

# Assessing the Real-Time Informational Content of Macroeconomic Data Releases for Now-/Forecasting GDP: Evidence for Switzerland<sup>§</sup>

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## Abstract

This study utilizes the dynamic factor model of Giannone et al. (2008) in order to make now-/forecasts of GDP quarter-on-quarter growth rates in Switzerland. It also assesses the informational content of macroeconomic data releases for forecasting of the Swiss GDP. We find that the factor model offers a substantial improvement in forecast accuracy of GDP growth rates compared to a benchmark naive constant-growth model at all forecast horizons and at all data vintages. The largest forecast accuracy is achieved when GDP nowcasts for an actual quarter are made about three months ahead of the official data release. We also document that both business tendency surveys as well as stock market indices possess the largest informational content for GDP forecasting although their ranking depends on the underlying transformation of monthly indicators from which the common factors are extracted.

*Keywords:* Business tendency surveys, Forecasting, Nowcasting, Real-time data, Dynamic factor model  
*JEL code:* C53, E37.

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# 1 Introduction

This paper explores the real-time informational content of various macroeconomic data releases both for nowcasting and one-quarter-ahead forecasting of the Swiss GDP employing the approach suggested in Giannone et al. (2008). Giannone et al. (2008) provide a unified statistical framework that combines the following aspects characterizing the real-life decision-making process of a policy maker: i) extraction of a (useful) signal from a large number of various economic indicators, ii) accounting for asynchronous releases of various blocks of macroeconomic data when updating actual now-/forecasts such that a typical situation of being confronted with an unbalanced panel of available indicators—a so called "jagged edge"—is naturally incorporated into the statistical model, iii) "bridging" the economic indicators available at the monthly frequency with the quarterly GDP now-/forecasts.

Giannone et al. (2008) suggest using an approximate dynamic factor model estimated in two steps. In the first step the common factors are extracted by the static principal components analysis using the balanced panel of monthly indicators. The balanced panel is achieved by truncation of the available unbalanced panel at the data block with the largest publication lag. In the second step the common factors are extracted by means of Kalman filter for the whole sample of interest.

By now, the use of a large-scale factor models for economic forecasting enjoy a wide popularity (e.g., see Siliverstovs and Kholodilin, 2009; Schumacher and Breitung, 2008; Schumacher, 2007; Kholodilin and Siliverstovs, 2006; Forni et al., 2005; Stock and Watson, 2002a,b; Sancho and Camacho, 2002; Artis et al., 2001; Forni et al., 2000, inter alia). The approach of Giannone et al. (2008) distinguishes itself from this extensive literature in that it is the first study attempting to single out marginal change in forecast accuracy attributable to a particular block release of macroeconomic data. According to Giannone et al. (2008), a block release that effects the forecast accuracy to the largest extent possesses also the most of real-time information helping predicting quarterly GDP.

Our study contributes to the literature in the following three ways. First, to the best of our knowledge, it represents the first attempt to predict the growth rate of the Swiss GDP for the current quarter (nowcast) as well as for the next quarter (forecast) using a large-scale factor model. The previous research either used a single leading indicator model (Müller and Köberl, 2008) or it used a leading indicator (KOF-Barometer) extracted from a small-scale static factor model (Graff, 2009; Siliverstovs, 2009) for predicting GDP growth rates in Switzerland. Our study also distinguishes itself from these studies in that we choose the quarter-on-quarter seasonally adjusted GDP growth rates as a target prediction variable rather than the year-on-year quarterly GDP growth rate that these earlier studies aimed to predict. In doing so, we conform to Giannone et al. (2008) in the choice of the variable of interest.

Second, despite a wide applicability of factor-based models, the research question on the informational content of different macroeconomic data releases pursued in Giannone et al. (2008) so far did not gain much popularity. In fact, we are aware of only one additional study that investigates this issue; Aastveit and Trovik (2007) provide another case study for Norway. It is worthwhile noting that these both studies arrive at somewhat contradictory conclusions regarding which block of variables has a largest positive impact on

forecast accuracy. Giannone et al. (2008) conclude that the Philadelphia Federal Bank surveys as well as the report on the employment situation contribute the most to increase in forecast accuracy whereas the impact of financial variables (including several stock market indices) is found to be negligible. On contrary, Aastveit and Trovik (2007) find that the stock market variables are an important factor in reducing forecast uncertainty<sup>1</sup>. In a given situation our study provides another case study investigating importance of various data releases for now-/forecasting GDP. In our study both stock market and the business tendency surveys are included in the factor model allowing us to compare the contribution of these variables to forecast accuracy reinforcing conclusions of either of these two studies.

Third, in our simulation of a real-time forecasting we attempt to perform as to the largest extent possible. In particular, we utilize the real-time vintages of the target variable—the seasonally adjusted quarter-on-quarter GDP growth rates—and access the contribution of various data releases to improvement of forecast accuracy with respect to the first official figure published by the State Secretariat for Economic Affairs (SECO). The importance of using real-time instead of latest-available data has been already emphasized in numerous studies as it has been shown, for example, by Diebold and Rudebusch (1991) and, more recently, by Croushore (2005) that the favorable conclusions on forecasting properties of leading indicator indexes obtained using latest-available data may be substantially weakened or even reversed when forecasting exercise is replicated using real-time data sets. Furthermore, the real-time flavor is also kept as much as possible in constructing the panel of our monthly indicators. Some of them undergo no (stock market variables, interest rates and exchange rates) or rather minor revisions (business tendency surveys). At the same time we have several blocks of the variables (trade and retail variables, prices, and employment) that were subject to both seasonal adjustment and later revisions for which we have no real-time vintages.

We find that the factor model offers a substantial improvement in forecast accuracy of GDP growth rates compared to a benchmark naive constant-growth model at all forecast horizons and all data vintages. The largest forecast accuracy is achieved when GDP nowcasts for an actual quarter are made about three months ahead of the official data release. We also document that both business tendency surveys as well as stock market indices possess the largest informational content for GDP forecasting although their ranking depends on the underlying transformation of monthly indicators from which the common factors are extracted.

The paper is structured as follows. In Section 2 the modeling approach of Giannone et al. (2008) is presented. Section 3 contains description of data used. The results of our forecasting exercise are presented in Section 4. In the next section the model performance in forecasting the current crisis is scrutinized. The final section concludes.

## 2 Model

As mentioned above, an important feature of the approach of Giannone et al. (2008) is that it allows to measure the marginal impact on reduction in model prediction uncertainty as new macroeconomic data are released. In order to see this, we need the following notation. Denote  $\Omega_t$  a collection of all information sets

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<sup>1</sup>Aastveit and Trovik (2007) does not include surveys in the their factor model as they are only available at the quarterly frequency in Norway.

that correspond to the flow of  $b$  blocks of newly released macroeconomic data during a month  $v$ , such that

$$\Omega_v = \{\Omega_{v_j}; j = 1, \dots, b\},$$

where

$$\Omega_{v_j} = \{X_{it|v_j}; t = 1, \dots, T_{iv_j}; i = 1, \dots, n\}$$

is an information set available to a forecaster after a block  $j$  was released in a given month  $v$ . This information set is comprised from monthly indicators  $X_{it|v_j}$  with the subindex  $i = 1, \dots, n$  indicating individual time series and the subindex  $t = 1, \dots, T_{iv_j}$  denotes the corresponding period of observed values for a given time series. This means that  $T_{iv_j}$  denotes the last period for which time series  $i$  in vintage  $v_j$  has a valid observation.

Furthermore, denote a quarter  $q$  by its last month. Then imposing the restriction that the sample starts in the first month of a quarter, we have  $q = 3k$  with  $k = 1, 2, \dots$ . Due to a stable release pattern of monthly data blocks a given vintage  $v_j$  is released three times per quarter generating the following information sets  $\Omega_{v_j}$  with  $v = 3k - 2, 3k - 1, 3k$  in the first, second and third months of quarter, respectively.

Let  $y_{3k}$  be GDP growth rate for a given quarter  $q = 3k$ . Then for each information set  $\Omega_{v_j}$  with  $v = 3k - 2, 3k - 1, 3k$  the forecast is computed as a projection of  $y_{3k}$  on the available information set

$$\hat{y}_{3k|v_j} = E [y_{3k} | \Omega_{v_j}; M], \quad v = 3(k - h) - 2, 3(k - h) - 1, 3(k - h), \quad j = 1, \dots, b \quad (1)$$

for a given underlying model  $M$ . The letter  $h$  denotes the forecast horizon such that for  $h = 1$  we produce one-quarter ahead forecasts and for  $h = 0$  we produce forecasts for the current quarter, i.e., nowcasts. Observe that Equation (1) denotes the so-called “bridge regression” that utilizes information available at monthly frequency in order to forecast quarterly variable of interest.

Recall that the magnitude of interest is the uncertainty surrounding the forecast at a given vintage, or, more precisely, its evolution over time from vintage to vintage. Following Giannone et al. (2008), we measure the forecast uncertainty associated with a given vintage as follows

$$V_{y_{3k|v_j}} = E [(\hat{y}_{3k|v_j} - y_{3k})^2; M]. \quad (2)$$

It is expected that as more timely data become available this uncertainty measure will have a tendency to decrease, i.e.,  $V_{y_{3k|v_j}} \leq V_{y_{3k|v_{j-1}}}$ , allowing to assess informational content of each data block release.

Giannone et al. (2008) suggest a following approximate dynamic factor model with the monthly indicators  $x_{t|v_j} = (x_{1t|v_j}, \dots, x_{nt|v_j})'$  are assumed to be driven by  $r$  unobserved common factors  $F_t = (f_{1t}, \dots, f_{rt})'$  with  $r \ll n$  and individual-specific idiosyncratic components  $\xi_{t|v_j} = (\xi_{1t|v_j}, \dots, \xi_{nt|v_j})'$  such that in matrix notation the model reads

$$x_{t|v_j} = \mu + \Lambda F_t + \xi_{t|v_j}, \quad (3)$$

where  $\mu = (\mu_1, \dots, \mu_n)'$  is a vector of individual specific intercepts and  $\Lambda$  is a  $n \times r$  matrix of factor loading

coefficients. The common factors are assumed to follow a vector autoregressive process

$$F_t = AF_{t-1} + Bu_t, \quad u_t \sim WN(0, I_q) \quad (4)$$

where  $A$  is a  $r \times r$  parameter matrix satisfying a stationarity restriction such that all roots of  $(I_r - Az)$  lie outside the unit circle,  $B$  is a  $r \times q$  matrix of full rank  $q$ , and  $u_t$  is a  $q$ -dimensional white-noise process, representing shocks to the common factors. Specifying the equation for factor dynamics allows one to implement the Kalman smoother in order to compute recursively the expected value of the common factors also in the presence of missing observations in the end of the sample, i.e., the “jagged edge”, due to asynchronous data releases.

Additional assumptions include a white-noise process for idiosyncratic shocks  $\xi_{t|v_j}$  in Equation (2), i.e.,  $E(\xi_{t|v_j}\xi'_{t-s|v_j})$  with  $s > 0$  for all  $j$  and  $v$ , zero cross-correlation, i.e.,  $E(\xi_{t|v_j}\xi'_{t|v_j}) = \Psi_{t|v_j} = \text{diag}(\psi_{1t|v_j}, \dots, \psi_{nt|v_j})$ , as well as the assumption of Gaussian error terms.

Denote the expected value of the common factors for a given underlying model  $M$  as

$$\widehat{F}_{t|v_j} = E(F_t|\Omega_{v_j}; M)$$

and the associated factor estimation uncertainty as

$$\widehat{V}_{v_j} = E[(F_t - \widehat{F}_{t|v_j})(F_t - \widehat{F}_{t|v_j})'; M].$$

Both these quantities of interest are available as a standard output of the Kalman filter.

Giannone et al. (2008) suggest to compute now-/forecasts GDP by projecting the quarterly GDP growth rates on the estimated monthly factors that have been converted to quarterly frequency by keeping only their values in the last month of quarter,  $F_{3k|v_j}$  with  $k = 1, \dots, \lfloor T_{yv_j}/3 \rfloor$  where  $T_{yv_j}$  is the last month in quarter for which GDP is available for a given vintage  $v_j$ . Thus, rather than projecting GDP on the whole information set available for some vintage  $v_j$  as shown in Equation (1) that may be a rather formidable task, Giannone et al. (2008) suggest projecting on a few common factors resulting in a parsimonious forecast model

$$\widehat{y}_{3k|v_j} = \widehat{\gamma}_0 + \widehat{\gamma}'\widehat{F}_{3k|v_j}, \quad (5)$$

whose parameters can be easily estimated by OLS. The  $h$ -quarter ahead forecasts are made for each of the following months in quarter  $v = 3(k-h) - 2, 3(k-h) - 1, 3(k-h)$ . Naturally, for  $h = 0$  the nowcasts of the current quarter GDP is produced.

The associated forecast uncertainty is computed as

$$V_{y_{3k|v_j}} = \widehat{\gamma}'\widehat{V}_{v_j}\widehat{\gamma} + \text{Var}(\widehat{e}_{3k|v_j}),$$

where  $\widehat{e}_{3k|v_j} = y_{3k|v_j} - \widehat{y}_{3k|v_j}$  are the estimated residuals in the forecasting model.

### 3 Data

The data set of monthly indicators consists of 562 indicators sub-divided into the following 10 blocks: Purchasing Managers Index in manufacturing supplied by Credit Suisse (9 time series, “PMGR”), consumer price indexes (30, “CPI”), labour market indicators (6, “LABOUR”), producer price indexes (11, “PPI”), business tendency surveys in manufacturing collected at the KOF Swiss Economic Institute (150, “CHINOGA”), retail trade (4, “RETAIL”), exports and imports (249, “TRADE”), stock market indices (80, “STMKT”), interest rates (20, “INT.RATE”), and exchange rates (3, “EXCH.RATE”). The chronological sequence of block releases has been recorded in October 2009 and the further assumption has been made that it was preserved during the forecast sample in our “pseudo” real-time exercise. It generally corresponds to the actual release pattern although its timing and ordering may slightly vary from month to month in real life. For each month we constructed 10 vintages of data reflecting gradual expansion of the available information set by the newly released data.

Information on the monthly indicators is presented in Table 1. Observe that blocks of macroeconomic data differ both in terms of size and timeliness. The largest block is the block containing the exports and imports statistics, followed by the KOF surveys. The smallest block is one with the exchange rates, followed by retail trade, labour-market indicators, and the PMGR block where the number of indicators is below 10. In our setup the timeliest block is the KOF surveys released in the middle of the month with zero publishing lag. Following Giannone et al. (2008), we consider only monthly averages of the financial variables that are incorporated in the model at the end of each month. Observe that these variables are available at the daily frequency and by considering their monthly averages we are likely to downplay importance of these variables for forecasting accuracy, on the one hand. On the other hand, the informational content of the financial variables, e.g., stock market indices, may be impaired by their high variability when those are followed at daily frequency. In this case, considering only monthly averages is likely to smooth the noise out, thus positively influencing forecast accuracy. The retail variables are those with the largest publication lag of two months. The rest of blocks are released with lag of one month.

Prior to estimation all data except both blocks of surveys have been transformed to stationarity<sup>2</sup>. Furthermore, Giannone et al. (2008) suggest to transform all variables in order to ensure that these correspond to a quarterly quantity when observed at the end of the quarter<sup>3</sup>. In sequel we will refer to such transformation as the end-of-quarter equivalent transformation (EQE-transformation, in short). For the sake of brevity, we present both sets of the results, i.e., those based on original stationary variables and their quarterly-quantity equivalents. The data set of monthly indicators that is balanced at the beginning of the estimation sample after all necessary transformations and which is used for extraction of common factors starts in the first month of last quarter of 2000, i.e., in 2000M10. A rather late starting date is mainly due to the fact that the KOF business tendency surveys in manufacturing (“CHINOGA”-block) are only available since 1999.

The target variable that we forecast are the quarter-on-quarter seasonally adjusted GDP growth rates.

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<sup>2</sup>See Appendix for the complete list of the monthly components and their transformation description.

<sup>3</sup>This is achieved by application of the following filter on the initial monthly time series  $x_t$ :  $y_t = x_t + 2 * x_{t-1} + 3 * x_{t-2} + 2 * x_{t-3} + x_{t-4}$ .

Since in real time a lot of attention is paid to the first officially released figures we assess the forecast accuracy of our factor model with respect to that figure. To this end, we utilize the real-time vintages of all releases of the target variable since the first quarter of 2005. The forecast sample ends in the second quarter of 2009, leaving us with 18 forecasts per vintage.

## 4 Results

In this section we describe the obtained results. We do it for two sets of indicator variables. First, we consider the data set composed using the variables transformed to stationarity (whenever necessary). In particular, we apply the stationarity transformation to all blocks of variables except “CHINOGA”- and “PMGR”-blocks. We spared these two blocks from stationarity transformation for following reasons: the application of first-differencing of survey indicators resulted in much worse forecasting performance of the factor model compared to the case without this transformation, and since these type of variables by construction are bounded—a feature which is not consistent with properties of unit-root processes. Secondly, we follow the suggestion of Giannone et al. (2008) and report the results obtained using the data set composed of the transformed-to-stationarity variables for which their quarterly equivalents observed at the end of each quarter were computed. For each data set we report the results obtained using the dynamic factor model based on one extracted factor and then we check the robustness of these results by reporting those obtained by extracting two factors.

We limit ourselves to the maximum of two extracted factors for the following reasons. First, the estimation sample is rather limited leaving us with 15 observations used for estimation of parameters of the bridging equation (5) in the very beginning of our forecasting exercise<sup>4</sup>. In the end, we have 34 observations for producing the nowcast using the latest available information set—in the last month of the last reference quarter 2009Q2. Hence by keeping the maximum number of factors to two we work with a parsimonious forecasting model and are not exposed to the risk of overfitting the model. Secondly, both Giannone et al. (2008) and Aastveit and Trovik (2007) use models with two common factors. Koop and Potter (2004) also emphasize the importance of parsimony in model selection for forecasting reporting that an optimal number of factors on average is close to two.

### 4.1 Data set with stationary indicators: without EQE-transformation

#### 4.1.1 A factor model with $q = 1, p = 1$

We start the analysis of the forecasting performance of the dynamic factor model with its simplest specification; we allow for one common factor, i.e.,  $p = 1$ , and, correspondingly, one common shock  $q = 1$ , see Equations (3) and (4) describing the model.

Figure 1 reports the relative RMSFE measure of the RMSFE obtained at a given vintage to the RMSFE

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<sup>4</sup>The estimation sample of the bridge equation covers 2000Q4–2004Q2 in order to make the first  $h = 2$  forecast of growth rate in 2005Q1 made in the last month of 2004Q3.

of a naive constant-growth model, estimated using the same period<sup>5</sup>. Each vintage within a given month is labeled by the name of the corresponding block that expands the available information set. Observe that in addition to ten vintages in each month we evaluate also the extent to which changes in forecasting accuracy can be attributed to extending by one quarter the estimation sample used in the forecasting “bridge regression” by incorporating the latest vintage of the quarterly GDP growth rates. We label such vintages as “UPDATE.GDP (h=1)” and “UPDATE.GDP (h=0)” depending on the timing of the GDP update. In this way we verify whether the estimated coefficients of the bridge regression change or not as a result of increasing the estimation sample and of revisions in quarterly growth rates. In case of coefficient instability we would observe large changes in the corresponding values of the RMSFE compared to that observed for the previous data vintage based on the same set of monthly indicators. As shown below the estimated coefficients in the bridge regression practically are not effected by such action.

In order to establish a benchmark for evaluating marginal changes in forecast uncertainty we started with two-quarter ahead forecasts,  $h = 2$ , computed when all data releases for the respective quarter were published. The corresponding relative RMSFE is the first bar on the left side of Figure 1. The next bar “PMGR” corresponds to the model where the factor has been extracted from the data set updated in the beginning of the first month in quarter by incorporating newly released Purchasing Managers’ Index block that typically takes place in the first working day of month, see Table 1. Starting with the bar “PMGR” the relative RMSFE are reported corresponding to one-quarter ahead forecasts produced during the next three months. After these three months the bars correspond to the RMSFE for the models evaluated during the forecast quarter, i.e., nowcasts.

Observe that the relative RMSFE is always less than one implying that our factor model offers an improvement in forecast accuracy over the constant-growth model as far as two quarters ahead. Furthermore, the relative RMSFE have a strong tendency to decrease as more and more information is utilized in making out-of-sample forecasts. In fact, it decreases from 87% for the only two-quarter ahead forecast to 70% for the best one-quarter ahead forecast, and then further to 52% for the best nowcast made in the last month of the reference quarter. According to Figure 1 the biggest marginal decrease in the relative RMSFE occurs when the business tendency surveys “CHINOGA” are incorporated into the model. According to Table 1, these surveys are the first block with zero publication lag, i.e., it is related to the actual month when forecasts being made. All data blocks released prior to “CHINOGA”-block have the publication lag of one month.

So far our results indicate that the largest informational content for forecasting have the business tendency surveys collected at KOF. In order to understand driving forces behind this finding we plotted the (absolute) correlations of extracted factors with the indicators, see Figures 3–5 for correlations with the first, the second, and the third factors, respectively. As seen, there is a strong association of each factor with a particular block(s) of variables. Thus, the first factor exhibits very high correlation with “PMGR”, “LABOUR”, and, especially, with “CHINOGA”, which is the largest block among these three blocks. There also a medium-strength correlation is observed with the block of interest rates. The second common factor primarily

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<sup>5</sup>Using the extended sample starting in 1992Q1 for out-of-sample growth forecasts for a constant-growth model results in practically the same results. Here we use the same estimation sample in order to make the RMSFE obtained by the competing models comparable.

correlates with the stock market indices “STMKT”. Finally, the third factor mostly correlates with the exports-imports indicators although correlation strength is not that large.

Based on the correlation analysis we can readily explain the finding that the block “CHINOGA” has the largest informational content in a given setup. First, this block of the variables exhibits the highest correlation with the first common factor used to produce forecasts. Second, this block is the timeliest one, i.e., in our chronological release sequence it is the first block containing information on the same month when it is released. Hence the fact that newly released information that primarily feeds into the first common factor and in doing so it clearly improves forecast accuracy seems to confirm aspirations of many economists and policy-makers that the qualitative soft data in the form of business tendency surveys provide a useful information on the current as well as future stand of economic activity in a timely manner. This finding also conforms to that reached in Giannone et al. (2008) regarding the importance of surveys for nowcasting the US economy.

#### **4.1.2 A factor model with $q = 2, r = 2$**

In this subsection we investigate the robustness of the obtained results by evaluating forecasting performance of the dynamic factor model with two common factors. Based on the results of the correlation analysis presented above we impose two common factors  $p = 2$  and two common shocks  $q = 2$  that feed into these common factors. Recall that the first common factor is primarily associated with “PMGR”, “LABOUR”, and “CHINOGA” data blocks, whereas the second factor—with the block of stock market indices “STMKT”.

The resulting relative RMSFE are displayed in Figure 2. Several observations can be made. First, adding the second factor to the forecasting model does not change the earlier result on the relatively large importance of surveys. In fact the associated marginal increase in forecast accuracy is much stronger pronounced for all “CHINOGA”-releases within a month except for the release in the last month of nowcasting quarter when no noticeable improvement can be observed. Second, the incorporation of the block of stock market indices “STMKT”, whose components are highly correlated with the second factor, somewhat obscures forecast accuracy in this two-factor model. A likely reason for this surprising finding is that when extracting common factors from the monthly data set we do not perform the transformation suggested in Giannone et al. (2008) that converts monthly time series to its end-of-quarter equivalents. The sensitivity of the results with respect to application of this transformation is investigated in the next subsection.

## **4.2 Data set with stationary indicators: EQE-transformation**

#### **4.2.1 A factor model with $q = 1, r = 1$**

In this section we repeat the forecasting exercise but this time using monthly indicators converted to its end-of-quarter equivalents as advocated in Giannone et al. (2008). Observe that this transformation is applied to all blocks of variables but the “CHINOGA”-block where this transformation appears to superfluous and unnecessary as it only results in much worse forecast performance. As the “PMGR”-block also represents the business tendency surveys we likewise retained untransformed indicators in this block. Although the

question of whether to transform or not to transform the “PMGR”-block is of much less importance due to the fact that it is released after the “CHINOGA”-block and its size is much smaller.

We start with the forecasting model based on one common factor. The corresponding relative RMSFE is displayed in Figure 6. The first observation is that our earlier conclusion on the largest informational content of surveys is no longer supported in this model. In fact, the largest marginal change occurs when the stock market indices are incorporated in the forecasting model. This is true for all months except the last one when inclusion of further data blocks starting with survey-block slightly worsens accuracy of nowcast. The second observation is that the overall forecast accuracy when compared with the one-factor model without such transformation has been boosted. Thus for the two-quarter ahead forecast the relative RMSFE ratio has gone down from 87% to 78%, for the best one-quarter ahead forecast—from 70% to 60%, and finally for the best nowcast—from 52% to 49% with an additional notice that the RMSFE ratio of 49% is achieved in the beginning of the last month of quarter for the model with transformed variables whereas the RMSFE ratio of 52% is achieved in the end of the same month, i.e., at a much later point of time. Figure 7 compares forecast performance of these two models confirming the superior forecast accuracy of the factor model based on the transformed data.

In order to understand the sources of improvement in forecast accuracy we compared correlations of the extracted factor with the transformed indicators, see Figure 8. The corresponding correlation with indicators without EQE-transformation is presented in Figure 9. Observe that in order to facilitate comparison we reported only correlations that in absolute value are larger than the chosen threshold of 0.60 in both figures. The first thing to notice immediately that the first factor in the former model is highly correlated with indicators from all blocks but “RETAIL” and “EXCH.RATE”. This is in sharp contrast to the earlier finding that the first factor mostly correlates with “PMGR”, “LABOUR”, and “CHINOGA” blocks and the selected correlations presented in Figure 9 further emphasize the point. Hence the former model exploits information contained in different blocks composing the large panel to much better extent.

Analysis of correlations suggests also a tentative explanation why the earlier observation presented in Section 4.1.1 on the largest informational content of “CHINOGA”-block is not supported in the current setup but it is rather attributed to “STMKT”-block. According to Figure 8 both “CHINOGA”- and “STMKT”-blocks appear to be the most important blocks that contribute to dynamics of the common factor. Hence the release of “CHINOGA”-block earlier in the month represents only partial information that determines the out-sample dynamics of the common factor, the remaining information is incorporated in the model only when “STMKT”-block is released, jointly leading to improved forecast accuracy.

We also would like to make a comment regarding performance of the Purchasing Managers’ Index (“PMGR”) block. According to both Figures 8 and 9 the variables in this block exhibit very high correlation with the extracted factor. Hence it appears to be a highly relevant indicator that deservingly attracts a lot of attention both by practitioners as well as by the media whenever it is released. In current setup we, however, did not find that this block has a significant impact on forecast accuracy. This can be traced to the fact that its release takes place more than two weeks later than the release of “CHINOGA”-block and is barely preceded by incorporation of “STMKT”-block into the forecasting model. Hence the information

contained in “PMGR”-block is likely to be already accommodated in the forecasting model at the moment of its release.

#### 4.2.2 A factor model with $q = 2, r = 2$ and $q = 1, r = 2$

In this section we investigate the forecasting performance of factor models with two factors. More specifically, first consider a model where we impose two common shocks  $q = 2$  as well as two common factors  $r = 2$ , similarly to the analysis reported in Section 4.1.2. Secondly, we consider an intermediate-case model with one common shock feeding into two common factors, i.e., imposing  $q = 1, r = 2$ . The forecast performance evaluation for the former and the latter models compared to that of the more parsimonious model with  $q = 1, r = 1$  considered in the previous section is presented in Figures 10 and 11, respectively. The main conclusion drawn from these figures is that inclusion of the second factor into the forecasting model only resulted in the inferior forecasting performance compared to a single-factor model. This implies that in a given setup the common dynamics in our panel which is relevant to forecasting GDP is well captured by the first common factor. This conclusion is also supported by the fact that in the forecasting “bridge regression” the second factor was found to be insignificantly different from zero at the usual levels.

## 5 Forecasting GDP during the current crisis

In this section we further investigate how the factor model in its preferred specification performed during the whole forecast sample paying a special attention to its ability to forecast the Swiss GDP during the current crisis. The relevant information is displayed in Figure 12. The upper panel of Figure 12 displays all vintage-specific forecasts, whereas the lower panel contains the variance of quarter-specific forecasts across all vintages, measuring response sensitivity of subsequent forecasts to the continuous flow of new information. It is striking to observe that during the pre-crisis period the computed dispersion has been largely constant whereas since 2008Q4 we observe a sharp increase in forecast responsiveness to new pieces of information illustrating the rapidly unfolding crisis triggered by the unexpected collapse of the Lehman Brothers in the middle of September 2008. This can be traced to the fact that the set of predictions for 2008Q4 consists both of the forecasts made prior to the bankruptcy of the Lehman Brothers as well as of the nowcasts made in the aftermath period. The high variability of forecasts has been retained in the following quarter 2009Q1 with subsequent decrease in 2009Q2 towards the pre-crisis level. Although it is difficult to generalize based on the experience from the single crisis our results indicate that this pattern may tentatively be used as an additional crisis indicator signalling rapid changes in the economic activity.

Finally, in Figure 13 we provide the actual values of the first release of the quarterly GDP and the forecasts from the preferred model produced during the vintage “UPDATE.GDP(h=0)” that corresponds to the lowest relative RMSFE observed, see Figure 7. The timing of this vintage is the very beginning of the last month of forecast quarter corresponding to nowcasts. We find that our nowcasts can rather good trace the actual growth rate. With respect to the predicting the current crisis we notice that our nowcasts correctly predict the negative quarterly growth rates in the last three quarters—2008Q4, 2009Q1, and 2009Q2—of our

forecast sample, although it is slightly optimistic in 2008Q3. It is remarkable that the overall good nowcast performance of the factor model has been achieved without any pre-selection of the indicators based, for example, on correlation strength with the reference variable or any other pre-selection procedure suggested in the literature (e.g., see Siliverstovs and Kholodilin, 2009; Bai and Ng, 2008; Boivin and Ng, 2006).

## 6 Conclusion

In this paper we utilize the dynamic factor model based on 562 monthly indicators for now-/forecasting the quarter-on-quarter growth rates of seasonally adjusted GDP in Switzerland. To the best of our knowledge our study represents the first attempt to employ this sort of models for predicting Swiss GDP. We find that the preferred version of the dynamic factor model offers substantial improvement in forecast accuracy when compared to that based on a naive constant-growth model. The highest forecast accuracy of the first official release of GDP growth rates for an actual quarter is achieved about three months before the release takes place. The corresponding ratio of the RMSFE of the factor model to that of the benchmark model is 49%.

Furthermore, we use the factor model in order to investigate the informational content of subsequent data releases of various macroeconomic variables. To this end, we perform a pseudo-real-time exercise where we simulate the asynchronous pattern of within-month releases of various blocks of data. We find that both business tendency surveys and stock market indices have the most informational content for predicting GDP in Switzerland. However, we must issue a warning here that the outcome in such exercises may crucially depend on the applied transformation of the monthly indicators—a topic that, in our view, largely seems to be overlooked in the routine applications involving large data sets. For example, we find that the largest marginal impact on forecast accuracy is attributed to surveys in the model where the monthly indicator were not subject to the end-of-quarter transformation. In the factor model where such transformation was applied we find that the largest informational content is attributable to the stock market variables.

We also find out that different transformations of the variables may not only result in different ranking of the importance of difference data blocks for forecasting GDP but also may influence the overall forecasting performance of the factor model. Thus, for our data set at hand we find out that the best forecasting results are achieved in the model where a single factor is extracted from the panel where the monthly survey indicators did not undergo any transformation (neither stationarity-related nor end-of-quarter equivalents) whereas the remaining blocks including the block of stock market indices undergo both types of transformation.

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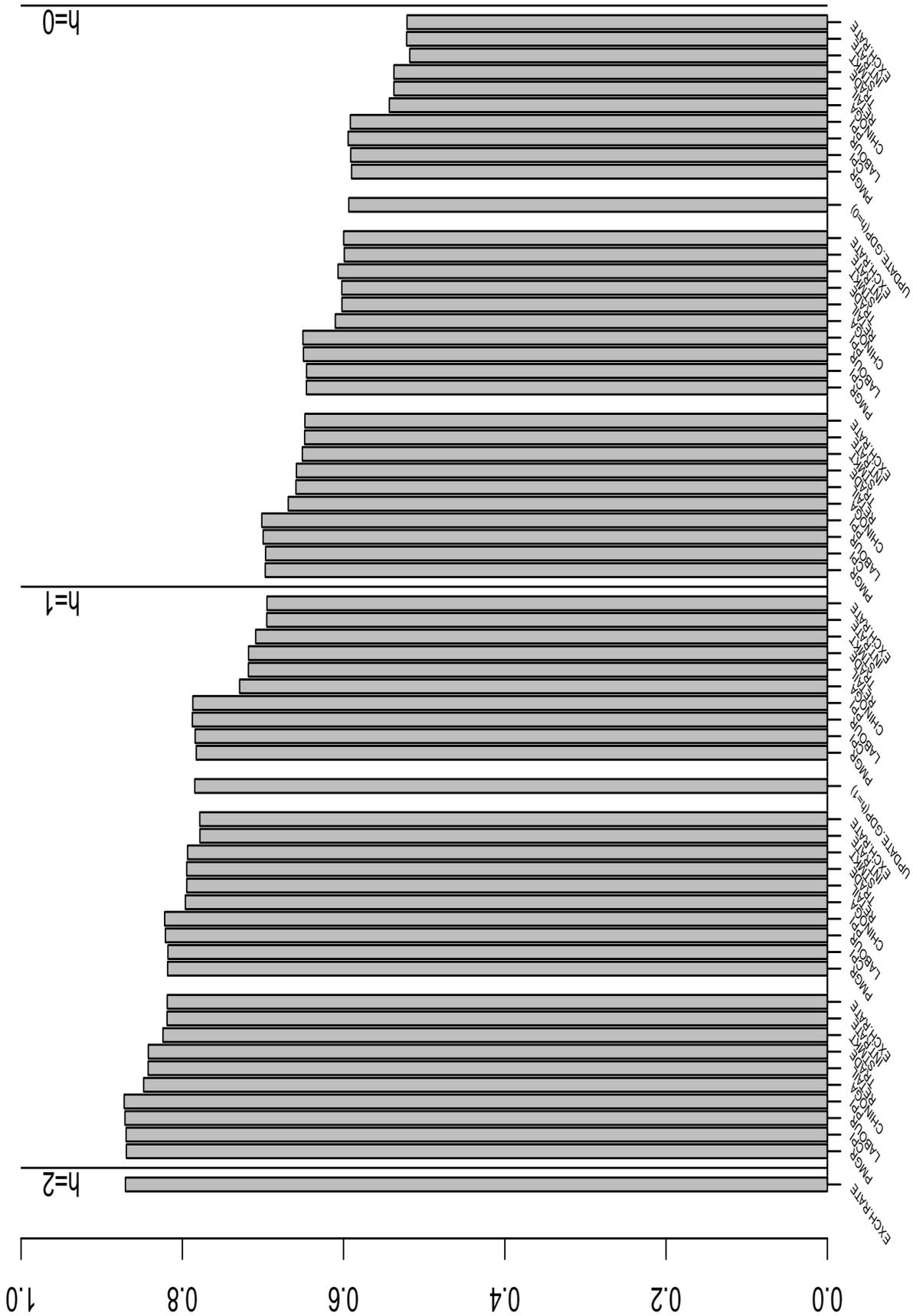


Figure 1: Relative RMSFE: Factor model  $q = 1, r = 1$  (without EQE-transformation) to a constant-growth model: 2005Q1–2009Q2

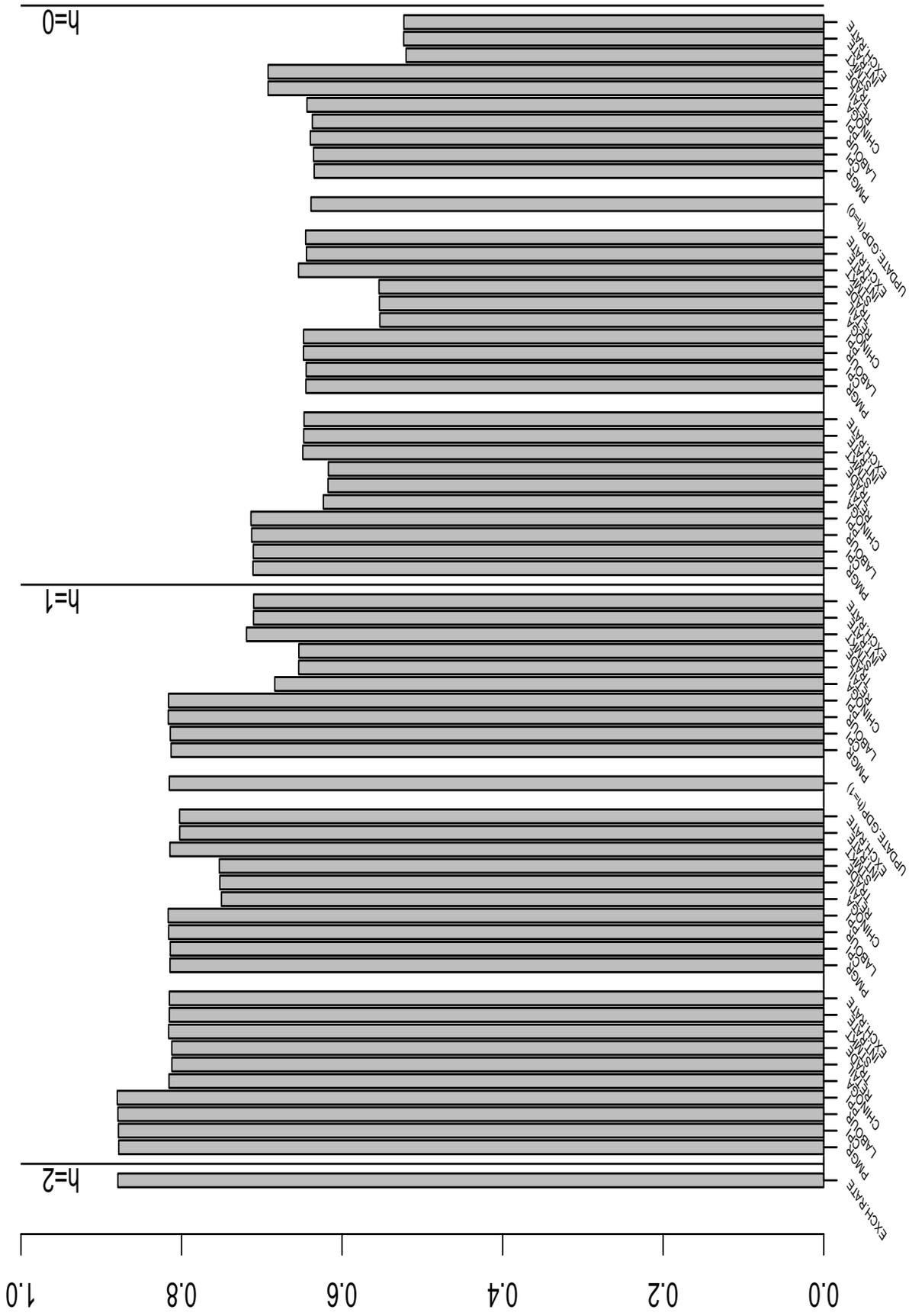


Figure 2: Relative RMSFE: Factor model  $q = 2, r = 2$  (without EQE-transformation) to a constant-growth model: 2005Q1–2009Q2

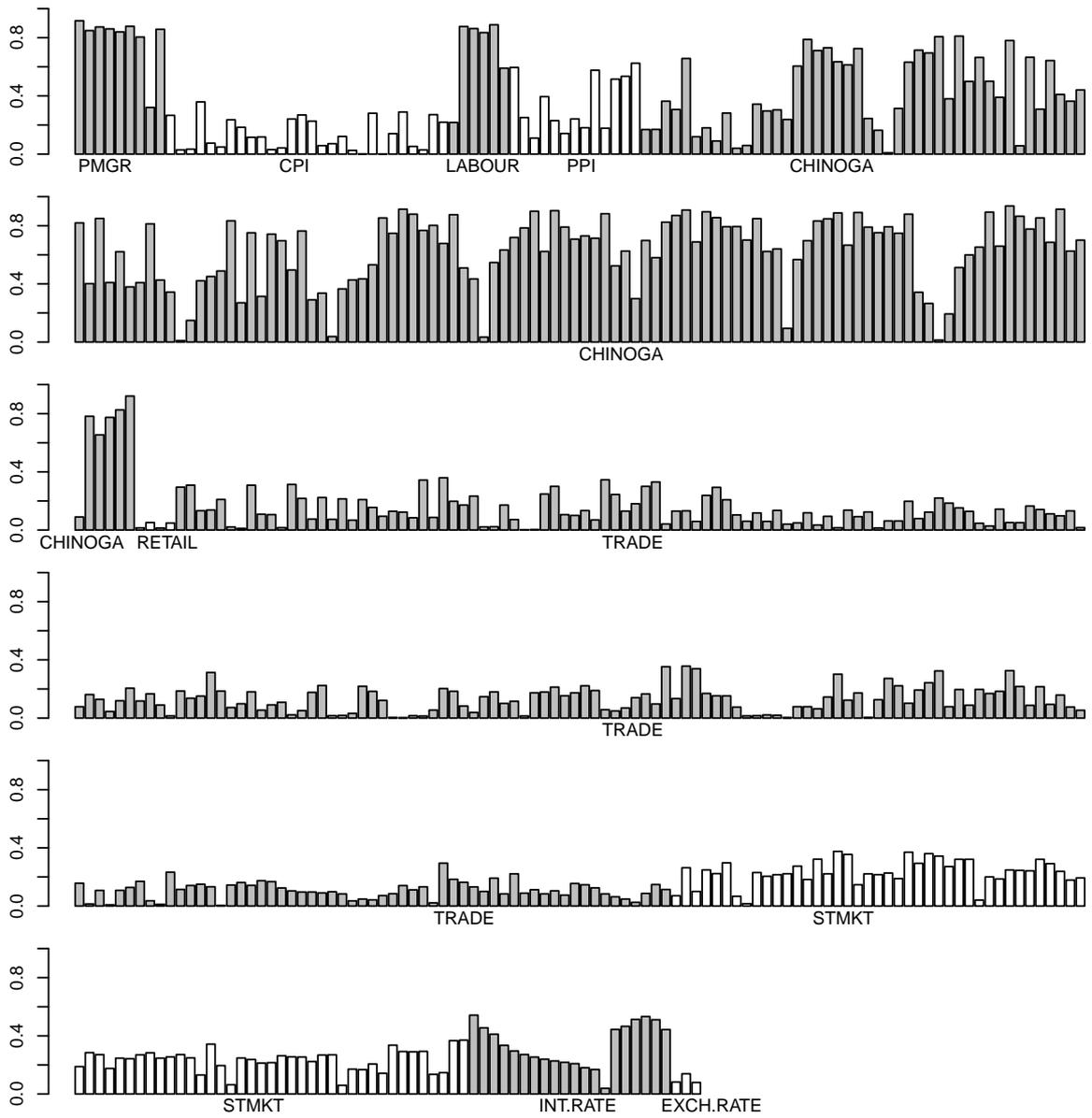


Figure 3: Stationary monthly indicators (without EQE-transformation); Correlation with the first factor: 2000M10–2009M6

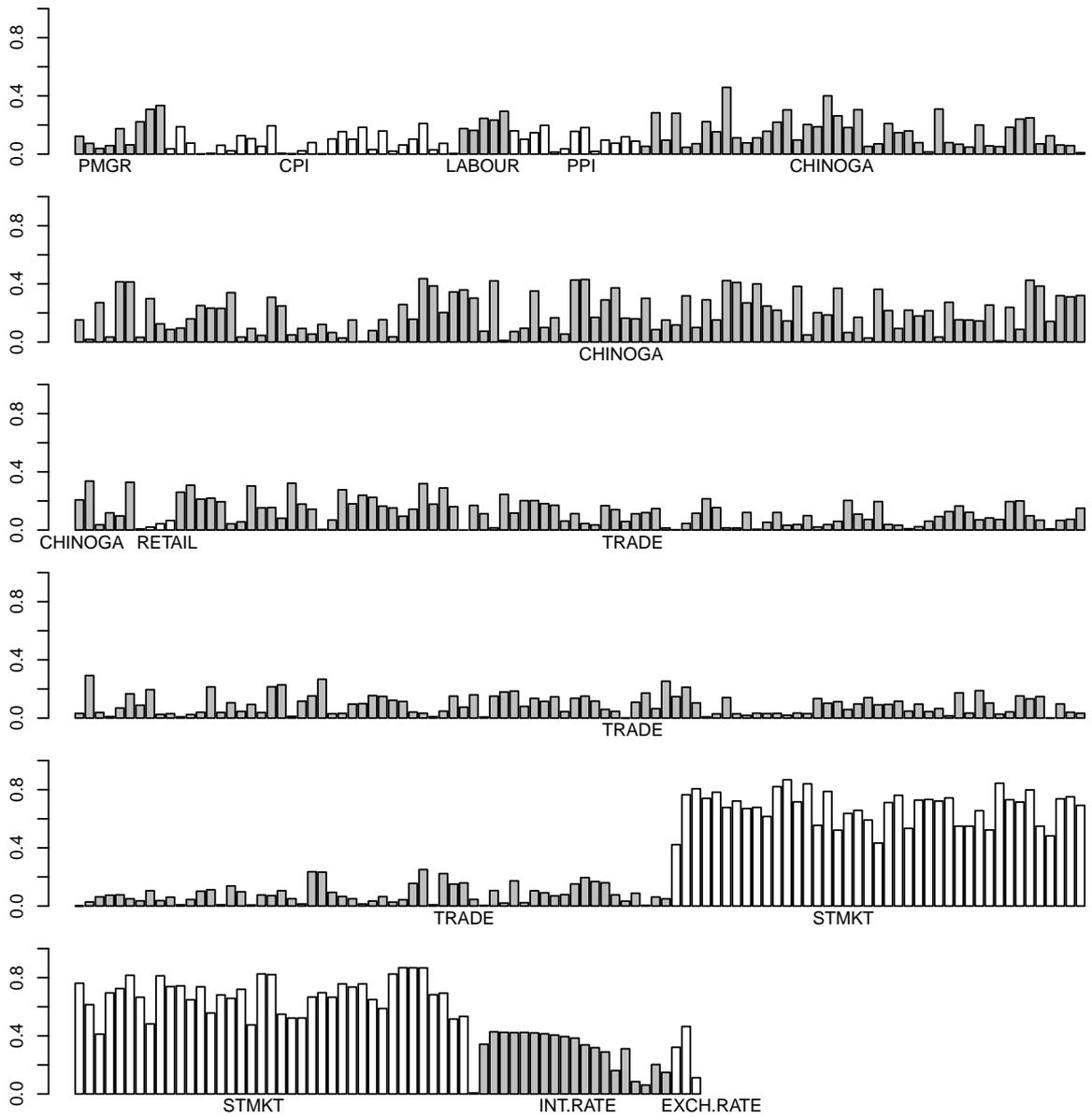


Figure 4: Stationary monthly indicators (without EQE-transformation); Correlation with the second factor: 2000M10–2009M6

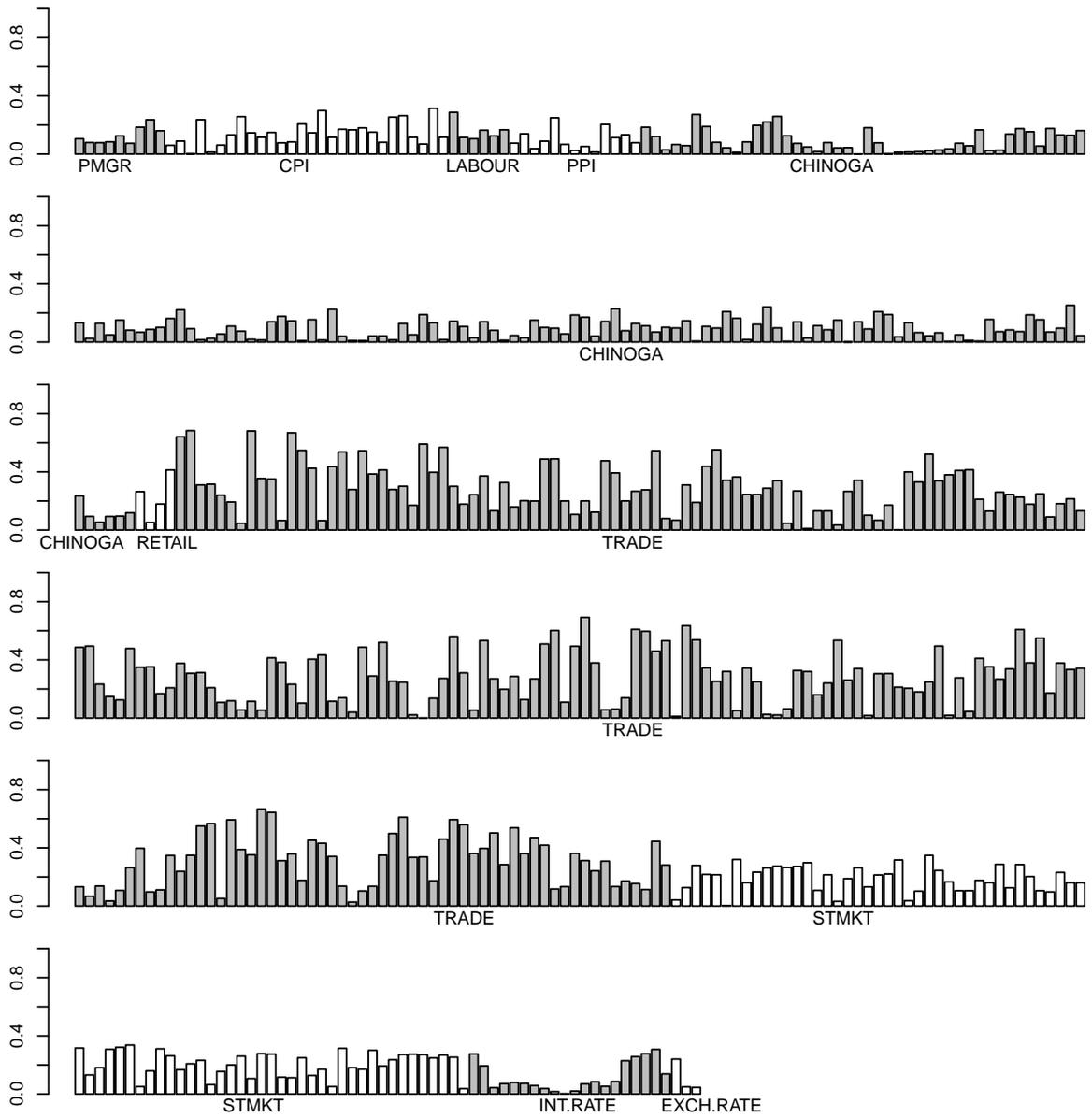


Figure 5: Stationary monthly indicators (without EQE-transformation); Correlation with the third factor: 2000M10–2009M6





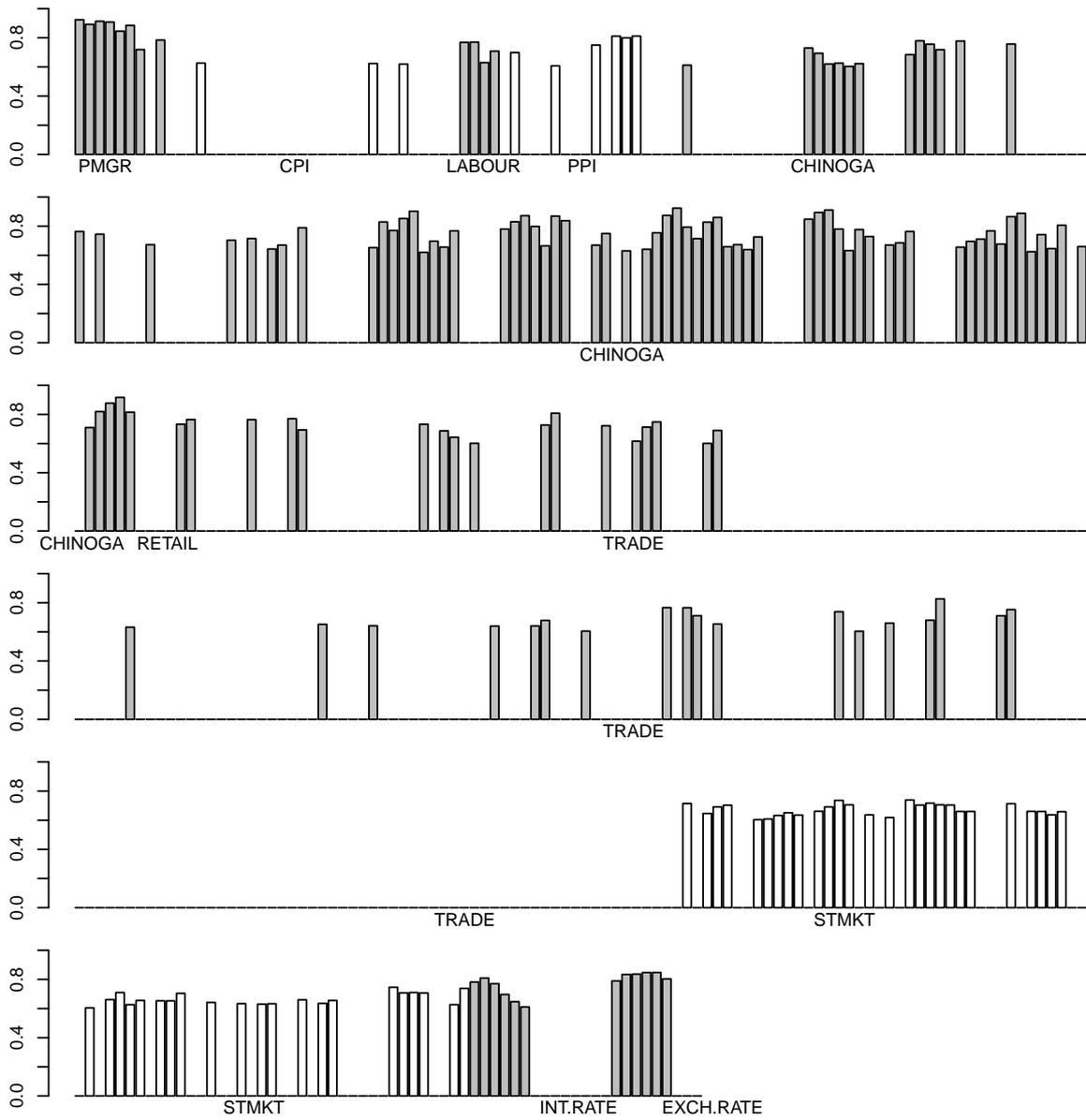


Figure 8: Stationary monthly indicators (with EQE-transformation); Correlation coefficient larger than 0.60 with the first factor: 2000M10–2009M6

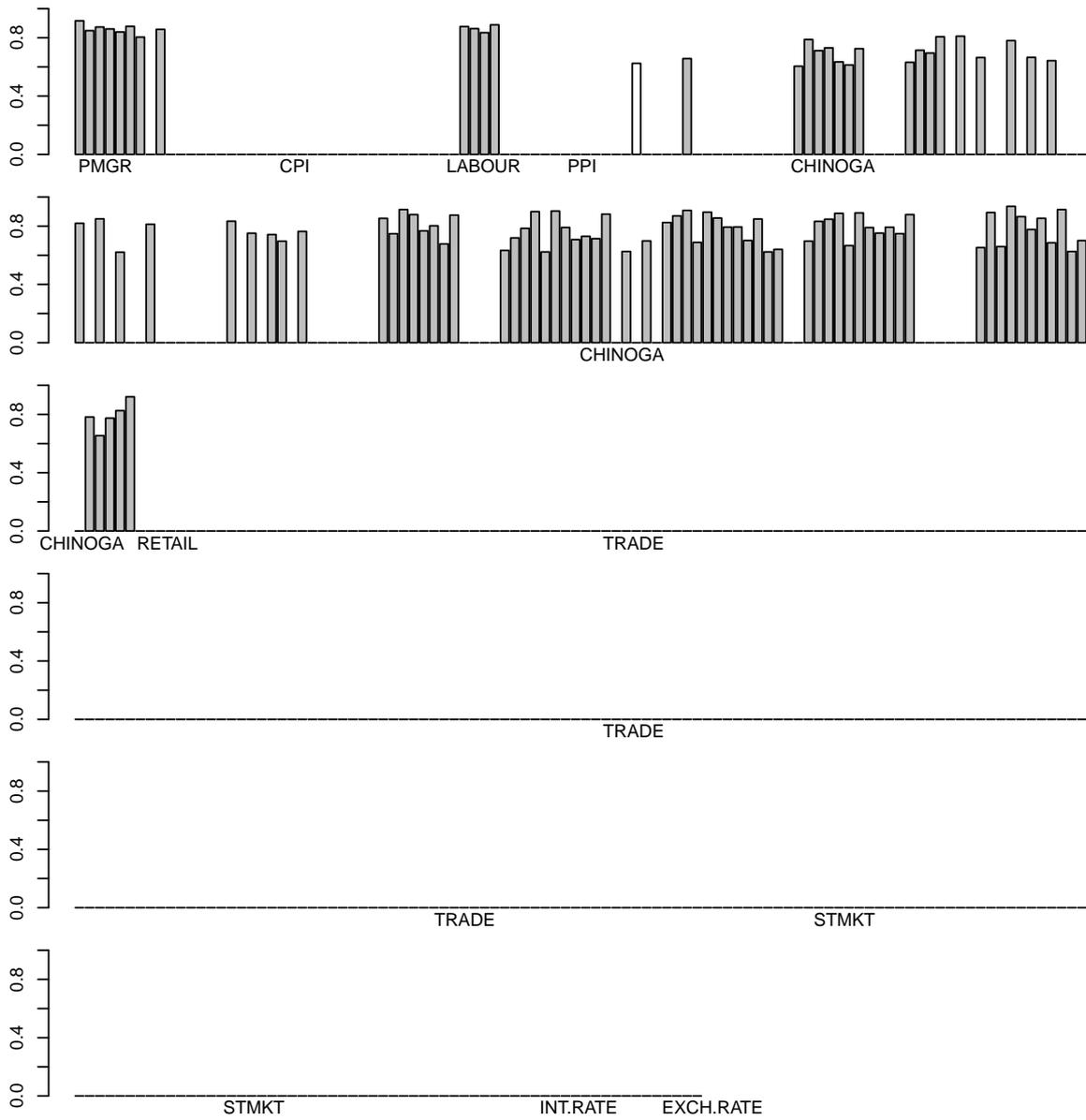


Figure 9: Stationary monthly indicators (without EQE-transformation); Correlation coefficient larger than 0.60 with the first factor: 2000M10–2009M6



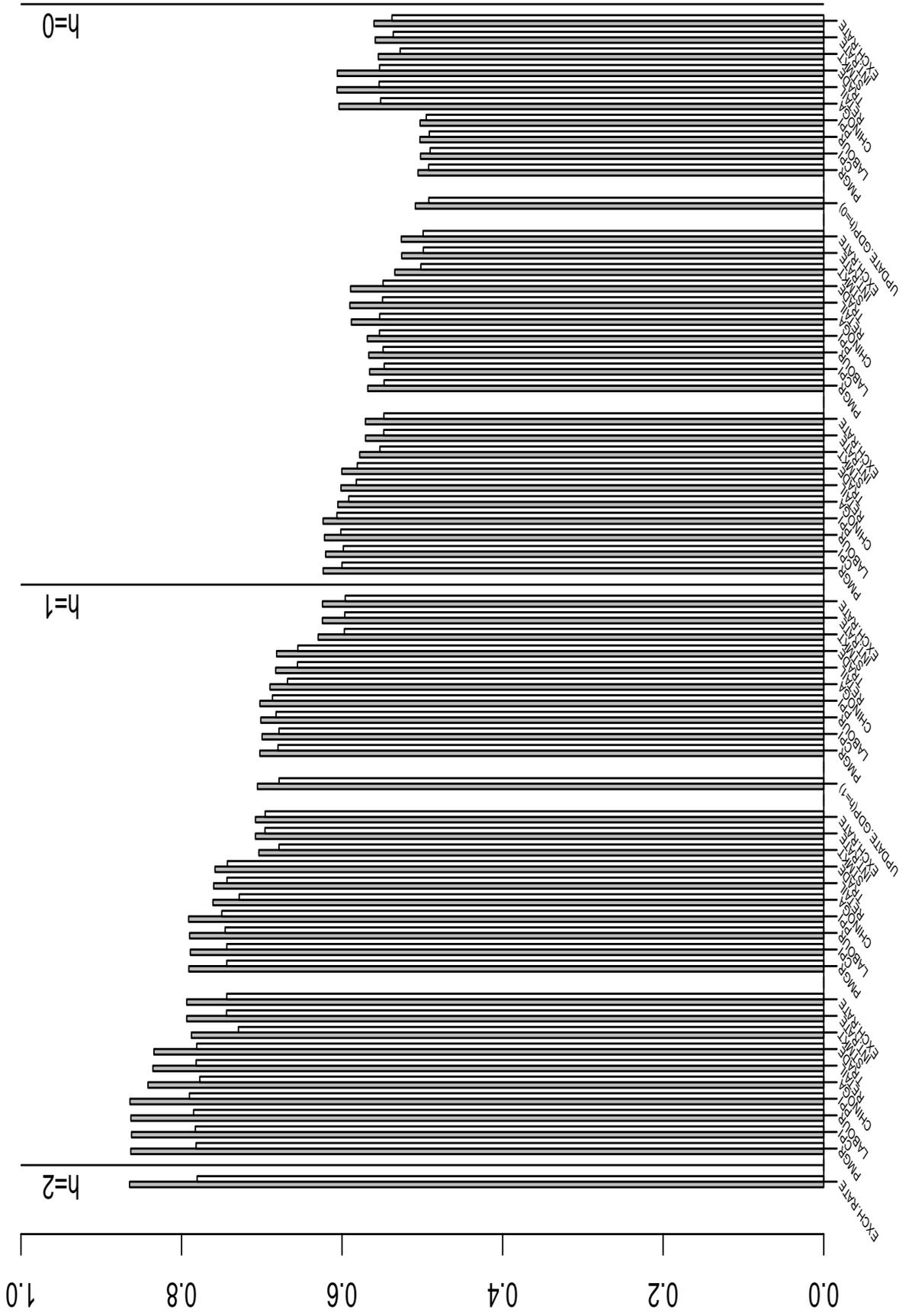


Figure 11: Relative RMSFE: Factor models  $q = 2$ ,  $r = 1$  (“filled bars”) and  $q = 1$ ,  $r = 1$  (“empty bars”) (with EQE-transformation) : 2005Q1–2009Q2

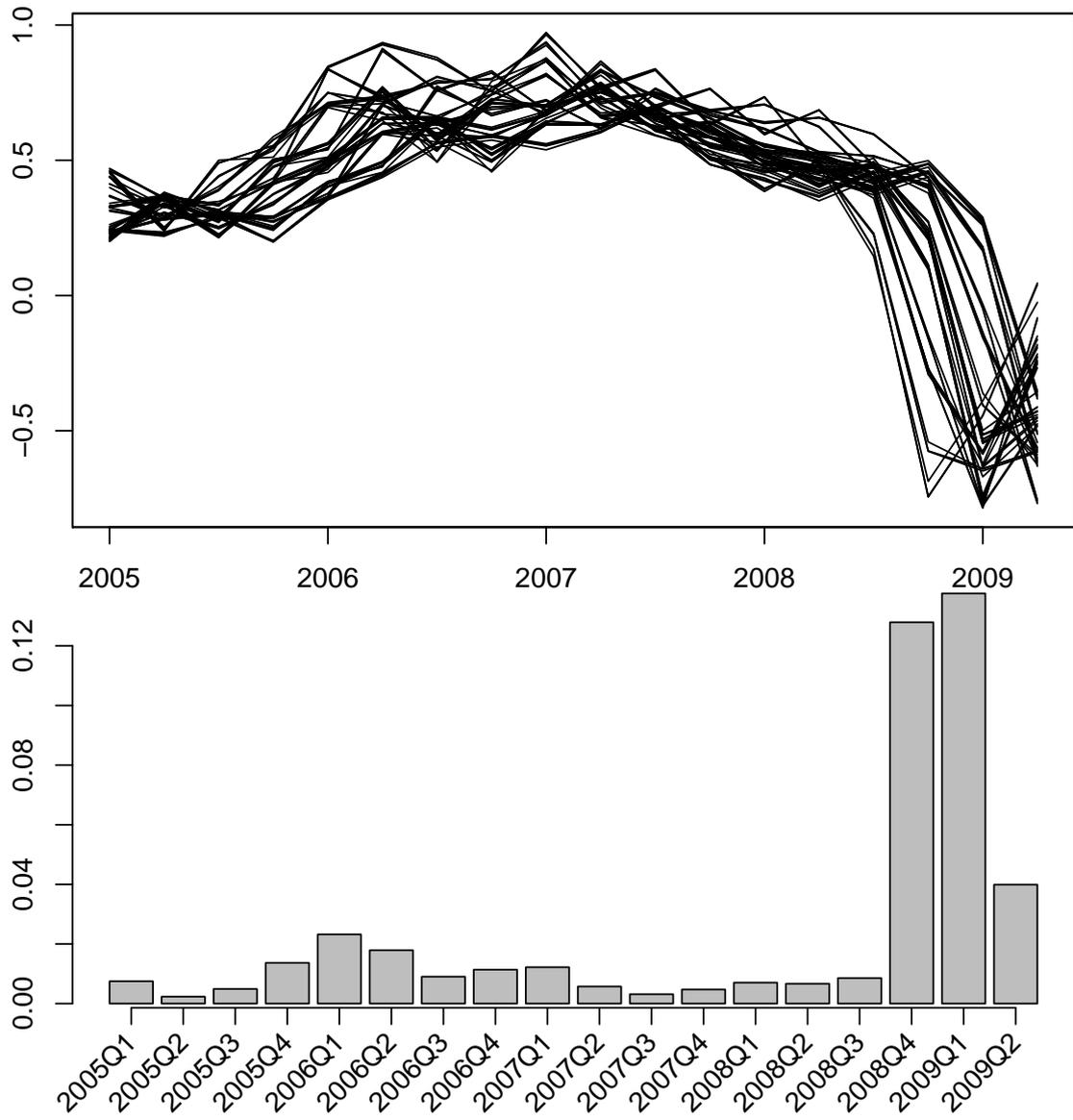


Figure 12: Vintages-specific forecasts from the best single-factor model  $q = 1, r = 1$  (the upper panel); Variance across all vintage-specific forecasts for a given quarter (the lower panel)

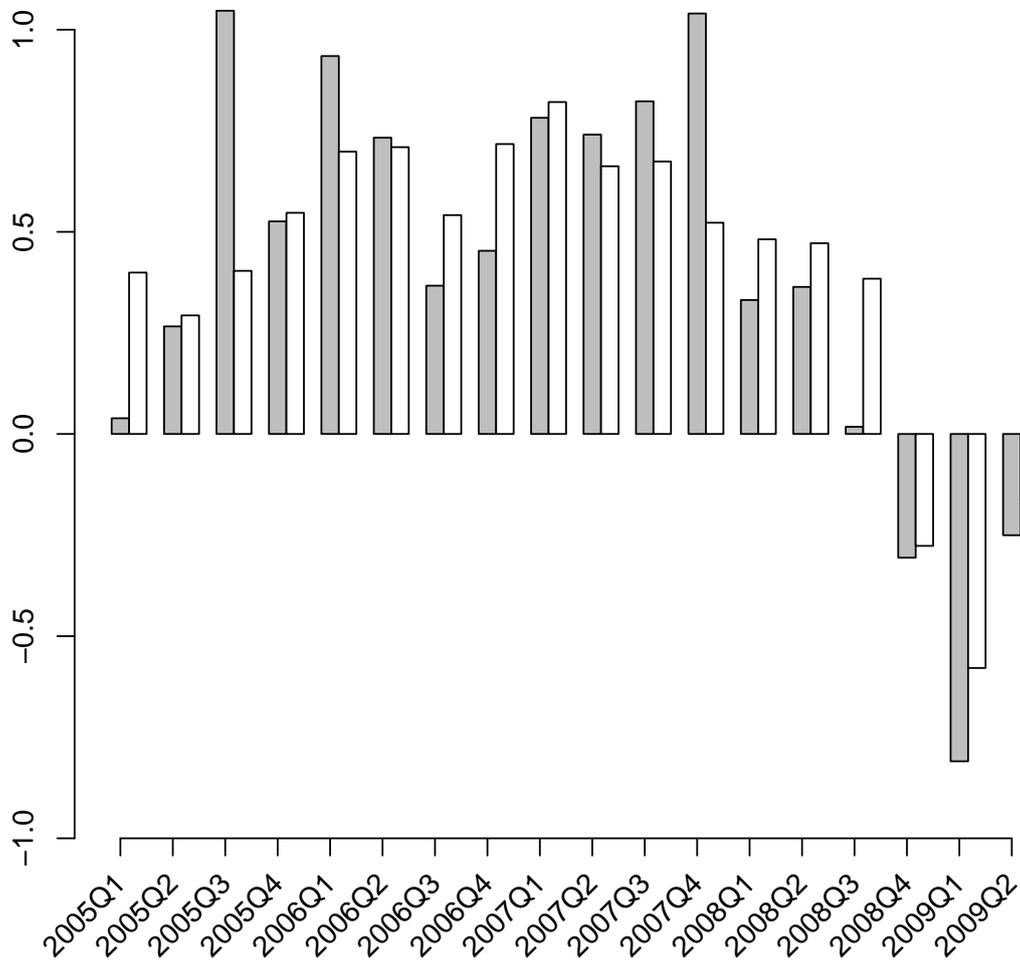


Figure 13: First-available GDP growth rates (seas.adj., q-on-q) (“filled bars”) and forecasts from the best single-factor model  $q = 1, r = 1$  (“empty bars”); vintage “UPDATE.GDP(h=2)”

Table 1: Chronology of data releases during the month

Block	Published by	Timing (approx.)	Publication lag (in months)	Block size
PMGR-manufacturing	Credit Suisse	1st working day of month	1	9
CPI	Swiss Federal Statistical Office	First week of month	1	28
Labour	State Secretariat for Economic Affairs	Second week of month	1	6
PPI	Swiss Federal Statistical Office	Second week of month	1	13
BTS in manufacturing	KOF Swiss Economic Institute	Middle of month	0	150
Retail	Swiss Federal Statistical Office	Middle of month	2	4
Exports/Imports	Swiss Federal Customs Administration	Middle of month	1	249
Stock market indices	Datastream	Last day of month (monthly average)	0	80
Interest rates	Datastream	Last day of month (monthly average)	0	20
Exchange rates	Datastream	Last day of month (monthly average)	0	3

The chronological sequence of block releases has been recorded in October 2009. We proceed under assumption that such ordering and timing has been constant over time. However, we readily acknowledge that the actual timing and ordering may slightly vary.