard data. However, the gains from the survey data may stem from improving the factor estimation rather than providing information independent from the hard data. Estimating the factors on two separate data sets would neglect this potential advantage. To illustrate this point, assume that the survey and hard data sets share one common factor. Then, estimating two factors on two separate data sets would likely yield less precise estimates than estimating one factor on the combined data set.

[14] For example, a question about the situation in the previous quarter is an equally-weighted average of the unobserved situation in the previous three months. See Stock and Watson (2002b) for examples how to specify A_n for flow and stock variables in various frequencies.

[15] To obtain starting values, $F^{(0)}$, the factors are estimated using the principal components estimator on a 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 $F^{(0)}$.

which is the full panel of the estimated monthly frequency data.

3. Calculate the average sum of squared residuals $1/(NT)\sum_n \sum_t (E[X_{n,t}^{(s)}|\bar{X}_n] - A_n F^{(s)}\lambda_n^{(s)})^2$ and check convergence.

Our analysis uses quarterly macroeconomic variables and therefore the factors have to be transformed to quarterly frequency. We use the aggregation rule of Mariano and Murasawa (2003) and Banbura et al. (2013), which is also consistent with the handling of various survey frequencies in the EM-algorithm. For macroeconomic variables in quarterly growth rates, the jth quarterly factor is calculated as

$$f_{j,t}^{Q} = \begin{cases} 1/3 f_{j,t} + 2/3 f_{j,t-1} + f_{j,t-2} + 2/3 f_{j,t-3} + 1/3 f_{j,t-4}, & \text{for } t = 3, 6, 9, ... \\ \text{discard observations} & \text{otherwise.} \end{cases} \tag{4}$$

where $f_{j,t}$ is its monthly counterpart. This rule is applied for explaining CPI inflation, GDP growth, as well as employment growth. For the output gap, we employ an equally-weighted average of the monthly factors in the corresponding quarter.

Our model summarises the information content through cross-sectional averaging as in Stock and Watson (2002a), Stock and Watson (2002b) and Bai (2003). The estimator based on principal components is simple to apply and the literature documents that it performs relatively well (see Boivin and Ng 2005, Marcellino and Schumacher 2010, Carriero and Marcellino 2011, for similar applications).

However, a shortcoming of the approach is that it does not model dynamics in the common factors and the idiosyncratic components. This can hamper factor estimation and yield less accurate forecasts particularly when a large fraction of the data is missing (see Banbura and Modugno 2014). One could therefore use a quasi-maximum likelihood approach based on Kalman filtering. For large data sets, a two-step approach has been proposed by Giannone et al. (2008) and the theory underlying the estimator has been developed in Doz et al. (2011) and Doz et al. (2012). However, while this approach handles missing values at the end of the sample, it does not readily extend to arbitrary patterns of missing data. Therefore, Jungbacker et al. (2011) and Banbura and Modugno (2014) propose to apply the EM-algorithm of Watson and Engle (1983) for parameter estimation within the state space system. Banbura and Modugno (2014) and Poncela and Ruiz

(2016) show that this can improve forecasts and inference relative to the EM-algorithm by Stock and Watson (2002b). However, because we focus on comparing the relative information content of various sources of data, an additional comparison among alternative approaches to factor estimation is beyond the scope of this paper.

3.2 Model selection and forecasting

Model selection and forecasting takes place at quarterly frequency within a factor-augmented regression framework. Besides the factors, we allow for autoregressive terms and exogenous benchmark variables and use a direct forecasting approach. The most general specification has the following structure

$$y_{t+h} \;=\; \alpha + \sum_{i=1}^{p_y} \rho_i y_{t-i} + \sum_{i=0}^{p_z} \sum_{j=1}^{k} \Delta^z_{i,j} \gamma_{i,j} z^Q_{j,t-i} + \sum_{i=0}^{p_f} \sum_{j=1}^{r} \Delta^f_{i,j} \beta_{i,j} f^Q_{j,t-i} + u_{t+h}, \qquad (5)$$

where h indexes the forecasting horizon and y_t is one of the four macroeconomic variables. Note that, for notational convenience, the time index t and forecast horizon h refer to quarters for the rest of the paper. In addition, the jth benchmark indicator in quarterly frequency is denoted by $z^Q_{j,t}$.[16] We include up to p_y consecutive autoregressive terms, as well as the concurrent and up to p_z and p_f lags of the benchmark variables and factors, respectively.[17] The parameters $\alpha, \rho_i, \gamma_{i,j}, \beta_{i,j}$ are estimated by OLS.

The benchmark variables and factors are premultiplied by two indicator functions $(\Delta^z_{i,j}, \Delta^f_{i,j})$ that assume 1 if the corresponding variable is included in the model and 0 otherwise. Those indicators, as well as the number of autoregressive terms p_y, are determined by the model selection approach put forward by Groen and Kapetanios (2013). They provide modified Bayesian and Hannan-Quinn information criteria (BICM, HQICM) that take into account that the factors are estimated regressors. The optimal subset of factors, benchmark variables as well as number of autoregressive terms is found by minimising either BICM $= \frac{T}{2}\ln(\hat{\sigma}^2_u) + K\ln(T) + R\ln(T)\left(1 + \frac{T}{N}\right)$ or HQICM $= \frac{T}{2}\ln(\hat{\sigma}^2_u) + 2K\ln(\ln(T)) + 2R\ln(\ln((T))\left(1 + \frac{T}{N}\right)$. $\hat{\sigma}^2_u$ denotes the estimated residual variance, whereas,

[16] The monthly measured PMI indicators are transformed to quarterly frequency using the same rules to aggregate the factors.

[17] Because we have to produce a nowcast for the macroeconomic variables (except inflation), the concurrent dependent variable is not included in the forecasting equation ($h > 0$).

Table 2 — Model specifications

(1)	In-sample	$y_t = \alpha + \sum_{i=0}^{3} \sum_{j=1}^{3} \Delta_{i,j}^{f} \beta_{i,j} f_{j,t-i}^{Q} + u_t$
(2)	Out-of-sample factor	$y_{t+h} = \alpha + \sum_{i=1}^{p_y} \rho_i y_{t-i} + \sum_{i=0}^{3} \sum_{j=1}^{3} \Delta_{i,j}^{f} \beta_{i,j} f_{j,t-i}^{Q} + u_{t+h}$
(3)	Out-of-sample benchmark	$y_{t+h} = \alpha + \sum_{i=1}^{p_y} \rho_i y_{t-i} + \sum_{i=0}^{3} \sum_{j=1}^{4} \Delta_{i,j}^{z} \gamma_{i,j} z_{j,t-i}^{Q} + u_{t+h}$

Note: The table shows the different model specifications for the in-sample and out-of-sample analysis. The lag length p_y as well as the subset restrictions ($\Delta_{i,j}^{z}, \Delta_{i,j}^{f}$) are jointly determined by the information criteria proposed by Groen and Kapetanios (2013).

K denotes the number of exogenous regressors (including lags, constant and autoregressive terms) and R denotes the number of factors (including lags). If $N = N_H + N_S$ is small relative to T, including an additional factor is penalised more heavily than including other exogenous variables. Therefore, we account for the fact that the factors are less precisely estimated if N is small. This strategy allows for various combinations of factors, benchmark variables and consecutive autoregressive terms to enter the forecasting equation. In what follows, we use the HQICM.[18]

In order to reduce the number of possible combinations of regressors we use several restricted variants of eq. (5), which are given in Table 2. To investigate the information content of various dimensions of the surveys, the in-sample analysis uses only the estimated factors as explanatory variables. The maximum number of factors is set to $r = 3$ and the number of lags to $p_f = 3$.[19] At least one of the (lagged) factors, however, has to be included in the model avoiding the possibility of a model including only a constant. For the out-of-sample analysis the model additionally includes consecutive autoregressive terms where the order (p_y) is determined by the information criterion as well. The maximum number of autoregressive terms is set to three. In the benchmark model we replace the factors with the four benchmark indicators. Note that this implies that the benchmark model potentially comprises a combination of all indicators not only the one specifically related to the corresponding macroeconomic concept.

[18] Additional robustness tests using the BICM are available upon request but not reported for brevity.

[19] Most results are robust with alternative choices for the maximum number of factors. We prefer a relatively small number, however, because our data set comprises a substantial fraction of missing values. Using an overly large number of factors may therefore worsen the model fit and reduce the predictive ability of the factor model. Schumacher and Breitung (2008) also report that the forecasting performance in the presence of mixed-frequency data is better using a small number of factors.

4 Results

This section examines whether business tendency surveys contain additional information relative to other timely available data and whether we can exploit this information for forecasting.

4.1 In-sample explanatory power

The in-sample analysis compares the explanatory power for the macroeconomic variables by excluding certain dimensions of the data from the factor estimation. After applying the model selection strategy using specification (1) in Table 2, we compute the share of variance explained by the model. A reduction of the R^2 thus implies that the excluded dimension contains additional information relative to the remaining data set. The R^2 may also increase when the excluded series are irrelevant or especially noisy and worsen the fit of the model.

Panel (A) of Table 3 shows that, using the entire data set, we explain a relevant share of the macro variables. The R^2 ranges from 0.48 for CPI inflation to a high 0.84 for the output gap. It turns out the explanatory power can partly be traced back to the business tendency surveys. When removing the surveys, the R^2 falls for CPI inflation, as well as for employment growth and the output gap. For CPI inflation, hard data seems to contain more relevant information than survey data because the decline in the R^2 is more pronounced, when excluding this dimension of the data. Interestingly, survey information is particularly informative relative to hard data for employment growth and the output gap. For the output gap, this is in line with many survey questions concerning an assessment relative to a normal situation. This information may be lacking in the hard data set which is mostly based on growth rates. By contrast, survey data slightly worsens the model fit for GDP growth. This finding is consistent with Banbura and Rünstler (2011) who find that for GDP growth, survey data contains little information if hard data is already available.

The remaining panels of Table 3 examine the value-added of the surveys in more detail by excluding various dimensions of the survey data set. We grouped the data according to sectors, time reference, frequency and economic concept. The sectors containing additional

Table 3 — Explanatory power survey data

	(A) Survey and hard data			
	CPI	GDP	Employment	Output gap
Entire data set	0.48	0.63	0.73	0.84
− surveys	0.28	0.66	0.60	0.68
− hard data	0.18	0.54	0.69	0.78
	(B) Sectors of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.48	0.63	0.73	0.84
− project engineering	0.43	0.65	0.72	0.84
− construction	0.36	0.63	0.62	0.82
− retail	0.36	0.61	0.71	0.77
− services	0.46	0.66	0.68	0.84
− hotels and restaurants	0.47	0.67	0.73	0.83
− wholesale	0.37	0.65	0.67	0.83
− manufacturing	0.35	0.57	0.72	0.77
	(C) Time reference of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.48	0.63	0.73	0.84
− current situation	0.31	0.64	0.70	0.72
− expected situation	0.40	0.65	0.74	0.81
− change last twelve months	0.38	0.59	0.72	0.79
− change last three months	0.36	0.64	0.73	0.79
− last quarter	0.39	0.63	0.73	0.81
− change to last years' quarter	0.37	0.59	0.73	0.78
− change to previous quarter	0.36	0.59	0.66	0.79
	(D) Frequency of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.48	0.63	0.73	0.84
− quarterly	0.37	0.69	0.72	0.78
	(E) Economic concept of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.48	0.63	0.73	0.84
− capacity constraints	0.35	0.67	0.71	0.82
− labour market	0.37	0.65	0.67	0.78
− prices	0.38	0.57	0.70	0.78
− real activity	0.30	0.65	0.72	0.78

Note: The first row of each panel shows the R^2 of the factor model based on model specification (1) in Table 2. Each subsequent row shows the R^2 after the removal of one dimension of the data set for estimating the factors.

information vary with the macroeconomic variable under investigation (Panel B). We do not observe a clear pattern but recognise that every sector adds information for at least one macroeconomic variable. There are only two exceptions for which we observe no relevant declines in the R^2: project engineering and hotels and restaurants.

More interesting patterns emerge when examining the time reference of the survey questions (see Panel C). For CPI inflation as well as the output gap, survey questions about the current situation are most relevant. For the same variables, survey questions about the future expected situation provide somewhat less additional information. Not surprisingly, perhaps, for GDP and employment growth questions about the changes relative to the previous situation, in particular the previous quarter, are more relevant.

As the KOF survey provides a substantial fraction of surveys that are conducted quarterly, it is worth investigating whether these surveys add some explanatory power to the monthly variables.[20] On the one hand, including quarterly data may add some additional information. On the other hand, the increase of the fraction of missing observation may lead to less precise estimates of the monthly factors. Panel (D) indicates that quarterly surveys add explanatory power for CPI inflation and the output gap. Meanwhile, quarterly questions do not help to explain GDP and employment growth. Therefore, the quarterly survey provides additional information, albeit, not for every macroeconomic variable under investigation.

Examining various economic concepts also reveals some interesting patterns (see Panel E). Not surprisingly, perhaps, survey questions about prices add information for CPI inflation. But also, excluding questions about capacity constraints, the labour market, and real activity reduces the R^2. Similarly, a wide range of variables add explanatory power for the output gap. Intuitively, labour market questions help explaining employment growth. Only for GDP, the link is less intuitive. This may reflect that the hard data set already contains most available relevant information for GDP growth. Overall, the mapping from economic concepts to the model fit implies that a broad range of dimensions is informative. This suggests that coincident or leading indicators that focus only on one specific economic concept can likely be improved.

[20] An important reason for conducting quarterly as well as monthly surveys is that the burden for participating firms is lower (the KOF survey is not mandatory). Therefore, we want to examine whether the quarterly questions add some information.

4.2 Out-of-sample predictive ability

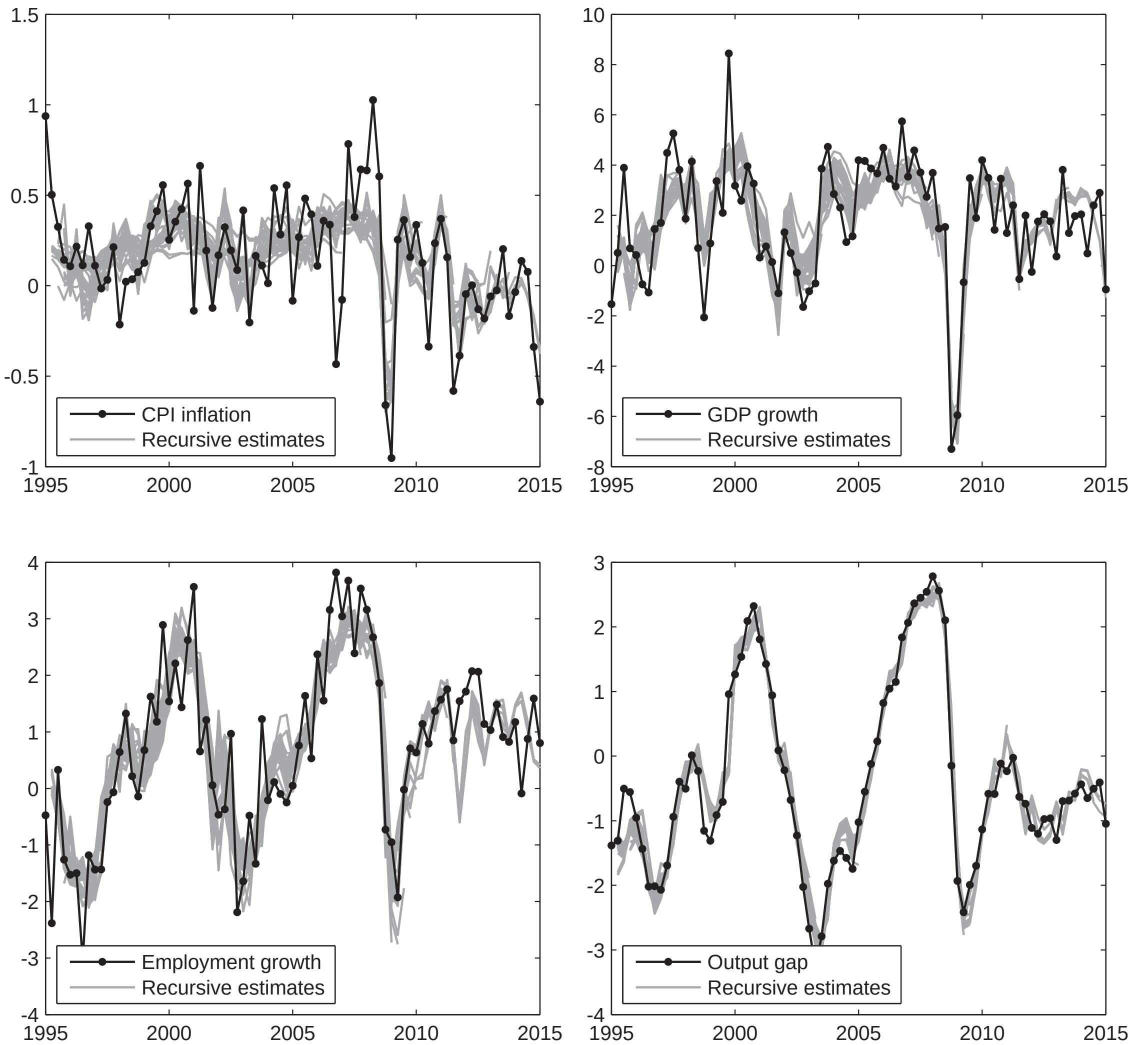
The out-of-sample forecasting exercise differs from the in-sample analysis in four dimensions. First, we take into account the typical state of information at the beginning of the first month of the quarter. Second, we recursively select and estimate the model and therefore take into account potential parameter instability. Third, we compare the predictive performance relative to the benchmark information set. Fourth, we allow for lagged dependent variables. The sample for the first forecast is Q1 1995–Q4 2002, implying that the first nowcast is produced for Q4 2002, and we repeat the exercise to produce 50 out-of-sample forecasts. The forecasts of the factor model are then evaluated relative to the predictive performance of the benchmark model (see specifications 2 and 3 in Table 2).

It is instructive to first examine the stability of the factor estimation in real time. Figure 2 shows the macroeconomic variables (line with bullets) in addition to the recursively estimated fitted values (grey). For GDP growth and the output gap the fitted values exhibit only small revisions when new data becomes available over time. For CPI inflation and employment growth, the revisions are more visual but not dramatic. In terms of GDP growth, the model accurately signals the recession during the Global Financial Crisis. In addition, the spike in inflation in 2008, which was largely due to an increase in oil prices, is not reflected in the estimates. Instead, the fitted values signal the subsequent drop in inflation early on. In addition, the persistent fall in inflation in the wake of the substantial appreciation of the Swiss franc since the Global Financial Crisis is captured by the factor model. Overall, the sensitivity to revisions is relatively small given the large number of missing observations at the beginning of the sample which suggests that the estimated factors may be suitable for out-of-sample prediction.

To understand the relative predictive performance of the factor models it is is also relevant to examine which indicators are selected in the benchmark models. We examined the shares of indicators and lags selected for each macroeconomic variable depending on the specific forecast horizon.[21] A general pattern is that for short forecast horizons ($h = 0$ or $h = 1$), the benchmark models include at most two indicators while, for longer horizons, more indicators and lags are selected. Moreover, in many cases there is an intuitive match

[21] The results are not reported for brevity but available upon request.

Figure 2 — Recursively fitted values



Note: Fitted values based on model specification (2) in Table 2 using all survey and hard data. The bullets show the actual macroeconomic variables and the grey lines the recursively fitted values. GDP and employment are measured in seasonally adjusted annualised growth rates, CPI inflation in seasonally adjusted growth rates and the output gap in percent.

between the indicators and the macroeconomic variable to be forecast. For inflation, the criterion selects the PMI prices most often. For the GDP nowcast, the PMI total index is always included. The KOF employment index is selected for employment, but also enters into the specifications for CPI inflation and the output gap. For the output gap, capacity utilisation is often selected, except for the nowcast, where the KOF employment indicator and the PMI are the dominant indicators.

In what follows, we examine the performance of the factor model relative to the benchmark models in terms of relative root-mean-squared errors (RMSE). A relative RMSE lower than unity implies that the factor model forecast is more accurate than the benchmark forecast. We employ a Diebold and Mariano (1995)-West (1996) test for the null hypothesis of equal predictive ability against the one-sided alternative that the factor model has a lower RMSE. Panel (A) of Table 4 shows the results for the factor model including survey and hard data. The relative RMSE is lower than unity for every macroeconomic variable and almost every forecast horizon. The factor model yields less accurate forecasts only for the nowcast and one-quarter-ahead forecast in the case of employment growth. In addition, the gains in predictive ability are often statistically significant. One striking feature is that the significance appears most strongly for medium-term rather than short-term forecasts.

To answer whether the survey data provide additional predictive information, we estimated the factor model separately on the survey and hard data (Panels B and C). The surveys perform well for CPI inflation, and medium-term forecasts of GDP and employment. Meanwhile, they do not significantly outperform the benchmark models for the output gap. This lines up well with the finding that the capacity utilization rate in the benchmark model is well suited to explain the output gap (see Graff and Sturm 2012). The most striking feature of the hard data factor model is that it does not significantly improve forecast accuracy for CPI inflation. For the other variables, however, it performs slightly better than the survey-factor model. Interestingly, for the output gap, the model using the combined data set significantly outperforms the benchmark model, whereas, there are almost no improvements using the individual data sets. This result highlights that, overall, a combination of survey and hard data performs best.

Interestingly, the factor model based on early available hard data does not outperform

Table 4 — Predictive ability relative to benchmark indicators

Horizon	CPI	GDP	Employment	Output gap
	(A) Hard and survey data			
0	–	0.87	1.00	0.92
1	0.97	0.94	1.13	0.69**
4	0.75**	0.73*	0.67	0.78*
8	0.83*	0.74**	0.59**	0.69*
	(B) Survey data			
0	–	1.03	1.11	1.17
1	0.96*	1.02	1.12	0.97
4	0.76**	0.77*	0.57*	0.97
8	0.84*	0.84*	0.70**	0.75
	(C) Hard data			
0	–	0.87	1.05	2.11
1	0.95	1.19	1.54	1.03
4	0.86	0.74*	0.72	0.86
8	0.86	0.71*	0.43***	0.62*
	(D) Monthly survey data			
0	–	1.12	1.20	1.12
1	0.99	0.97	1.16	0.92
4	0.78**	0.69**	0.58*	0.73*
8	0.84*	0.75**	0.54**	0.63*
	(E) Balanced survey data			
0	–	1.13	1.08	1.22
1	0.93**	1.11	1.12	0.90
4	0.76**	0.81	0.55*	0.80
8	0.80**	0.75**	0.49***	0.55*

Note: The table shows relative root-mean-squared errors (RMSE) for the nowcast (horizon = 0) and forecast (horizons = 1–8). The factor model is based on specification (2) in Table 2 and the benchmark model on specification (3). We use a Diebold and Mariano (1995)-West (1996) test for the null of equal predictive ability against the one-sided alternative that the factor model has a lower RMSE. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% level.

the benchmark models for nowcasting. This implies that the aggregate benchmark indicators, which are all based on surveys, perform well for short-term forecasting as in Matheson (2010) and Banbura and Rünstler (2011), and underlines that the early availability of survey data is a key advantage. However, the aggregate indicators included in the benchmark models are clearly designed for short-term prediction and the results in Panels (A) and (B) suggest that they can be improved using disaggregate survey and hard data for medium-term forecasts.

The in-sample analysis has shown that the quarterly surveys add explanatory power. Estimating the factors on a mixed-frequency data set with missing data may introduce instability, however, such that it does not necessarily follow that we can exploit this information for forecasting. Comparing Panel (B) to Panel (D) indeed shows that the mixed-frequency survey factor model performs somewhat worse compared to a model based exclusively on monthly survey data. Another source of instability is the fact that we introduce a large amount of new surveys over time. Again, comparing Panel (B) to Panel (F) shows that estimating the survey factor model only on series that are available over the entire sample period yields slightly better results. Except for the output gap, however, the differences are relatively small. This suggests that the highly unbalanced mixed-frequency survey information can be exploited for forecasting in real-time, although a balanced sample with monthly data would be in principle preferable.

Table 5 — Predictive information of early survey information

Horizon	CPI	GDP	Employment	Output gap
0	0.90*	0.70*	0.81	0.57**
1	0.98	0.87	0.85	0.57***
4	1.05	0.93*	1.00	0.74
8	1.06	1.08	1.20	1.71

Note: The table shows relative root-mean-squared errors (RMSE) for the nowcast (horizon = 0) and forecast (horizons = 1–8). The factor model uses hard and survey data and is based on specification (2) in Table 2. The benchmark model is also based on specification (2) but replaces the last quarter of survey information with missing values. Therefore, a relative RMSE smaller than unity indicates that the last quarter of survey information improves predictive ability of the factor model. We use a Diebold and Mariano (1995)-West (1996) test for the null of equal predictive ability against the one-sided alternative that the factor model based on the complete survey data set has a lower RMSE. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% level.

We expect that one particular advantage of survey data is its early availability relative to hard data. To test this hypothesis, Table 5 shows the relative performance of the factor model based on hard and survey data when all survey information is available relative to the same model when the last quarter of survey data is missing. A RMSE smaller than unity indicates that the availability of the last quarter of the survey data improves the predictive ability of the model. Indeed, the relative RMSE are smaller than unity for CPI inflation and employment (nowcast and one-quarter ahead) and for GDP growth and the output gap (up to four-quarters-ahead). In some cases, the difference in predictive ability is significant at the 10% level for the CPI, GDP and at least at the 5% level for the output gap. Note that in the previous exercises, the benchmark variables were also based on survey data which may explain why we did not find significantly better performance of the factor model for short-term forecasting. Overall, this evidence is therefore consistent with the idea that the early availability of survey data is an advantage.

We also examined whether various dimensions of the survey differ with respect to their predictive ability. For brevity, the results are not reported and discussed only qualitatively. We follow the same strategy as for the in-sample analysis and remove one dimension of the survey data at a time to examine, whether the predictive performance worsens. We find that the predictive performance falls for many dimensions of the survey data but no clear pattern emerges. This suggests that the information content of the survey for forecasting is relatively broad-based and combining the various dimensions yields a better performance than limiting the data set, for example, to survey questions about the future expected situation or to questions about prices.

Forecasting performance may depend on whether macroeconomic variables are revised (see Croushore 2011, and references therein). As a robustness test, we therefore estimate the factor model using 47 real-time vintages assembled by Indergand and Leist (2014) where the most recent vintage ends in Q1 2014.[22] We use their data of seasonally adjusted GDP growth and employment growth. In addition, we examine confidential vintages of the production function output gap over the same period by the Swiss National Bank. Note that CPI inflation is not revised up to seasonal adjustment.

For brevity, the results are not reported but only discussed qualitatively. Overall, the factor model outperforms the benchmark models somewhat less. In particular, the forecast

[22] Note that the monthly hard data set may also be subject to some revisions, which is not taken into account in this analysis.

performance becomes worse for the long forecast horizon of two years. The exception is the forecasting model for the output gap, where the factor model significantly outperforms the benchmark at horizons of four and eight quarters. Interestingly, this can be traced back to the survey information and corroborates the finding by Graff and Sturm (2012) that survey information helps to predict revisions of the output gap.

In addition, the factor model still outperforms the benchmark in the case of GDP growth. Therefore, the previous results come with the caveat that the medium-term forecasting performance for GDP growth worsens relative to the benchmark indicators. For employment growth, the real-time results are in line with the previous finding that the KOF employment indicator included in the benchmark model is difficult to beat.

5 Conclusions

In Switzerland, sectoral business tendency surveys provide additional information for tracking the state of the economy relative to early available hard data and aggregate coincident and leading indicators. The information content is broadly distributed among various dimensions of the survey (such as sectors or economic concepts). An interesting feature of the Swiss questionnaire is that firms are not only asked about the change relative to the previous period, but also, the situation relative to a normal level of activity. This may explain the high explanatory power for the output gap but lower explanatory power for GDP growth. The out-of-sample forecasting exercise suggests that the surveys are particularly informative for medium-term forecasts of CPI inflation. By contrast, the sectoral survey contains no additional information for short-term forecasting despite taking into account the longer publication lags of the quantitative hard data.

The KOF business tendency survey is thus useful for explaining the cyclical characteristics of macroeconomic variables while it contributes less for explaining short-term changes in real economic activity. This lines up well with the fact that during the last decades, early available quantitative hard data has become more readily available. Additionally, this indicates that aggregate survey indicators, such as the PMI or the KOF employment indicator, make efficient use of disaggregate survey information for tracking GDP growth. Our findings suggest that disaggregate survey data provides additional information mainly for monetary and fiscal policy makers interested in the state of the business cycle or the medium-term evolution of inflation.

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Appendix

Table 6 — Data set

No.	Description	Sector	Frequency	Econ. concept	Unit	Type
1	CPI inflation	Entire economy	Quarterly	Prices	Growth rate	Macro data
2	GDP growth	Entire economy	Quarterly	Real activity	Growth rate	Macro data
3	Employment growth	Entire economy	Quarterly	Labour market	Growth rate	Macro data
4	Output gap	Entire economy	Quarterly	Capacity constraints	Percent	Macro data
5	PMI prices	Manufacturing	Monthly	Prices	Balance	Benchmark data
6	PMI	Manufacturing	Monthly	Real activity	Balance	Benchmark data
7	KOF Employment Index	Entire economy	Quarterly	Labour market	Balance	Benchmark data
8	Capacity utilisation	Manufacturing	Quarterly	Capacity constraints	Percent	Benchmark data
9	New orders, last 1M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
10	New orders, last 12M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
11	Order books, last 1M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
12	Order books, judgement	Manufacturing	Monthly	Real activity	CP mean	KOF survey
13	Foreign order books, judgement	Manufacturing	Monthly	Real activity	CP mean	KOF survey
14	Production, last 1M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
15	Production, last 12M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
16	Stock primary products, last 1M	Manufacturing	Monthly	Capacity constraints	CP mean	KOF survey
17	Stock primary products, judgement	Manufacturing	Monthly	Capacity constraints	CP mean	KOF survey
18	Stock, last 1M	Manufacturing	Monthly	Capacity constraints	CP mean	KOF survey
19	Stock, judgement	Manufacturing	Monthly	Capacity constraints	CP mean	KOF survey
20	Employment, judgement	Manufacturing	Monthly	Labour market	CP mean	KOF survey
21	Business situation, judgement	Manufacturing	Monthly	Real activity	CP mean	KOF survey
22	New orders, next 3M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
23	Production, next 3M	Manufacturing	Monthly	Real activity	CP mean	KOF survey

Continued on next page

Table 6 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Unit	Type
24	Purchases, next 3M	Manufacturing	Monthly	Real activity	CP mean	KOF survey
25	Employment, next 3M	Manufacturing	Monthly	Labour market	CP mean	KOF survey
26	Technical capacities, last 3M	Manufacturing	Quarterly	Capacity constraints	CP mean	KOF survey
27	Technical capacities, judgement	Manufacturing	Quarterly	Capacity constraints	CP mean	KOF survey
28	Prices, last 3M	Manufacturing	Quarterly	Prices	CP mean	KOF survey
29	Profitability, last 3M	Manufacturing	Quarterly	Real activity	CP mean	KOF survey
30	Range of orders in hand, # of months	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
31	Competitive position, last 3M	Manufacturing	Quarterly	Capacity constraints	CP mean	KOF survey
32	Competitive position within EU, last 3M	Manufacturing	Quarterly	Capacity constraints	CP mean	KOF survey
33	Competitive position outside EU, last 3M	Manufacturing	Quarterly	Capacity constraints	CP mean	KOF survey
34	Obstacles - insufficient demand, judgement	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
35	Obstacles - shortage of labour force, judgement	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
36	Obstacles - insufficient technical capacities, judgement	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
37	Obstacles - financial constraints, judgement	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
38	Obstacles - other factors, judgement	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
39	Obstacles - none, judgement	Manufacturing	Quarterly	Capacity constraints	Percentage share	KOF survey
40	Exports, next 3M	Manufacturing	Quarterly	Real activity	CP mean	KOF survey
41	Purchase prices, next 3M	Manufacturing	Quarterly	Prices	CP mean	KOF survey
42	Prices, next 3M	Manufacturing	Quarterly	Prices	CP mean	KOF survey
43	Business situation, next 6M	Manufacturing	Quarterly	Real activity	CP mean	KOF survey

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No.	Description	Sector	Frequency	Econ. concept	Unit	Type
44	Business situation, judgement	Construction	Monthly	Real activity	CP mean	KOF survey
45	Business situation, last 3M	Construction	Monthly	Real activity	CP mean	KOF survey
46	Business situation, next 6M	Construction	Monthly	Real activity	CP mean	KOF survey
47	Demand, last 3M	Construction	Monthly	Real activity	CP mean	KOF survey
48	Demand, next 3M	Construction	Monthly	Real activity	CP mean	KOF survey
49	Order books, judgement	Construction	Monthly	Real activity	CP mean	KOF survey
50	Activity, last 3M	Construction	Monthly	Real activity	CP mean	KOF survey
51	Activity, next 3M	Construction	Monthly	Real activity	CP mean	KOF survey
52	Obstacles - none, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
53	Obstacles - insufficient demand, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
54	Obstacles - weather conditions, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
55	Obstacles - shortage of labour force, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
56	Obstacles - shortage of space and/or equipment, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
57	Obstacles - financial constraints, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
58	Obstacles - other factors, judgement	Construction	Monthly	Capacity constraints	Percentage share	KOF survey
59	Employment, judgement	Construction	Monthly	Labour market	CP mean	KOF survey
60	Employment, last 3M	Construction	Monthly	Labour market	CP mean	KOF survey
61	Employment, next 3M	Construction	Monthly	Labour market	CP mean	KOF survey
62	Prices, next 3M	Construction	Monthly	Prices	CP mean	KOF survey
63	Range of orders in hand, # of months	Construction	Quarterly	Real activity	Percentage share	KOF survey
64	Technical capacities, judgement	Construction	Quarterly	Capacity constraints	CP mean	KOF survey

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No.	Description	Sector	Frequency	Econ. concept	Unit	Type
65	Capacity utilisation, average last 3M	Construction	Quarterly	Capacity constraints	Percentage share	KOF survey
66	Renovation and maintenance, last 1Q	Construction	Quarterly	Capacity constraints	Percentage share	KOF survey
67	Profitability, last 3M	Construction	Quarterly	Real activity	CP mean	KOF survey
68	Profitability, next 3M	Construction	Quarterly	Real activity	CP mean	KOF survey
69	Competitive position, last 3M	Construction	Quarterly	Capacity constraints	CP mean	KOF survey
70	Business situation, last 3M	Project engineering	Monthly	Real activity	CP mean	KOF survey
71	Business situation, next 6M	Project engineering	Monthly	Real activity	CP mean	KOF survey
72	Demand, last 3M	Project engineering	Monthly	Real activity	CP mean	KOF survey
73	Demand, next 3M	Project engineering	Monthly	Real activity	CP mean	KOF survey
74	Activity, last 3M	Project engineering	Monthly	Real activity	CP mean	KOF survey
75	Activity, next 3M	Project engineering	Monthly	Real activity	CP mean	KOF survey
76	Employment, judgement	Project engineering	Monthly	Labour market	CP mean	KOF survey
77	Employment, last 3M	Project engineering	Monthly	Labour market	CP mean	KOF survey
78	Employment, next 3M	Project engineering	Monthly	Labour market	CP mean	KOF survey
79	Prices, next 3M	Project engineering	Monthly	Prices	CP mean	KOF survey
80	Order books, last 3M	Project engineering	Quarterly	Real activity	CP mean	KOF survey
81	Technical capacities, judgement	Project engineering	Quarterly	Capacity constraints	CP mean	KOF survey
82	Obstacles - none, judgement	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey
83	Obstacles - insufficient demand, judgement	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey
84	Obstacles - shortage of labour force, judgement	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey
85	Obstacles - shortage of technical capacities, judgement	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey

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Table 6 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Unit	Type
86	Obstacles - financial constraints, judgement	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey
87	Obstacles - other factors, judgement	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey
88	Renovation and maintenance, last 1Q	Project engineering	Quarterly	Capacity constraints	Percentage share	KOF survey
89	Construction sum - house building, last 1Q	Project engineering	Quarterly	Real activity	CP mean	KOF survey
90	Construction sum - industrial construction, last 1Q	Project engineering	Quarterly	Real activity	CP mean	KOF survey
91	Construction sum - public construction, last 1Q	Project engineering	Quarterly	Real activity	CP mean	KOF survey
92	Construction sum - total, last 1Q	Project engineering	Quarterly	Real activity	CP mean	KOF survey
93	Profitabilty, last 3M	Project engineering	Quarterly	Real activity	CP mean	KOF survey
94	Profitability, next 3M	Project engineering	Quarterly	Real activity	CP mean	KOF survey
95	Competitive position, last 3M	Project engineering	Quarterly	Capacity constraints	CP mean	KOF survey
96	Business situation, judgement	Services	Quarterly	Real activity	CP mean	KOF survey
97	Demand, last 3M	Services	Quarterly	Real activity	CP mean	KOF survey
98	Employment, judgement	Services	Quarterly	Labour market	CP mean	KOF survey
99	Technical capacities, judgement	Services	Quarterly	Capacity constraints	CP mean	KOF survey
100	Profitability, last 3M	Services	Quarterly	Real activity	CP mean	KOF survey
101	Competitive position, last 3M	Services	Quarterly	Capacity constraints	CP mean	KOF survey
102	Obstacles - insufficient demand, judgement	Services	Quarterly	Capacity constraints	Percentage share	KOF survey
103	Obstacles - shortage of labour force, judgement	Services	Quarterly	Capacity constraints	Percentage share	KOF survey

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Table 6 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Unit	Type
104	Obstacles - shortage of technical capacities, judgement	Services	Quarterly	Capacity constraints	Percentage share	KOF survey
105	Obstacles - economic and legal conditions, judgement	Services	Quarterly	Capacity constraints	Percentage share	KOF survey
106	Obstacles - financial constraints, judgement	Services	Quarterly	Capacity constraints	Percentage share	KOF survey
107	Obstacles - none, judgement	Services	Quarterly	Capacity constraints	Percentage share	KOF survey
108	Demand, next 3M	Services	Quarterly	Real activity	CP mean	KOF survey
109	Employment, next 3M	Services	Quarterly	Labour market	CP mean	KOF survey
110	Prices, next 3M	Services	Quarterly	Prices	CP mean	KOF survey
111	Business situation, next 6M	Services	Quarterly	Real activity	CP mean	KOF survey
112	Sales, last 4Q	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
113	Turnover, last 4Q	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
114	Turnover, last 4Q in %	Hotels and restaurants	Quarterly	Real activity	Percentage share	KOF survey
115	Demand, last 3M	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
116	Employment, last 3M	Hotels and restaurants	Quarterly	Labour market	CP mean	KOF survey
117	Employment, judgement	Hotels and restaurants	Quarterly	Labour market	CP mean	KOF survey
118	Operational facilities, judgement	Hotels and restaurants	Quarterly	Capacity constraints	CP mean	KOF survey
119	Profitability, last 3M	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
120	Business situation, judgement	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
121	Sales, next 1Q	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
122	Demand, next 3M	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey
123	Prices, next 3M	Hotels and restaurants	Quarterly	Prices	CP mean	KOF survey
124	Employment, next 3M	Hotels and restaurants	Quarterly	Labour market	CP mean	KOF survey
125	Business situation, next 6M	Hotels and restaurants	Quarterly	Real activity	CP mean	KOF survey

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Table 6 – continued from previous page

No.	Description	Sector	Frequency	Econ. concept	Unit	Type
126	Business situation, judgement	Wholesale	Quarterly	Real activity	CP mean	KOF survey
127	Demand, last 3M	Wholesale	Quarterly	Real activity	CP mean	KOF survey
128	Sales, last 4Q	Wholesale	Quarterly	Real activity	CP mean	KOF survey
129	Stock, last 4Q	Wholesale	Quarterly	Capacity constraints	CP mean	KOF survey
130	Stock, judgement	Wholesale	Quarterly	Capacity constraints	CP mean	KOF survey
131	Delivery time, last 4Q	Wholesale	Quarterly	Capacity constraints	CP mean	KOF survey
132	Employment, last 3M	Wholesale	Quarterly	Labour market	CP mean	KOF survey
133	Employment, judgement	Wholesale	Quarterly	Labour market	CP mean	KOF survey
134	Technical facilities, judgement	Wholesale	Quarterly	Capacity constraints	CP mean	KOF survey
135	Obstacles - insufficient demand, judgement	Wholesale	Quarterly	Capacity constraints	Percentage share	KOF survey
136	Obstacles - shortage of labour force, judgement	Wholesale	Quarterly	Capacity constraints	Percentage share	KOF survey
137	Obstacles - insufficient technical capacities, judgement	Wholesale	Quarterly	Capacity constraints	Percentage share	KOF survey
138	Obstacles - economic and legal conditions, judgement	Wholesale	Quarterly	Capacity constraints	Percentage share	KOF survey
139	Obstacles - financial constraints, judgement	Wholesale	Quarterly	Capacity constraints	Percentage share	KOF survey
140	Obstacles - none, judgement	Wholesale	Quarterly	Capacity constraints	Percentage share	KOF survey
141	Profitability, last 3M	Wholesale	Quarterly	Real activity	CP mean	KOF survey
142	Competitive position, last 3M	Wholesale	Quarterly	Capacity constraints	CP mean	KOF survey
143	Demand, next 3M	Wholesale	Quarterly	Real activity	CP mean	KOF survey
144	Delivery time, next 3M	Wholesale	Quarterly	Capacity constraints	CP mean	KOF survey
145	Purchase prices, next 3M	Wholesale	Quarterly	Prices	CP mean	KOF survey
146	Sales prices, next 3M	Wholesale	Quarterly	Prices	CP mean	KOF survey

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No.	Description	Sector	Frequency	Econ. concept	Unit	Type
147	Employment, next 3M	Wholesale	Quarterly	Labour market	CP mean	KOF survey
148	Business situation, next 6M	Wholesale	Quarterly	Real activity	CP mean	KOF survey
149	Turnover, next 3M	Retail	Monthly	Real activity	CP mean	KOF survey
150	Business situation, judgement	Retail	Monthly	Real activity	CP mean	KOF survey
151	Sales, last 3M	Retail	Monthly	Real activity	CP mean	KOF survey
152	Customer frequency, last 12M	Retail	Monthly	Real activity	CP mean	KOF survey
153	Stock, judgement	Retail	Monthly	Capacity constraints	CP mean	KOF survey
154	Employment, judgement	Retail	Monthly	Labour market	CP mean	KOF survey
155	Prices, next 3M	Retail	Monthly	Prices	CP mean	KOF survey
156	Employment, next 3M	Retail	Quarterly	Labour market	CP mean	KOF survey
157	Stock, last 12M	Retail	Quarterly	Capacity constraints	CP mean	KOF survey
158	Profitability, last 3M	Retail	Quarterly	Real activity	CP mean	KOF survey
159	Purchases, next 3M	Retail	Quarterly	Real activity	CP mean	KOF survey
160	Business situation, next 6M	Retail	Quarterly	Real activity	CP mean	KOF survey
161	Social security payments	Entire economy	Monthly	Labour market	Growth rate	Hard data
162	Registered unemployed	Entire economy	Monthly	Labour market	Growth rate	Hard data
163	Short-time workers	Entire economy	Monthly	Labour market	Growth rate	Hard data
164	Full-time job openings	Entire economy	Monthly	Labour market	Growth rate	Hard data
165	Job seekers	Entire economy	Monthly	Labour market	Growth rate	Hard data
166	Unemployment	Entire economy	Monthly	Labour market	Growth rate	Hard data
167	Electricity production	Entire economy	Monthly	Real activity	Growth rate	Hard data
168	Overnight stays	Hotels and restaurants	Monthly	Real activity	Growth rate	Hard data
169	New cars	Retail	Monthly	Real activity	Growth rate	Hard data
170	Clothing and footwear	Retail	Monthly	Real activity	Growth rate	Hard data
171	Food and beverages	Retail	Monthly	Real activity	Growth rate	Hard data

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No.	Description	Sector	Frequency	Econ. concept	Unit	Type
172	Other consumption	Retail	Monthly	Real activity	Growth rate	Hard data
173	Retail sales, excluding fuels	Retail	Monthly	Real activity	Growth rate	Hard data
174	Export chemical products	Manufacturing	Monthly	Real activity	Growth rate	Hard data
175	Export energy	Manufacturing	Monthly	Real activity	Growth rate	Hard data
176	Exports intermediate goods	Manufacturing	Monthly	Real activity	Growth rate	Hard data
177	Export machinery and equipment	Manufacturing	Monthly	Real activity	Growth rate	Hard data
178	Exports	Entire economy	Monthly	Real activity	Growth rate	Hard data
179	Exports watches	Wholesale	Monthly	Real activity	Growth rate	Hard data
180	Imports carts	Wholesale	Monthly	Real activity	Growth rate	Hard data
181	Imports chemical products	Manufacturing	Monthly	Real activity	Growth rate	Hard data
182	Imports energy	Entire economy	Monthly	Real activity	Growth rate	Hard data
183	Imports investment goods	Manufacturing	Monthly	Real activity	Growth rate	Hard data
184	Imports	Entire economy	Monthly	Real activity	Growth rate	Hard data
185	CRB index	Entire economy	Monthly	Prices	Growth rate	Hard data
186	Coroporate loans	Entire economy	Monthly	Financial variables	Growth rate	Hard data
187	Government bond yield	Entire economy	Monthly	Financial variables	Difference	Hard data
188	12M Libor	Entire economy	Monthly	Financial variables	Difference	Hard data
189	3M Libor	Entire economy	Monthly	Financial variables	Difference	Hard data
190	M1	Entire economy	Monthly	Financial variables	Growth rate	Hard data
191	M2	Entire economy	Monthly	Financial variables	Growth rate	Hard data
192	M3	Entire economy	Monthly	Financial variables	Growth rate	Hard data
193	Trade-weighted exchange rate	Entire economy	Monthly	Financial variables	Growth rate	Hard data
194	CHF/EUR	Entire economy	Monthly	Financial variables	Growth rate	Hard data
195	CHF/USD	Entire economy	Monthly	Financial variables	Growth rate	Hard data
196	Swiss Bond Index	Entire economy	Monthly	Financial variables	Growth rate	Hard data
197	Swiss Market Index	Entire economy	Monthly	Financial variables	Growth rate	Hard data

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No.	Description	Sector	Frequency	Econ. concept	Unit	Type
198	Swiss Performance Index	Entire economy	Monthly	Financial variables	Growth rate	Hard data
199	Term spread (10Y - 12M)	Entire economy	Monthly	Financial variables	Percentage points	Hard data
200	Term spread (10Y - 3M)	Entire economy	Monthly	Financial variables	Percentage points	Hard data
201	Oil price (USD, Brent)	Entire economy	Monthly	Prices	Growth rate	Hard data
202	Producer price index	Entire economy	Monthly	Prices	Growth rate	Hard data
203	IP EUA	Foreign variables	Monthly	Real activity	Growth rate	Hard data
204	IP Japan	Foreign variables	Monthly	Real activity	Growth rate	Hard data
205	IP UK	Foreign variables	Monthly	Real activity	Growth rate	Hard data
206	IP US	Foreign variables	Monthly	Real activity	Growth rate	Hard data

Note: The data stem from KOF Swiss Economic Institute, Swiss Federal Statistical Office, State Secretariat for Economic Affairs, Swiss National Bank, Credit Suisse. CP denotes the Carlson and Parkin (1975) transformation.

Not-for-publication Appendix

Table 7 — Explanatory power various transformations

	CPI	GDP	Employment	Output gap
Balance	0.36	0.59	0.70	0.82
CP (I)	0.48	0.63	0.73	0.84
CP (II)	0.26	0.59	0.73	0.73
Unrestricted	0.35	0.58	0.69	0.88

Note: The table shows the R^2 of the factor model based on model specification (1) in Table 2. Each row uses a different transformation of the survey data. The balance statistic is the share of positive minus the share of negative answers CP (I) and (II) use the Carlson and Parkin (1975) transformation including only the mean and the mean as well as the dispersion, respectively. The last row includes the share of positive and negative answers separately.

Table 8 — Explanatory power using BICM

	CPI	GDP	Employment	Output gap
	(A) Survey and hard data			
	CPI	GDP	Employment	Output gap
Entire data set	0.41	0.63	0.68	0.80
− surveys	0.28	0.66	0.60	0.58
− hard data	0.18	0.47	0.69	0.78
	(B) Sectors of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.41	0.63	0.68	0.80
− project engineering	0.36	0.61	0.72	0.80
− construction	0.36	0.58	0.62	0.81
− retail	0.36	0.61	0.66	0.77
− services	0.33	0.64	0.68	0.79
− hotels and restaurants	0.47	0.59	0.68	0.79
− wholesale	0.37	0.63	0.67	0.8
− manufacturing	0.35	0.57	0.67	0.73
	(C) Time reference of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.41	0.63	0.68	0.80
− current situation	0.31	0.64	0.62	0.72
− expected situation	0.40	0.59	0.74	0.81
− change last twelve months	0.38	0.59	0.64	0.79
− change last three months	0.36	0.64	0.67	0.79
− last quarter	0.39	0.63	0.67	0.81
− change to last years' quarter	0.37	0.59	0.69	0.78
− change to previous quarter	0.36	0.59	0.66	0.79
	(D) Frequency of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.41	0.63	0.68	0.80
− quarterly	0.37	0.69	0.66	0.74
	(E) Economic concept of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.41	0.63	0.68	0.80
− capacity constraints	0.35	0.67	0.66	0.82
− labour market	0.37	0.60	0.67	0.78
− prices	0.38	0.57	0.63	0.78
− real activity	0.30	0.65	0.72	0.78

Note: The first row of each panel shows the R^2 of the factor model based on model specification (1) in Table 2. Each subsequent row shows the R^2 after the removal of one dimension of the data set for estimating the factors.

Table 9 — Explanatory power $r = 2$

	CPI	GDP	Employment	Output gap
	(A) Survey and hard data			
	CPI	GDP	Employment	Output gap
Entire data set	0.38	0.63	0.68	0.81
− surveys	0.28	0.66	0.55	0.60
− hard data	0.14	0.53	0.66	0.75
	(B) Sectors of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.38	0.63	0.68	0.81
− project engineering	0.37	0.58	0.73	0.8
− construction	0.33	0.63	0.71	0.83
− retail	0.39	0.59	0.67	0.78
− services	0.39	0.64	0.69	0.81
− hotels and restaurants	0.39	0.64	0.68	0.79
− wholesale	0.39	0.63	0.69	0.80
− manufacturing	0.32	0.66	0.69	0.76
	(C) Time reference of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.38	0.63	0.68	0.81
− current situation	0.17	0.64	0.73	0.72
− expected situation	0.42	0.64	0.68	0.83
− change last twelve months	0.39	0.63	0.68	0.81
− change last three months	0.38	0.63	0.68	0.77
− last quarter	0.40	0.59	0.71	0.82
− change to last years' quarter	0.39	0.63	0.68	0.81
− change to previous quarter	0.39	0.63	0.68	0.81
	(D) Frequency of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.38	0.63	0.68	0.81
− quarterly	0.38	0.62	0.73	0.76
	(E) Economic concept of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.38	0.63	0.68	0.81
− capacity constraints	0.35	0.63	0.71	0.80
− labour market	0.39	0.64	0.69	0.80
− prices	0.38	0.64	0.68	0.78
− real activity	0.40	0.59	0.73	0.79

Note: The first row of each panel shows the R^2 of the factor model based on model specification (1) in Table 2. Each subsequent row shows the R^2 after the removal of one dimension of the data set for estimating the factors.

Table 10 — Explanatory power $r = 4$

	(A) Survey and hard data			
	CPI	GDP	Employment	Output gap
Entire data set	0.34	0.67	0.72	0.85
− surveys	0.29	0.67	0.70	0.61
− hard data	0.27	0.51	0.74	0.87
	(B) Sectors of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.34	0.67	0.72	0.85
− project engineering	0.39	0.63	0.73	0.80
− construction	0.44	0.61	0.72	0.82
− retail	0.38	0.66	0.66	0.84
− services	0.35	0.65	0.68	0.84
− hotels and restaurants	0.34	0.67	0.73	0.84
− wholesale	0.21	0.62	0.68	0.85
− manufacturing	0.39	0.64	0.69	0.75
	(C) Time reference of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.34	0.67	0.72	0.85
− current situation	0.31	0.64	0.70	0.75
− expected situation	0.35	0.69	0.78	0.85
− change last twelve months	0.33	0.64	0.69	0.85
− change last three months	0.35	0.67	0.72	0.80
− last quarter	0.44	0.63	0.74	0.84
− change to last years' quarter	0.43	0.64	0.68	0.85
− change to previous quarter	0.35	0.67	0.72	0.84
	(D) Frequency of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.34	0.67	0.72	0.85
− quarterly	0.35	0.68	0.76	0.82
	(E) Economic concept of surveys			
	CPI	GDP	Employment	Output gap
Entire data set	0.34	0.67	0.72	0.85
− capacity constraints	0.39	0.67	0.71	0.87
− labour market	0.37	0.68	0.78	0.85
− prices	0.35	0.66	0.72	0.83
− real activity	0.34	0.62	0.75	0.79

Note: The table shows relative root-mean-squared errors (RMSE) for the nowcast (horizon = 0) and forecast (horizons = 1–8). The factor model is based on specification (2) in Table 2 and the benchmark model on specification (3). We use a Diebold and Mariano (1995)-West (1996) test for the null of equal predictive ability against the one-sided alternative that the factor model has a lower RMSE. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% level.

Table 11 — Share of selected benchmark indicators

	(A) $h = 0$			
	CPI	GDP	Employment	Output gap
Lags	0.00	0.00	0.00	1.00
PMI prices	0.72	0.18	0.06	0.00
PMI	0.02	1.00	0.48	0.98
KOF employment Index	0.34	0.00	1.00	0.62
Capacity utilisation	0.12	0.00	0.00	0.00
	(B) $h = 1$			
	CPI	GDP	Employment	Output gap
Lags	0.16	0.00	0.00	0.88
PMI prices	0.20	0.08	0.22	0.26
PMI	0.26	0.12	0.84	0.76
KOF Employment Index	0.78	0.92	1.00	1.00
Capacity utilisation	0.20	0.08	0.00	0.62
	(C) $h = 4$			
	CPI	GDP	Employment	Output gap
Lags	0.10	0.14	0.16	0.90
PMI prices	0.62	0.28	0.30	0.28
PMI	0.44	0.30	1.00	0.28
KOF Employment Index	0.10	0.80	0.16	0.96
Capacity utilisation	0.14	0.20	0.34	0.88
	(D) $h = 8$			
	CPI	GDP	Employment	Output gap
Lags	0.28	0.60	0.12	1.00
PMI prices	0.16	0.48	0.70	0.36
PMI	0.50	0.28	0.60	0.58
KOF Employment Index	0.58	0.78	0.78	0.90
Capacity utilisation	0.22	0.18	0.70	0.98

Note: The table shows the share of selected benchmark indicators and lags using model specification (3) in Table 2 at various forecast horizons.

Table 12 — Relative predictive ability time reference

	(A) Survey-factor model current situation			
Horizon	CPI	GDP	Employment	Output gap
0	–	1.22	1.12	1.07
1	0.97	1.16	1.21	0.95
4	0.83*	0.77*	0.61*	0.77*
8	0.86*	0.78**	0.50***	0.69
	(B) Survey-factor model future expected situation			
Horizon	CPI	GDP	Employment	Output gap
0	–	0.99	1.13	0.99
1	0.97	1.07	1.23	0.78*
4	0.78*	0.78*	0.78	0.72*
8	0.80**	0.84	0.60**	0.76
	(C) Survey-factor model past			
Horizon	CPI	GDP	Employment	Output gap
0	–	1.25	1.33	1.15
1	0.96	1.02	1.23	0.96
4	0.80**	0.78*	0.69*	0.74**
8	0.86	0.70*	0.55**	0.87

Note: The table shows relative root-mean-squared errors (RMSE) for the nowcast (horizon = 0) and forecast (horizons = 1–8). The factor model is based on specification (2) in Table 2 and the benchmark model on specification (3). We use a Diebold and Mariano (1995)-West (1996) test for the null of equal predictive ability against the one-sided alternative that the factor model has a lower RMSE. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% level.

Table 13 — Relative predictive ability economic concepts

Horizon	CPI	GDP	Employment	Output gap
	(A) Survey-factor model capacity constraints			
0	–	1.36	1.05	1.24
1	0.97	1.10	1.18	1.08
4	0.81*	0.81*	0.64*	0.79*
8	0.86*	0.67**	0.55**	0.91
	(B) Survey-factor model labour market			
0	–	1.28	1.24	1.23
1	0.96	1.08	1.35	1.03
4	0.84*	0.76	0.62*	0.96
8	0.92	0.81**	0.59**	0.63**
	(C) Survey-factor model prices			
0	–	1.22	1.25	1.35
1	1.01	1.18	1.27	1.14
4	0.83*	0.75*	0.71	0.84
8	0.78**	0.70**	0.50***	0.65*
	(D) Survey-factor model real activity			
0	–	1.04	1.07	0.98
1	0.95*	0.97	1.16	0.74**
4	0.77**	0.76	0.69	0.64**
8	0.85*	0.61**	0.56**	0.58*

Note: The table shows relative root-mean-squared errors (RMSE) for the nowcast (horizon = 0) and forecast (horizons = 1–8). The factor model is based on specification (2) in Table 2 and the benchmark model on specification (3). We use a Diebold and Mariano (1995)-West (1996) test for the null of equal predictive ability against the one-sided alternative that the factor model has a lower RMSE. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% level.

Table 14 — Relative predictive ability robustness tests

Horizon	CPI	GDP	Employment	Output gap
	(A) Mixed-frequency survey-factor model ($r = 2$)			
0	–	1.06	0.96	1.03
1	0.94**	1.15	0.98	0.89
4	0.85	0.78*	0.51**	0.75**
8	0.88	0.86*	0.50***	0.65*
	(B) Mixed-frequency survey-factor model ($r = 4$)			
0	–	1.09	1.09	1.19
1	0.88***	1.00	1.11	1.00
4	0.79*	0.94	0.62*	0.79*
8	0.85**	1.09	0.76**	0.80
	(C) Mixed-frequency survey-factor model (BICM)			
0	–	1.04	1.13	1.23
1	0.93**	1.14	0.99	0.96
4	0.89*	0.87	0.56*	0.74**
8	0.85**	0.94	0.69*	0.72
	(D) Hard and survey data (real-time vintages)			
0		0.82*	0.97	1.02
1		0.95	0.99	1.03
4		0.76*	0.69	0.75**
8		1.10	1.18	0.85*
	(E) Survey data (real-time vintages)			
0		1.02	1.06	0.94
1		1.32	0.94	1.04
4		0.82	0.65*	0.73**
8		1.24	0.97	0.73***

Note: The table shows relative root-mean-squared errors (RMSE) for the nowcast (horizon = 0) and forecast (horizons = 1–8). The factor model is based on specification (2) in Table 2 and the benchmark model on specification (3). We use a Diebold and Mariano (1995)-West (1996) test for the null of equal predictive ability against the one-sided alternative that the factor model has a lower RMSE. ***, **, * denote rejection of the null hypothesis at the 1%, 5%, and 10% level.