Short-term forecasting with mixed-frequency data: A MIDASSO approach*

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Abstract

In this paper we extend the targeted-regressor approach suggested in Bai and Ng (2008) for variables sampled at the same frequency to mixed-frequency data. Our MIDASSO approach is a combination of the unrestricted MIxed-frequency DAta-Sampling approach (U-MIDAS) (see Foroni et al., 2015; Castle et al., 2009; Bec and Mogliani, 2013), and the LASSO-type penalised regression used in Bai and Ng (2008), called the elastic net (Zou and Hastie, 2005). We illustrate our approach by forecasting the quarterly real GDP growth rate in Switzerland.

Keywords: Forecasting, MIDAS, LASSO, real-time data, Switzerland

JEL code: C22, C53

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1 Introduction

The outbreak of the Great Recession in 2008-2009 significantly spurred interest in continuous monitoring of economic conditions and their accurate short-term forecasting. In this respect the use of much earlier available economic and sentiment indicators for inferring official statistical data, typically released with a substantial publication delay, is crucial. Such inference is further complicated by an important constraint that forecasting practitioners face, namely, the fact that economic data are sampled at different frequencies. For example, GDP figures are released every quarter, whereas economic indicators are published at the monthly, or even higher, frequency. Hence, much of the recent research has been focusing on how to bridge this discrepancy in data sampling frequencies in some optimal way.

In this paper we likewise address this problem and suggest a simple and robust approach for short-term forecasting with mixed-frequency data sets. Our approach, to which we refer as MIDASSO in sequel, is based on combination of the two recent advances in econometrics of big data and mixed-frequency data sets. The first methodology, advanced in Bai and Ng (2008), is the use of targeted predictors for forecasting variables of interest. The main idea of Bai and Ng (2008) is that prior to extracting diffusion indices from large panels of economic indicators, a pre-selection of most relevant indicators for a particular target variable is highly advisable. For example, for forecasting GDP growth in the current quarter it is reasonable to rely more on coincident indicators, whereas for forecasting GDP growth in a more distant future more weight should be put on leading economic indicators. More generally, by including too many irrelevant and noisy indicators in the information set may result in suppressing the signal-to-noise ratio in the data, and hence obscure accurate signal detection leading to worsening of forecast quality. Bai and Ng (2008) suggest to use penalized least squares regressions—a so-called elastic net—that can be formulated in terms of the Least Absolute Shrinkage and Selection Operator (LASSO) of Tibshirani (1996), for a pre-selection of so-called targeted predictors that are most relevant for a specific variable of interest.

The modelling approach of Bai and Ng (2008) is applied to single-frequency (monthly) data but as it will be shown in our paper, its extension to mixed-frequency data sets is straightforward. To do so, we will rely on recently proposed unrestricted MIDAS (U-MIDAS) regressions (Foroni, Marcellino, and Schumacher, 2015) as a simple variant of the sophisticated MIDAS approach of Ghysels, Santa-Clara, and Valkanov (2004) and Ghysels, Sinko, and Valkanov (2007). Both the classical and the U-MIDAS regressions are based on the skip-sampling procedure, when a time series observed at the higher frequency is converted to a number of lower-frequency time series. For example, in case of variables observed at the monthly and quarterly frequencies, the monthly indicators are broken into three quarterly time series, each retaining the corresponding values in first, second and third months of each quarter in the sample. The difference between the MIDAS regressions of Ghysels et al. (2004) and Ghysels et al. (2007) and U-MIDAS regressions is that the latter is based on the direct estimation of the coefficients of the skip-sampled time series by means of ordinary least squares, whereas the former approach involves the use of tightly specified functional lag polynomials, e.g., exponential Almon lag polynomials or Beta probability density functions, and the subsequent need for non-linear optimisation techniques for coefficient estimation.

The rest of the paper is organised as follows. The next section contains an overview of the relevant literature as well as a detailed motivation for our modelling approach. We give a more formal econometric presentation of the MIDASSO approach in Section 3. In Section 4 we present empirical data used in order to illustrate our approach. In Section 5 results are presented. The final section concludes.

2 Literature overview

In the earlier literature the use of so-called "bridge" models was popular (Baffigi et al., 2004). In these models higher frequency variables were converted to lower-frequency variables by averaging over values available for a low-frequency time unit. In case of monthly and quarterly frequencies this amounts to taking average value of the monthly observations in each quarter. Another, more flexible, approach to linking monthly and quarterly variables was suggested in Koenig et al. (2003). Koenig et al. (2003) use the logarithmic approximation expressing quarterly growth rates of the dependent variable in terms of underlying monthly growth rates of coincident economic indicators available at the monthly frequency.[1] A slight modification of the approach undertaken in Koenig et al. (2003) is suggested in Castle et al. (2009), where each monthly variable is split into three quarterly time series, each corresponding either to the first, second, or third month of the quarters in the sample. The approaches of Koenig et al. (2003) and Castle et al. (2009) in dealing with variables observed at mixed frequencies is that a standard OLS regression can be used in order to estimate model parameters at the cost of a slight inflation of a number of explanatory variables. Following Bec and Mogliani (2013), this approach is referred to as the *blocking* approach in line with the terminology stemming from the control engineering literature (Chen et al., 2012). The blocking approach also relaxes the implicit restriction in the bridge equation that equal weights are imposed on the monthly observations in each quarter for every converted high-frequency variable in the OLS regression.

Ghysels et al. (2004) and Ghysels et al. (2007) observe that when discrepancy between frequencies is large, for example, when dealing with monthly and daily data, splitting one high-frequency variable into a number of low-frequency variables significantly inflates the number of explanatory variables leading to a so-called curse of dimensionality. This problem is further aggravated if more than one explanatory variable is available. The solution suggested in Ghysels et al. (2004) is to combine the blocking approach with the traditional literature on lag polynomials labelled by the authors as a MIxed-frequency DAta-Sampling (MIDAS) approach. The use of lag polynomials—e.g., an exponential Almon lag polynomial—solves the curse of dimensionality by controlling the weights on converted explanatory variables through a relatively small number of hyper-parameters

[1] See also Mariano and Murasawa (2003) for the use of the same approximation in order to link quarterly and monthly variables in the small-scale dynamic factor model put into the state-space form with unobserved factor and estimated using the Kalman filter.

determining the shape of the corresponding lag polynomial. However, this comes at a cost of using non-linear least squares instead of the standard OLS regression in order to estimate model parameters. Foroni et al. (2015) observe that the gains from using lag polynomials are most likely to materialise when dealing with variables observed with large difference in sampling frequency. In cases with the small discrepancy in the sampling frequency, like quarterly and monthly, where parameter inflation is correspondingly relatively small, the likely gains are relatively small compared to increase in estimation complexity from using non-linear least squares and suggest to use a so-called unrestricted MIDAS (U-MIDAS) model, which exactly corresponds to the blocking approach described above.

In most empirical applications univariate models using the mixed-frequency variables, especially those that use lag polynomials, are estimated using one (e.g. Clements and Galvão, 2008, 2009) or at most a handful (Koenig et al., 2003) of explanatory variables. In the former case it is related to the convergence problems of the non-linear numerical optimisation methods and in the latter case—to parameter inflation. Consequently, when dealing with large data panels some model or variable combination schemes need to be employed in order to produce viable forecasts of macroeconomic variables, for example, GDP growth. One approach undertaken in Drechsel and Scheufele (2012) is to estimate univariate MIDAS models linking observed GDP variables with one monthly explanatory variable and then use model combination schemes in order to come up with a single forecast for GDP growth. A different approach is undertaken in the two-step procedure of Marcellino and Schumacher (2010) labelled as a Factor-Augmented MIDAS (FAMIDAS) approach, where in the first step common factors are extracted from the panel of monthly variables and in the second step the MIDAS regression is carried out linking quarterly GDP observations and the extracted monthly common factors.

In case when large-scale data sets of explanatory variables are available, it may be beneficial before extraction of common factors used in forecasting to pre-select the most relevant variables first rather than extract common factors from all available variables. For example, Bai and Ng (2008) propose to use a penalised regression technique in order to pre-select the most relevant variables prior to factor extraction. In other words, the explanatory variables are targeted to retain the best predictors of the dependent variable. Bai and Ng (2008), however, carry out their exercise in a single-frequency case. To the best of our knowledge, Marsilli (2014) and Bulligan et al. (2014) were the first to extend the targeted-predictors approach of Bai and Ng (2008) to data with non-homogeneous sampling frequencies.

In particular, Marsilli (2014) suggests two approaches for variable selection within the MIDAS framework. The first approach is to combine the MIDAS regression of Ghysels et al. (2004) and the LASSO estimator put forward by Tibshirani (1996), where the term LASSO is deciphered as the Least Absolute Shrinkage and Selection Operator. The resulting model is referred to as the LASSO-MIDAS model. Observe that the LASSO-MIDAS model retains the non-linear specification of the MIDAS regression and relies on the optimisation algorithm of Nesterov (2005) to the LASSO-defined objective function. The second variant of targeted-predictors approach, suggested in Marsilli (2014), is an application of the Bayesian technique based on the stochastic search variable selection method, referred as the BAYESIAN-MIDAS Stochastic Search method. Model specification as well as estimation is carried out in one step by means of a computer-intensive Gibbs sampling. In our opinion, the reliance on the non-linear optimisation algorithms in the former case and compute-intensive estimation technique in the latter case restricts the applicability of these approaches to data panels of small to moderate sizes. Indeed, the illustration of these two approaches is based on the use of only 24 explanatory variables employed for prediction of US GDP growth.

Bulligan et al. (2014) suggest an alternative approach for predictive regressions with mixed-frequency data. However, their method is heavily influenced by the bridge-equation literature. Bulligan et al. (2014) solve the temporal aggregation problem by simply taking quarterly averages of monthly economic indicators at hand—a typical procedure when running bridge regressions.

In doing so, they effectively set aside the whole MIDAS-related literature. In the second step, a targeted-predictors approach of Bai and Ng (2008) can be straightforwardly implemented since now both a target variable and the potential predictors are available at the same quarterly frequency. In addition, Bulligan et al. (2014) acknowledge the fact that in real-time forecasting one has to deal with the problem of the "ragged-edge" data caused by staggered data releases and by the fact that forecasts are often made in the middle of a quarter, i.e. when not all monthly values of a time series are available. In order to achieve a balanced panel, allowing to take quarterly averages, Bulligan et al. (2014) fill in missing observations by means of predictions from univariate autoregressive models. The approach of Bulligan et al. (2014) can be used for large data panels. Bulligan et al. (2014) use 247 indicators to select from for predicting the growth rate of Italian GDP and its demand-side subcomponents. Girardi et al. (2014) provide another application of the Bulligan et al. (2014) procedure to forecasting Euro area GDP growth based on 259 indicators.

Rather than relying on the output of penalised regressions, Rünstler (2010) suggests an alternative method for selecting most informative indicators that is based on the forecast weights of individual indicators derived from the Kalman smoother recursions. Correspondingly, only indicators with relatively high forecast weights are retained in the model.

In this paper we likewise suggest to extend the targeted-predictor approach of Bai and Ng (2008) to modelling mixed-frequency data. However, in contrast to the LASSO-MIDAS model of Marsilli (2014) our modelling approach does not require non-linear optimisation techniques and solely relies only on closed-form solution techniques for variable selection and parameter estimation of the forecasting model. This ensures its fast and efficient implementation. In comparison to the approach undertaken in Bulligan et al. (2014), we adopt a blocking approach, typically used in MIDAS regressions, as a less restrictive temporal aggregation alternative than taking quarterly averages. In addition, rather than relying on the univariate autoregressive predictive models to fill in missing observations at the end of the sample, we adopt the procedure of Giannone et al. (2008), based on the estimation of a dynamic factor model, that allows us to efficiently utilise multivariate information in order to extract common factors from data panels plagued by the “ragged-edge” problem.

In the nutshell, our approach to predictive regression with mixed-frequency data is based on a combination of a number of well-known and widely applied econometric techniques. In the first step, we transform monthly variables into their quarterly counterparts by resorting to the blocking or U-MIDAS, using the terminology of Foroni et al. (2015), approach. Then, following Bai and Ng (2008) and Schumacher (2010), we suggest to apply the least angle regression with elastic net (LARS-EN), which as discussed in Bai and Ng (2008) can be reformulated as LASSO, in order to preselect the most informative variables for a target variable in question. Third, we extract common factors from targeted predictors by means of the the two-step procedure of Giannone et al. (2008), effectively dealing with ragged-edge data. As the result of application of the Giannone et al. (2008) procedure we obtain estimates of common factors not only in- but also out of sample. Hence, out-of-sample forecasts of the variable of interest can be based on its projection on the estimated factors at a chosen forecast horizon. We label this approach to modelling mixed-frequency data as the MIDASSO approach in order to distinguish it from the LASSO-MIDAS model of Marsilli (2014). In the next section, we give a more formal econometric description of the MIDASSO approach.

3 Econometric methodology

3.1 Targeted-predictors approach for single-frequency variables

Let $t = 1, 2, ..., T-1, T$ denote a time scale at the quarterly frequency at which we observe a target variable y_t. For now, we can also assume that potential predictors, collected in $N \times 1$ vector X_t, are also available at the quarterly frequency. Bai and Ng (2008) propose to apply a penalized regression to the following forecasting model

$$y^h_{t+h} = \alpha' W_t + \gamma' X_t + \epsilon_{t+h}, \tag{1}$$

where W_t is a vector of predetermined regressors like a constant and lagged values of the dependent variable. Equation (1) is specified according to the direct forecasting approach (see discussion in Marcellino et al., 2006) directly relating the dependent variable of interest to observed values of W_t and X_t. Note that the model specification is specific for every forecasting horizon, h. The penalized regression—a so-called elastic net of Zou and Hastie (2005)—is capable not only to estimate slope parameter but also remove irrelevant regressors, i.e., perform variable selection. The corresponding optimization problem is

$$\widehat{\beta}(\lambda_1, \lambda_2) = \arg\min_{\beta} \left\{ RSS + \lambda_2 \left\| \beta \right\|^2 + \lambda_1 \left\| \beta \right\|_1 \right\}, \tag{2}$$

where RSS is the residual sum of squares of Equation (1) and $\beta = (\alpha', \gamma')'$. For a fixed value of λ_2, this minimisation problem can be reformulated in terms of the LASSO estimator of Tibshirani (1996) and the efficient algorithm based on the least angle regression can be used in order to estimate model parameters. The optimal value of λ_1, governing the strength of L1-penalty and, as a result, the severance of the regressor selection procedure, can be chosen by cross-validation, for example. When the dimension of X_t is very large the cross-validation becomes a prohibitively computer-intensive procedure. In this case, one can follow Bai and Ng (2008) and extract common factors from a fixed number of regressors ranked first by the elastic net.

Let X^*_t be a subset of predictors for which $\gamma \neq 0$, i.e., $X^*_t \subset X_t$. Even though the elastic net algorithm delivers values of the non-zero slope coefficients, we are not interested in these values as such. Following Bai and Ng (2008), our main interest lies in the ranking of the predictors, allowing us to separate relevant predictors from irrelevant ones for a particular target variable. At this stage we discard irrelevant ones and for the further analysis we use only selected or so-called targeted predictors. As in Bai and Ng (2008), one can extract common factors from these selected variables by means of the principal components analysis and plug them in Equation (1) in place of X_t. Then the forecasting equation transforms into

$$y_{t+h}^h = \alpha' W_t + \theta(L)' f_t + \epsilon_{t+h}, \tag{3}$$

where $\theta(L)$ denotes a lag polynomial, allowing for a richer regressor dynamics in the predictive equation.

3.2 Targeted-predictors approach for mixed-frequency variables (MIDASSO)

As above, let $t = 1, 2, ..., T-1, T$ denote a time scale at the quarterly frequency at which we observe a target variable y_t. Then, by assigning integer values of the time scale to the last month of each quarter, the corresponding time scale at the monthly frequency can be represented as $t_m = 1/3, 2/3, 1, 1+1/3, 1+2/3, 2, ..., T-1, T-2/3, T-1/3, T$. Let $X_{t_m} = (X_{1,t_m}, X_{2,t_m}, ..., X_{N,t_m})'$ denote a $N \times 1$ vector of potential predictors. The first step, that is common both to the MIDAS and U-MIDAS regressions, and which is also adopted here as the first step in the MIDASSO approach is to apply the blocking approach by skip-sampling each monthly variable into three quarterly time series, each of them retaining values of the monthly variables in the first, second and third months. If we correspondingly denote by $X_t^{(1)}$ values of the monthly variables observed in the first month of each quarter $t^{(1)} = 1/3, 1+1/3, ..., T-2/3$, by $X_t^{(2)}$ — in the second month of each quarter $t^{(2)} = 2/3, 1+2/3, ..., T-1/3$, and by $X_t^{(3)}$ — in the third month of each quarter $t^{(3)} = 1, 2, ..., T$, then instead of the $N \times 1$ vector of monthly predictors X_{t_m} we have a $(3 * N) \times 1$ vector of original predictors converted to the quarterly frequency $X_t = \left(X_t^{(1)'}, X_t^{(2)'}, X_t^{(3)'}\right)'$.

The dimension of X_t can be further increased by including their lagged values. For example, allowing for up to p additional lags of the explanatory variables we get a $(3 \times N \times (p+1))$-

dimensional vector $X_t = \left(X_t^{(1)'}, X_t^{(2)'}, X_t^{(3)'}, X_{t-1}^{(1)'}, X_{t-1}^{(2)'}, X_{t-1}^{(3)'}, ..., X_{t-p}^{(1)'}, X_{t-p}^{(2)'}, X_{t-p}^{(3)'}\right)'$. This may be particularly beneficial if among original monthly variables one have both leading and coincident indicators. Hence by differentiating leads of explanatory variables with respect to the target time series one may improve upon estimating common latent factors (e.g. see Siliverstovs, 2012, for an illustration of this approach in a small-scale dynamic factor model).

Conceptually, as a result of the skip-sampling procedure, we have both dependent and explanatory variables at the common frequency, implying that the targeted-regressor approach of Bai and Ng (2008) is straightforward to apply. However, one aspect still needs to be clarified. Namely, the problem of the "ragged edge" or an unbalanced panel of the explanatory variables. When forecasts are made in real time, the missing values at the edge of the data panel are brought about by staggered releases of the explanatory variables as well as the skip-sampling procedure. For example, consider a situation when the last data point for some original monthly time series is available for the first month. Then after application of the skip-sampling procedure the quarterly time series comprising all observations pertaining to the first month of each quarter will have an observation for the last quarter, whereas for the quarterly time series consisting of observations pertaining to the second and third months of each quarter the corresponding observations will be missing in this quarter. Also by allowing up to p additional lags of the explanatory variables makes the "ragged-edge" problem inevitable. Hence in such unbalanced panels the principal components analysis, for instance, cannot be used to extract common factors.

We suggest to circumvent the "ragged-edge" problem by resorting to the two-step procedure suggested in Giannone et al. (2008), that is specifically designed for extracting common factors from unbalanced data panels. In the first step, an initial estimate of common factors are obtained using a balanced data panel which cuts off the periods with missing values. The principal component analysis (PCA) is used for this purpose. The number of factors is determined by means of the eigenvalue ratio (EVR) criterion suggested in Ahn and Horenstein (2013). The initially estimated common factors are used in order to deduce parameters of a dynamic factor model cast into a state-space form. In the second step, the application of the Kalman smoother delivers estimates of common factors both for the samples covered by the balanced and unbalanced panels and, if necessary, further out of sample.

As in Giannone et al. (2008), out-of-sample forecasts of the target variable can be obtained by its projection on the estimated factors, f_t:

$$y_{t+h} = \alpha + \theta' f_{t+h} + \epsilon_{t+h}. \tag{4}$$

The factor-augmented Autoregressive Distributed Lag (ARDL) model in the following form:

$$y_{t+h} = \alpha' W_{t+h} + \theta' f_{t+h} + \epsilon_{t+h}, \tag{5}$$

can also be used for generating out-of-sample forecasts, where W_t is a vector of predetermined regressors like a constant and lagged values of the dependent variable. Observe that the model specification in each of Equations (4) and (5) remains the same for each forecast horizon. This is opposite to the direct forecasting approach, also widely applied for short-term forecasting, e.g. in Bai and Ng (2008), when a model specification varies with the forecast horizon, h.

Last but not least, until now we assumed that common factors f_t are extracted from all variables X_t collected into a $T \times [3 \times N \times (p+1)]$ panel for $t = 1, ..., T$. Since now both dependent and explanatory variables are observed at the same quarterly frequency, it is straightforward to apply the elastic net for variables selection. The corresponding optimization problem is

$$\widehat{\beta}(\lambda_1, \lambda_2) = \arg\min_{\beta} \left\{ RSS + \lambda_2 \|\beta\|^2 + \lambda_1 \|\beta\|_1 \right\}, \tag{6}$$

where RSS is the residual sum of squares of either of the following equations

$$y_t = \alpha + \gamma' X_t + \epsilon_t \tag{7}$$

or

$$y_t = \alpha' W_t + \gamma' X_t + \epsilon_t, \tag{8}$$

corresponding to Equations (4) or (5) above and $\beta = (\alpha', \gamma')'$.

Let X_t^* be a subset of selected predictors for which $\gamma \neq 0$ in Equation (6), i.e., $X_t^* \subset X_t$. As in the single-frequency case, we extract common factors from these selected variables by means of the two-step procedure of Giannone et al. (2008) and plug them either in Equation (9) and (10) below:

$$y_{t+h} = \alpha + \theta^{*\prime} f_{t+h}^* + \epsilon_{t+h}, \tag{9}$$

and

$$y_{t+h} = \alpha' W_{t+h} + \theta^{*\prime} f_{t+h}^* + \epsilon_{t+h}, \tag{10}$$

which delivers out-of-sample forecasts of the target variable. The final specification of these predictive regressions is chosen by means of the Bayesian Information Criterion (BIC).

In the sequel we will refer to the forecasts obtained using common factors f_{t+h}^* extracted from the targeted regressors X_t^* as those produced by the MIDASSO approach. Forecasts based on the models in Equations (4) and (5), i.e. common factors extracted from all variables without pre-selection, are referred as those obtained by a U-MIDAS-DFM approach, reflecting two essential steps in extracting common factor from mixed-frequency data: 1) application of the skip-sampling procedure of the U-MIDAS approach transforming each monthly variable into three quarterly time series and 2) application of the procedure of Giannone et al. (2008) for factor estimation by means of a dynamic factor model.

4 Data

The data set of monthly indicators, comprising 559 variables, is essentially the same as used in Siliverstovs and Kholodilin (2012). The complete list of variables and their transformations is given in Appendix. The data set is sub-divided into the following 9 blocks[2]: Purchasing Managers' Index in manufacturing supplied by Credit Suisse (9 time series, *PMI*), consumer price indices (28, *CPI*), labour market indicators (6, *LABOUR*), producer price indices (12, *PPI*), business tendency surveys in manufacturing collected at the KOF Swiss Economic Institute (150, *CHINOGA*), exports and imports (249), stock market indices (80, *STOCK*), interest rates (22, *INTEREST*), and exchange rates (3, *CURRENCY*).

Information on the monthly indicators is presented in Table 1. Observe that blocks of macroeconomic data differ both in terms of size and publication lag. The block containing the exports and imports statistics is the largest one. The KOF manufacturing surveys and stock market indices comprise the two next-largest blocks. The smallest blocks, each consisting of less than ten variables are exchange rates, labour-market indicators and the Purchasing Managers' Index and its sub-components.

We perform our forecasting exercise in a pseudo real time, as no historical vintages are available for all indicators. However, we explicitly accommodate the block-specific publication lags, simulating the actual information availability in the past. We assume that forecasts are made on the first business day of each month. This date is chosen for the following two reasons. First, it coincides with the release of Purchasing Managers' Index for the previous month. Second, for the daily time series like interest and exchange rates as well as stock market indices are available for the previous month. Following Giannone et al. (2008), we take monthly averages of these financial variables. This choice of the forecast origin implies that the following blocks are released with the one-month lag: *PMI*, *CHINOGA*, *STOCK*, *INTEREST* and *CURRENCY*. The data in the remaining blocks

[2]The block with retail trade statistics containing 4 indicators, that was present in Siliverstovs and Kholodilin (2012), was omitted in the current exercise due to data availability issues.

(*CPI*, *PPI*, *LABOUR*, *TRADE*) are released with the publication lag of two months.

The variables undergo the following transformations.[3] Since the business tendency surveys (*PMI* and *CHINOGA*), expressed as *Net Balances*, are bounded by construction, we apply no transformation of those and use them in levels. The rest of the data is initially transformed either to monthly changes (*INTEREST*) or monthly growth rates. Then following Giannone et al. (2008) we express these monthly changes or growth rates in terms of quarter-on-quarter growth applying the following filter $(1 + 2L + 3L^2 + 2L^3 + L^4)$, see also Mariano and Murasawa (2003) for application of this transformation for modelling a latent factor in mixed-frequency dynamic factor model. As shown in Siliverstovs and Kholodilin (2012), such transformation ensures that the single common factor extracted from the monthly variables loads rather uniformly across different blocks of variables.

The target variable that we forecast is quarter-on-quarter seasonally adjusted growth of the Swiss GDP, for which we have real-time vintages. The official data are released by the State Secretariat for Economics Affairs (SECO) in about two months after the end of the reference quarter.

5 Results

We perform a pseudo real-time forecasting exercise using the sample 2007Q1—2014Q1. The first forecast origin is dated by the first business day of March 2007. Since at this date the official GDP data are available until 2006Q4, the corresponding estimation sample both used for variable selection and estimation of the parameters of a forecasting regression is 2001Q1—2006Q4. Correspondingly, we produce forecasts for the current (2007Q1), next (2007Q2) and over-next (2007Q3) quarters. The next forecast round is run on the first business day of April 2007. Since there no new GDP data were released in the meantime, we retain the same subset of selected indicators

[3]See Appendix in Siliverstovs and Kholodilin (2012) for description of indicators and their transformations.

used in the previous forecast round. However, due to the fact that for monthly indicators we have one month of additional information, we update the estimates of common factors as well as the parameters of the forecasting equation. As before, the forecasts are made for the three followings quarters: 2007Q1, 2007Q2 and 2007Q3. We repeat this forecasting steps also in the beginning of May, producing forecasts for the same three months. The fourth forecast round takes place on the first business day of June 2007. At this date the new official GDP data spanning the period through 2007Q1 is available. We use this information to extend our estimation sample 2001Q1—2007Q1, adopting a recursively expanding-window approach. We use this new information in order to re-select variables, re-estimate common factors and parameters of the forecasting equation. At this forecast origin forecast are made for 2007Q2, 2007Q3 and 2007Q4. We proceed in this fashion until the last forecast round with the forecast origin of the first business day of May 2014, when we make only one forecast for 2014Q1, which is the last quarter in our out-of-sample forecast period.

We label the corresponding forecasts by a number of months left until the end of the forecast quarter. This means that for the forecast made in the beginning of March for the current quarter the corresponding horizon is $h = 1$, for the next quarter—it is $h = 4$ and for the over-next quarter—it is $h = 7$. Similarly, for the forecasts made in the beginning of April and May the corresponding forecast horizons are $h = 0, 3, 6$ and $h = -1, 2, 5$.[4] We repeat this labelling of the forecasts performed on the first business day of the next troika of months: June, July and August. As the result of this forecasting exercise we have 29, 28 and 27 out-of-sample forecasts made at the following forecast horizons $h = -1, 0, 1$, $h = 2, 3, 4$ and $h = 5, 6, 7$, correspondingly.

We report the forecast accuracy of the proposed modelling approaches in Table 2. As the benchmark model we chose the second-order autoregressive model, AR(2).[5] We use the Root Mean Squared Forecast Error as a metric to gauge the forecasting ability of the models in question. The

[4] The negative value of the forecast horizon indicates that the corresponding forecast or, more precisely, backcast is made one month later after the end of the reference quarter.

[5] We also experimented with an alternative benchmark autoregressive model, where the number of lags were allowed to be selected by the Akaike Information Criterion, AIC. The forecasting accuracy of the AR(AIC) model was very similar to that of the AR(2) model, though slightly worse.

row entries corresponding to the AR(2) model are the RMSFE of the benchmark model for each forecast horizon. The row entries corresponding to the MIDASSO and U-MIDAS-DFM models are RMSFE ratios of the respective model to that of the AR(2) model. Below the ratios we report one-sided p-values of the Diebold and Mariano (1995) test that we use to test the hypothesis of equal forecast accuracy of factor-augmented models with the univariate autoregressive model. The use of one-sided p-values is motivated by the fact that our main interest is in those models that demonstrate a superior forecasting ability compared to the benchmark model. Observe that we omit lagged dependent variable from the specification of forecasting regressions in both MIDASSO and U-MIDAS-DFM approaches. The reason is that retaining lags of the dependent variable generally resulted in the inferior forecasting performance in comparison with the simple projection models in Equations (9) and Equations (4). An additional benefit is that we compare non-nested models in terms of their forecasting accuracy, avoiding associated problematic issues when comparing nested models (Clark and McCracken, 2015).

First we discuss the forecasting accuracy of the MIDASSO model. As discussed above, the dimension of the panel of potential predictors X_t is $(3 \times N \times (p+1))$-dimensional. Given that we have 559 monthly variables, as the result of the blocking procedure we get a 1677-, 3354- and 5031-dimensional vectors for $p = 0$, $p = 1$ and $p = 2$, correspondingly. Since application of the cross-validation procedure in such large data panels is very computationally intensive, we simply fix the number of targeted predictors, as ranked by the elastic net, to 50 and use for extract of common factors.[6]

As expected, from Table 2 we observe that forecast accuracy of the MIDASSO approach increases with the decreasing forecasting horizon. This result is broadly in line with similar studies in the short-term forecasting literature. For $p = 0$, for every but the longest forecast horizon ($h = 7$) the reported RMSFE ratios are below one. However, we can reject the null hypothesis of equal

[6] Bai and Ng (2008) fix the number of targeted predictors to 30 arguing that for a reliable estimation of common factors it is sufficient. Since we work with a much larger data panel, from which we select variables, we correspondingly increase the number of retained targeted predictors.

forecast accuracy of the MIDASSO and the AR(2) model only for the forecast horizons $h = 0$ and $h = -1$. At these two forecast horizons the improvement in terms of the RMSFE is about 30%, indicating that the most accurate forecasts are made as soon as the quarter ends. Extending the information set by one more month does not bring about any noticeable further improvement in the forecast accuracy.

The fact that we observe the strongest evidence of forecasting superiority of the factor model at the forecast horizons $h = 0$ and $h = -1$ deserves a comment. We let the selection procedure decide which skip-sampled variables will be chosen to form a factor. Recall from Section 3.2 that for $p = 0$ each monthly variable was decomposed into three variable transformations $X_t = \left(X_t^{(1)'}, X_t^{(2)'}, X_t^{(3)'}\right)'$. For $p = 1$ and $p = 2$, there are six $X_t = \left(X_t^{(1)'}, X_t^{(2)'}, X_t^{(3)'}, X_{t-1}^{(1)'}, X_{t-1}^{(2)'}, X_{t-1}^{(3)'}\right)'$ and nine $X_t = \left(X_t^{(1)'}, X_t^{(2)'}, X_t^{(3)'}, X_{t-1}^{(1)'}, X_{t-1}^{(2)'}, X_{t-1}^{(3)'}, X_{t-2}^{(1)'}, X_{t-2}^{(2)'}, X_{t-2}^{(3)'}\right)'$ transformations, respectively. So, potentially, each transformation has an equal chance to be selected by the elastic net. In practice, we recorded the actual selection incidence of each variable transformation. An example is given in Table 3 for the full estimation window at our disposal, 2001Q1—2014Q1. As seen, for different values of p the transformation $X_t^{(3)}$, corresponding to observations pertaining for the third month of the current quarter, has the highest selection frequency. Consequently, in the composition of the common factor this transformation plays a dominating role. Incidentally, the increase in forecast accuracy is observed at the forecast horizons of $h = 0$ and $h = 1$, coinciding with the release timing of data for the third month in the targeted forecast quarter. Hence the highest in-sample explanatory power of $X_t^{(3)}$ is also translated into the out-of-sample forecasting superiority.

Another interesting observation is that increasing the number of potential variables, that feed into the elastic net, generally results in worsening of the forecasting performance of the MIDASSO approach. This holds for longer forecast horizons except for $h = 0$ and $h = -1$. As seen from the table, the forecast accuracy at these two forecast horizons remains practically constant irrespective of the number of potential indicators to select from, which, as discussed above, varies from 1677 to 5031 for different values of p.

It is of a great interest to single out the role of variable selection in boosting forecast accuracy in comparison with the benchmark model. To this end, one can compare the results reported in the upper panel of Table 2 for the MIDASSO model that uses variable selection with those reported in the lower panel of Table 2 for the U-MIDAS-DFM model that extracts common factors from the whole data panel. It turns out that the outcome of this comparison depends on whether one increases the dimension of the data panel by adding lagged values of the variables. One can distinguish between the results obtained for $p = 0$ and those for a larger data panel with $p = 1$ and $p = 2$.

For $p = 0$, the forecast accuracy results for the panel consisting of 559 monthly variables that were transformed into 1677 quarterly variables as a result of skip-sampling, the model without variable selection demonstrates a comparable forecasting performance to that with variable selection at the two shortest forecast horizons ($h = -1$ and $h = 0$) and substantially better forecasting accuracy at the forecast horizon $h = 1$. At the latter forecast horizon the corresponding RMSFE ratio reported in the table is 0.686, indicating the decrease in the RMSFE in comparison with the benchmark model of about 30%. This RMSFE ratio can be compared with the corresponding RMSFE ratio for the MIDASSO model at this forecast horizon, which is 0.908.

This is an unexpected outcome that runs contrary to the argument of Bai and Ng (2008) in favour of using targeted predictors in large panels. The main motivation of using targeted predictors is that it is likely that a factor capturing business cycle dynamics that is dominant in a small panel of relevant variables may become dominated in a larger, more heterogeneous panel. Apparently this is not the case in the panel based on 1677 variables. The corresponding variable composition as well as their transformation proposed in the earlier paper of Siliverstovs and Kholodilin (2012), specifying a large-scale dynamic factor model for short-term forecasting of GDP growth in Switzerland, appears to be right also for the modelling approaches of mixed-frequency data proposed in this paper. The extracted first principal component from the panel of this dimension serves as a reliable estimate of the dominant factor underlying business cycle dynamics diffused across the variables in question.

For $p = 1$ and $p = 2$, when dealing with 3354- and 5031-dimensional data panels, respectively, the argument of the Bai and Ng (2008) carries through, i.e. the forecast accuracy drops substantially compared to the case of $p = 0$, discussed above. Allowing for additional lags makes the data panel more heterogeneous suppressing signal-to-noise ratio and acting detrimentally on forecasting ability of the extracted common factor. In the extreme case with 5031-dimensional panel the null hypothesis of equal predictive ability of the U-MIDAS-DFM and AR(2) models cannot be rejected at the usual significance levels for all forecast horizons. This is contrary to the targeted-predictor approach which forecasting accuracy at the horizons $h = 0$ and $h = -1$ is practically not affected by expansion of the data dimension.

The graphical presentation of the forecasting accuracy of the models in question is displayed in Figure 1. The straight line correspond to the RMSFE of the benchmark AR(2) model, reported in the corresponding row of Table 2. The dark- and light-grey bars correspond to the absolute rather than relative measures of forecast accuracy in terms of RMSFE of the MIDASSO and U-MIDAS-DFM models, respectively.

We conclude the paper with presenting the composition of selected indicators by data blocks, see Figure 2. Each bar in the figure displays indicator selection by the elastic net at each forecast origin. Observe that the last bar corresponds to the indicator selection using the full sample 2001Q1—2014Q1. As seen, the most frequently selected indicators come from the three following data blocks: *STOCK*, *CHINOGA* and *TRADE*, which are also the largest blocks. The elastic net selected also indicators from smaller data blocks like *PMI* and *LABOUR*. Indicators from the former block were selected in all but two earliest data vintages, whereas indicators from the latter block were selected in all but three latest data vintages. Indicators from PPI and CURRENCY blocks were among the least frequently selected indicators.

6 Conclusion

In this paper we extend the targeted-regressor approach suggested in Bai and Ng (2008) for variables sampled at the same frequency to the mixed-frequency data. Our MIDASSO approach is essentially a combination of the MIxed-frequency DAta-Sampling (MIDAS) approach of Ghysels et al. (2004) and Ghysels et al. (2007) or, more precisely, an unrestricted MIDAS approach (U-MIDAS) (see Foroni et al., 2015; Castle et al., 2009; Bec and Mogliani, 2013) and the LASSO-type penalised regression called the elastic net (Zou and Hastie, 2005), also used in Bai and Ng (2008).

We illustrate the MIDASSO approach forecasting the quarterly seasonally adjusted real GDP growth rate in Switzerland. We use the data panel comprising 559 monthly variables which we convert to the three panels of quarterly data using the skip-sampling procedure of the MIDAS approach. The smallest panel consists of 1677 variables retaining only contemporaneous values. Allowing for additional first and up to the second lag of the variables results in the panels containing 3354 and 5031 variables, respectively.

Our main finding is that in the dataset in question the gains from targeting predictors are mainly realised when dealing with 3354- and 5031-dimensional data panels. In these panels the forecasting accuracy of the MIDASSO approach at the shortest forecast horizons, for which we can reject the null hypothesis of equal predictive ability with the benchmark AR(2) model, is comparable to that observed in the panel containing 1677 variables. This is opposite to what we observe when forecasting with factors extracted without variable screening. In this case, the forecasting accuracy markedly deteriorates with the increase of data panel dimension.

The MIDASSO approach is based on several econometric techniques that rely on the closed-form solutions and requires neither optimisation of non-linear functions nor computer intensive simulation techniques. This ensures a straightforward and efficient implementation of the MIDASSO approach, which we hope, will contribute to its widespread use as a viable complement or even an alternative to already existing methods primarily developed for macroeconomic forecasting with mixed-frequency data.

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Table 1: Chronology of data releases during the month

Block		Published by	Release timing	Last value	Block size
PMGR-manufacturing	PMI	Credit Suisse	1st working day of month	Previous month	9
CPI	CPI	Swiss Federal Statistical Office	First week of month	Previous month	28
Labour	LABOUR	State Secretariat for Economic Affairs	Second week of month	Previous month	6
PPI	PPI	Swiss Federal Statistical Office	Second week of month	Previous month	12
Surveys in manufacturing	CHINOGA	KOF Swiss Economic Institute	Middle of month	Current month	150
Exports/Imports	TRADE	Swiss Federal Customs Administration	Middle of month	Previous month	249
Stock market indices	STOCK	Datastream	1st working day of month	Previous month	80
Interest rates	INTEREST	Datastream	1st working day of month	Previous month	22
Exchange rates	CURRENCY	Datastream	1st working day of month	Previous month	3

Table 2: Out-of-sample forecast accuracy, 2007Q1—2014Q1

Model	p^{c}	Forecast horizon in months, h: 7	6	5	4	3	2	1	0	-1
AR(2)[a]		0.467	0.467	0.467	0.402	0.402	0.402	0.372	0.372	0.372
MIDASSO[b]	0	1.039 (0.753)	0.915 (0.143)	0.980 (0.435)	0.969 (0.421)	0.812 (0.163)	0.845 (0.255)	0.908 (0.228)	**0.693** (**0.012**)	**0.691** (**0.013**)
	1	1.021 (0.546)	0.986 (0.467)	1.053 (0.660)	1.148 (0.901)	1.101 (0.806)	0.992 (0.480)	1.066 (0.701)	**0.691** (**0.011**)	**0.691** (**0.011**)
	2	0.987 (0.460)	1.068 (0.667)	1.037 (0.589)	1.133 (0.847)	1.103 (0.776)	1.009 (0.528)	1.050 (0.653)	**0.707** (**0.012**)	**0.706** (**0.012**)
U-MIDAS-DFM[b]	0	0.968 (0.254)	0.946 (0.146)	0.822 (0.107)	0.908 (0.197)	0.868 (0.156)	0.711 (0.134)	**0.686** (**0.007**)	**0.653** (**0.004**)	**0.657** (**0.004**)
	1	1.100 (0.786)	1.030 (0.638)	1.018 (0.540)	1.035 (0.597)	0.918 (0.290)	0.847 (0.183)	0.865 (0.106)	**0.806** (**0.039**)	**0.802** (**0.035**)
	2	1.016 (0.576)	0.952 (0.296)	0.921 (0.240)	1.086 (0.798)	0.998 (0.491)	0.944 (0.273)	0.981 (0.445)	0.928 (0.293)	0.923 (0.278)

[a] The row entries indicate the horizon-specific RMSFE.
[b] The row entries indicate the horizon-specific RMSFE ratio of respectively MIDASSO or U-MIDAS-DFM models with respect to that of the benchmark AR(2) model. Below RMSFE ratios the one-sided p-values of equal forecast accuracy test of Diebold and Mariano (1995) are reported in parentheses.
[c] The p parameter indicates the maximum number of lags of explanatory variables that are allowed to enter the variable selection procedure based on the elastic net. For $p = 0$, as the result of skip-sampling the 559 original monthly variables are converted to 1677 quarterly variables. For $p = 1$ and $p = 2$, the corresponding number of variables to select from is 3354 and 5031, respectively.

Table 3: Selection frequency of variable transformations, 2001Q1—2014Q1

	$X_t^{(3)}$	$X_t^{(2)}$	$X_t^{(1)}$	$X_{t-1}^{(3)}$	$X_{t-1}^{(2)}$	$X_{t-1}^{(1)}$	$X_{t-2}^{(3)}$	$X_{t-2}^{(2)}$	$X_{t-2}^{(1)}$	TOTAL
$p = 0$	40	7	3	.	.	.	.	.	.	50
$p = 1$	39	7	3	0	0	1	.	.	.	50
$p = 2$	36	6	3	0	0	1	0	3	1	50

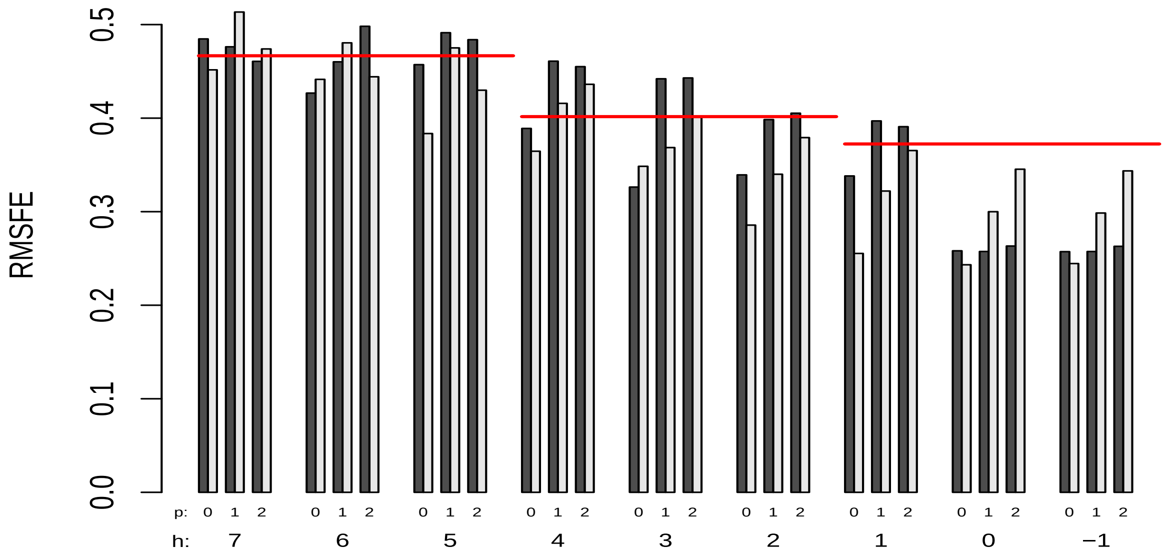

Figure 1: RMSFE: the benchmark AR(2) model (straight line); dark- and light-grey bars correspond to RMSFE of the MIDASSO and U-MIDAS-DFM models. The p parameter indicates the maximum number of lags of explanatory variables that are allowed to enter the variable selection procedure based on the elastic net. For $p = 0$, as the result of skip-sampling the 559 original monthly variables are converted to 1677 quarterly variables. For $p = 1$ and $p = 2$, the corresponding number of variables to select from is 3354 and 5031, respectively. The variable h denotes the forecast horizon that ranges from 7 months until the end of the reference quarter till -1, indicating that a forecast is made one month after the end of the reference quarter.

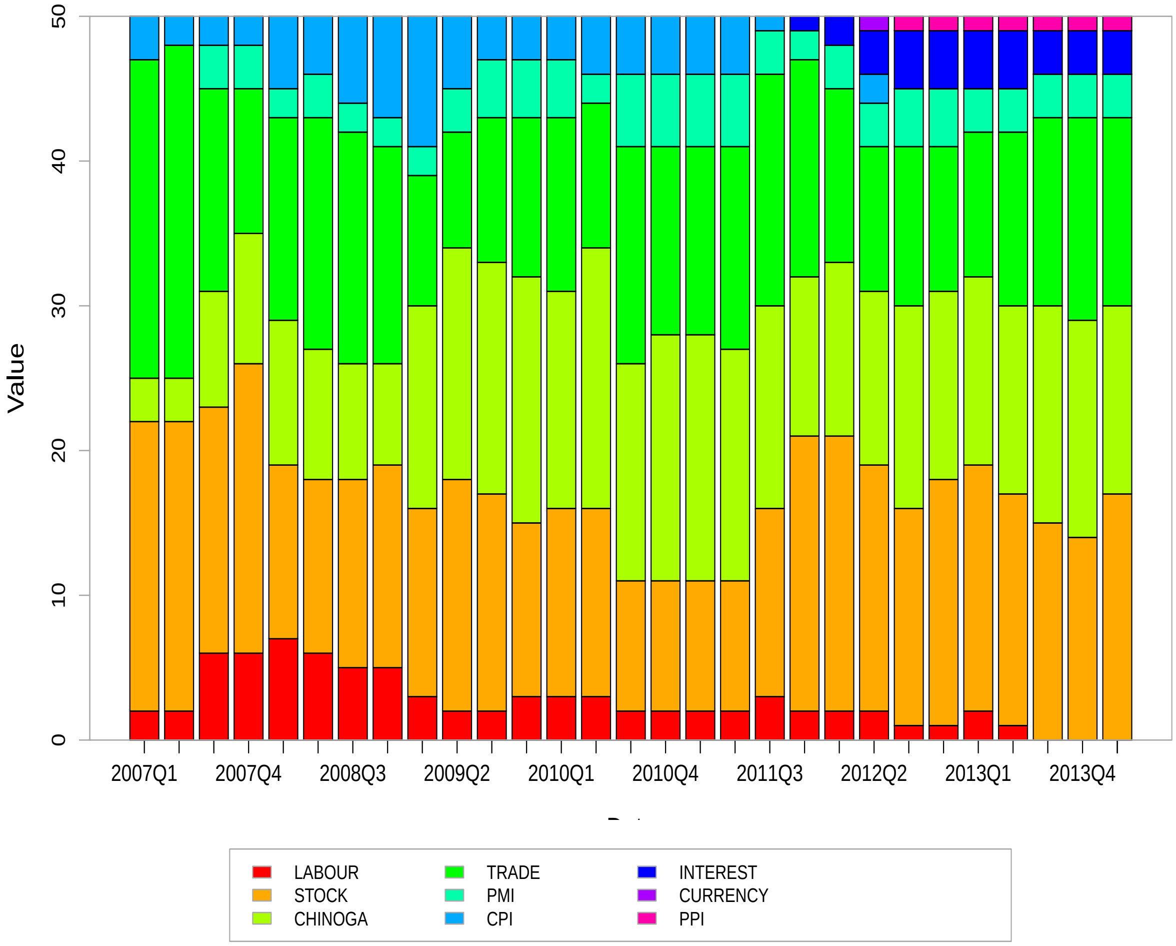

Figure 2: MIDASSO(50): indicator composition by data blocks.

A Appendix

Table A-1: Indicators

Nr.	Block	Indicator	Seas. Adjustment	Transformation
1	PMI	Purchasing Managers' Index (PMI) - Total	yes	0
2	PMI	PMI subindex: Output	yes	0
3	PMI	PMI subindex: Backlog of orders	yes	0
4	PMI	PMI subindex: Quantity of purschase	yes	0
5	PMI	PMI subindex: Purchase prices	yes	0
6	PMI	PMI subindex: Suppliers' delivery times	yes	0
7	PMI	PMI subindex: Stocks of purchases	yes	0
8	PMI	PMI subindex: Stocks of finished goods	yes	0
9	PMI	PMI subindex: Employment	yes	0
10	CPI	Consumer Price Index (CPI) - Total	yes	1
11	CPI	CPI: Food and non-alcoholic beverages	yes	1
12	CPI	CPI: Alcoholic beverages and tobacco	yes	1
13	CPI	CPI: Residential rent and energy	yes	1
14	CPI	CPI: Household utensils and housekeeping	yes	1
15	CPI	CPI: Health care	yes	1
16	CPI	CPI: Transportation	yes	1
17	CPI	CPI: Communication	yes	1
18	CPI	CPI: Leisure and culture	yes	1
19	CPI	CPI: Education	yes	1
20	CPI	CPI: Restaurants and hotels	yes	1
21	CPI	CPI: Other goods and services	yes	1
22	CPI	CPI: Commodities	yes	1
23	CPI	CPI: Non-durables	yes	1
24	CPI	CPI: Semi-durables	yes	1
25	CPI	CPI: Durables	yes	1
26	CPI	CPI: Services	yes	1
27	CPI	CPI: Private services	yes	1
28	CPI	CPI: Public services	yes	1
29	CPI	CPI: Domestic	yes	1
30	CPI	CPI: Foreign	yes	1
31	CPI	CPI: Seasonal products	yes	1
32	CPI	CPI: Residential rent	yes	1
33	CPI	CPI: Petroleum products	yes	1
34	CPI	CPI: Tobacco	yes	1
35	CPI	CPI: Alcoholic beverages	yes	1
36	CPI	CPI: Heating oil	yes	1
37	CPI	CPI: Motor fuel	yes	1
38	LABOUR	Vacancies	yes	1
39	LABOUR	Total, unemployed	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
40	LABOUR	Full-time unemployed	yes	1
41	LABOUR	Part-time unemployed	yes	1
42	LABOUR	Total, registered job-seekers	yes	1
43	LABOUR	Long-time unemployed	yes	1
44	PPI	PPI: A Agriculture and forestry products	yes	1
45	PPI	PPI: 01 Agriculture products	yes	1
46	PPI	PPI: 02 Forestry products	yes	1
47	PPI	PPI: B Natural stones, sand and gravel, Salt	yes	1
48	PPI	PPI: 16 Wood, wooden products	yes	1
49	PPI	PPI: 19 Mineral products	yes	1
50	PPI	PPI: 22 Rubber and plastic products	yes	1
51	PPI	PPI: 23 Products out of glass, ceramic, concrete products	yes	1
52	PPI	PPI: D Energy supply (Electricity and gas)	yes	1
53	PPI	PPI: Agriculture and forestry products	yes	1
54	PPI	IPI: Import price index: total	yes	1
55	PPI	PPI: Price index total supply: total	yes	1
56	CHINOGA	Food, beverages, tobacco: orders, previous month	no	0
57	CHINOGA	Food, beverages, tobacco: orders, same month last year	no	0
58	CHINOGA	Food, beverages, tobacco: orders on hand, previous month	no	0
59	CHINOGA	Food, beverages, tobacco: orders on hand, assessment	no	0
60	CHINOGA	Food, beverages, tobacco: orders on hand abroad, assessment	no	0
61	CHINOGA	Food, beverages, tobacco: production, previous month	no	0
62	CHINOGA	Food, beverages, tobacco: production, same month last year	no	0
63	CHINOGA	Food, beverages, tobacco: primary products, inventory previous month	no	0
64	CHINOGA	Food, beverages, tobacco: primary products, inventory assessment	no	0
65	CHINOGA	Food, beverages, tobacco: finished products, inventory previous month	no	0
66	CHINOGA	Food, beverages, tobacco: finished products, inventory assessment	no	0
67	CHINOGA	Food, beverages, tobacco: expected orders	no	0
68	CHINOGA	Food, beverages, tobacco: expected production	no	0
69	CHINOGA	Food, beverages, tobacco: expected primary product purchase	no	0
70	CHINOGA	Food, beverages, tobacco: business climate	no	0
71	CHINOGA	Textile, clothing, leather, footwear: orders, previous month	no	0
72	CHINOGA	Textile, clothing, leather, footwear: orders, same month last year	no	0
73	CHINOGA	Textile, clothing, leather, footwear: orders on hand, previous month	no	0
74	CHINOGA	Textile, clothing, leather, footwear: orders on hand, assessment	no	0
75	CHINOGA	Textile, clothing, leather, footwear: orders on hand abroad, assessment	no	0
76	CHINOGA	Textile, clothing, leather, footwear: production, previous month	no	0
77	CHINOGA	Textile, clothing, leather, footwear: production, same month last year	no	0
78	CHINOGA	Textile, clothing, leather, footwear: primary products, inventory previous month	no	0
79	CHINOGA	Textile, clothing, leather, footwear: primary products, inventory assessment	no	0
80	CHINOGA	Textile, clothing, leather, footwear: finished products, inventory previous month	no	0
81	CHINOGA	Textile, clothing, leather, footwear: finished products, inventory assessment	no	0
82	CHINOGA	Textile, clothing, leather, footwear: expected orders	no	0

Continued on next page

Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
83	CHINOGA	Textile, clothing, leather, footwear: expected production	no	0
84	CHINOGA	Textile, clothing, leather, footwear: expected primary product purchase	no	0
85	CHINOGA	Textile, clothing, leather, footwear: business climate	no	0
86	CHINOGA	Wood; other non-metal: orders, previous month	no	0
87	CHINOGA	Wood; other non-metal: orders, same month last year	no	0
88	CHINOGA	Wood; other non-metal: orders on hand, previous month	no	0
89	CHINOGA	Wood; other non-metal: orders on hand, assessment	no	0
90	CHINOGA	Wood; other non-metal: orders on hand abroad, assessment	no	0
91	CHINOGA	Wood; other non-metal: production, previous month	no	0
92	CHINOGA	Wood; other non-metal: production, same month last year	no	0
93	CHINOGA	Wood; other non-metal: primary products, inventory previous month	no	0
94	CHINOGA	Wood; other non-metal: primary products, inventory assessment	no	0
95	CHINOGA	Wood; other non-metal: finished products, inventory previous month	no	0
96	CHINOGA	Wood; other non-metal: finished products, inventory assessment	no	0
97	CHINOGA	Wood; other non-metal: expected orders	no	0
98	CHINOGA	Wood; other non-metal: expected production	no	0
99	CHINOGA	Wood; other non-metal: expected primary product purchase	no	0
100	CHINOGA	Wood; other non-metal: business climate	no	0
101	CHINOGA	Paper, printing, publishing: orders, previous month	no	0
102	CHINOGA	Paper, printing, publishing: orders, same month last year	no	0
103	CHINOGA	Paper, printing, publishing: orders on hand, previous month	no	0
104	CHINOGA	Paper, printing, publishing: orders on hand, assessment	no	0
105	CHINOGA	Paper, printing, publishing: orders on hand abroad, assessment	no	0
106	CHINOGA	Paper, printing, publishing: production, previous month	no	0
107	CHINOGA	Paper, printing, publishing: production, same month last year	no	0
108	CHINOGA	Paper, printing, publishing: primary products, inventory previous month	no	0
109	CHINOGA	Paper, printing, publishing: primary products, inventory assessment	no	0
110	CHINOGA	Paper, printing, publishing: finished products, inventory previous month	no	0
111	CHINOGA	Paper, printing, publishing: finished products, inventory assessment	no	0
112	CHINOGA	Paper, printing, publishing: expected orders	no	0
113	CHINOGA	Paper, printing, publishing: expected production	no	0
114	CHINOGA	Paper, printing, publishing: expected primary product purchase	no	0
115	CHINOGA	Paper, printing, publishing: business climate	no	0
116	CHINOGA	Chemistry; petroleum processing; rubber: orders, previous month	no	0
117	CHINOGA	Chemistry; petroleum processing; rubber: orders, same month last year	no	0
118	CHINOGA	Chemistry; petroleum processing; rubber: orders on hand, previous month	no	0
119	CHINOGA	Chemistry; petroleum processing; rubber: orders on hand, assessment	no	0
120	CHINOGA	Chemistry; petroleum processing; rubber: orders on hand abroad, assessment	no	0
121	CHINOGA	Chemistry; petroleum processing; rubber: production, previous month	no	0
122	CHINOGA	Chemistry; petroleum processing; rubber: production, same month last year	no	0
123	CHINOGA	Chemistry; petroleum processing; rubber: primary products, inventory previous month	no	0
124	CHINOGA	Chemistry; petroleum processing; rubber: primary products, inventory assessment	no	0
125	CHINOGA	Chemistry; petroleum processing; rubber: finished products, inventory previous month	no	0
126	CHINOGA	Chemistry; petroleum processing; rubber: finished products, inventory assessment	no	0
127	CHINOGA	Chemistry; petroleum processing; rubber: expected orders	no	0

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
128	CHINOGA	Chemistry; petroleum processing; rubber: expected production	no	0
129	CHINOGA	Chemistry; petroleum processing; rubber: expected primary product purchase	no	0
130	CHINOGA	Chemistry; petroleum processing; rubber: business climate	no	0
131	CHINOGA	Metal industry: orders, previous month	no	0
132	CHINOGA	Metal industry: orders, same month last year	no	0
133	CHINOGA	Metal industry: orders on hand, previous month	no	0
134	CHINOGA	Metal industry: orders on hand, assessment	no	0
135	CHINOGA	Metal industry: orders on hand abroad, assessment	no	0
136	CHINOGA	Metal industry: production, previous month	no	0
137	CHINOGA	Metal industry: production, same month last year	no	0
138	CHINOGA	Metal industry: primary products, inventory previous month	no	0
139	CHINOGA	Metal industry: primary products, inventory assessment	no	0
140	CHINOGA	Metal industry: finished products, inventory previous month	no	0
141	CHINOGA	Metal industry: finished products, inventory assessment	no	0
142	CHINOGA	Metal industry: expected orders	no	0
143	CHINOGA	Metal industry: expected production	no	0
144	CHINOGA	Metal industry: expected primary product purchase	no	0
145	CHINOGA	Metal industry: business climate	no	0
146	CHINOGA	Machine construction, vehicle construction: orders, previous month	no	0
147	CHINOGA	Machine construction, vehicle construction: orders, same month last year	no	0
148	CHINOGA	Machine construction, vehicle construction: orders on hand, previous month	no	0
149	CHINOGA	Machine construction, vehicle construction: orders on hand, assessment	no	0
150	CHINOGA	Machine construction, vehicle construction: orders on hand abroad, assessment	no	0
151	CHINOGA	Machine construction, vehicle construction: production, previous month	no	0
152	CHINOGA	Machine construction, vehicle construction: production, same month last year	no	0
153	CHINOGA	Machine construction, vehicle construction: primary products, inventory previous month	no	0
154	CHINOGA	Machine construction, vehicle construction: primary products, inventory assessment	no	0
155	CHINOGA	Machine construction, vehicle construction: finished products, inventory previous month	no	0
156	CHINOGA	Machine construction, vehicle construction: finished products, inventory assessment	no	0
157	CHINOGA	Machine construction, vehicle construction: expected orders	no	0
158	CHINOGA	Machine construction, vehicle construction: expected production	no	0
159	CHINOGA	Machine construction, vehicle construction: expected primary product purchase	no	0
160	CHINOGA	Machine construction, vehicle construction: business climate	no	0
161	CHINOGA	Electrical, electronic equipment: orders, previous month	no	0
162	CHINOGA	Electrical, electronic equipment: orders, same month last year	no	0
163	CHINOGA	Electrical, electronic equipment: orders on hand, previous month	no	0
164	CHINOGA	Electrical, electronic equipment: orders on hand, assessment	no	0
165	CHINOGA	Electrical, electronic equipment: orders on hand abroad, assessment	no	0
166	CHINOGA	Electrical, electronic equipment: production, previous month	no	0
167	CHINOGA	Electrical, electronic equipment: production, same month last year	no	0
168	CHINOGA	Electrical, electronic equipment: primary products, inventory previous month	no	0
169	CHINOGA	Electrical, electronic equipment: primary products, inventory assessment	no	0
170	CHINOGA	Electrical, electronic equipment: finished products, inventory previous month	no	0
171	CHINOGA	Electrical, electronic equipment: finished products, inventory assessment	no	0
172	CHINOGA	Electrical, electronic equipment: expected orders	no	0

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
173	CHINOGA	Electrical, electronic equipment: expected production	no	0
174	CHINOGA	Electrical, electronic equipment: expected primary product purchase	no	0
175	CHINOGA	Electrical, electronic equipment: business climate	no	0
176	CHINOGA	Other industry: orders, previous month	no	0
177	CHINOGA	Other industry: orders, same month last year	no	0
178	CHINOGA	Other industry: orders on hand, previous month	no	0
179	CHINOGA	Other industry: orders on hand, assessment	no	0
180	CHINOGA	Other industry: orders on hand abroad, assessment	no	0
181	CHINOGA	Other industry: production, previous month	no	0
182	CHINOGA	Other industry: production, same month last year	no	0
183	CHINOGA	Other industry: primary products, inventory previous month	no	0
184	CHINOGA	Other industry: primary products, inventory assessment	no	0
185	CHINOGA	Other industry: finished products, inventory previous month	no	0
186	CHINOGA	Other industry: finished products, inventory assessment	no	0
187	CHINOGA	Other industry: expected orders	no	0
188	CHINOGA	Other industry: expected production	no	0
189	CHINOGA	Other industry: expected primary product purchase	no	0
190	CHINOGA	Other industry: business climate	no	0
191	CHINOGA	Total industry: orders, previous month	no	0
192	CHINOGA	Total industry: orders, same month last year	no	0
193	CHINOGA	Total industry: orders on hand, previous month	no	0
194	CHINOGA	Total industry: orders on hand, assessment	no	0
195	CHINOGA	Total industry: orders on hand abroad, assessment	no	0
196	CHINOGA	Total industry: production, previous month	no	0
197	CHINOGA	Total industry: production, same month last year	no	0
198	CHINOGA	Total industry: primary products, inventory previous month	no	0
199	CHINOGA	Total industry: primary products, inventory assessment	no	0
200	CHINOGA	Total industry: finished products, inventory previous month	no	0
201	CHINOGA	Total industry: finished products, inventory assessment	no	0
202	CHINOGA	Total industry: expected orders	no	0
203	CHINOGA	Total industry: expected production	no	0
204	CHINOGA	Total industry: expected primary product purchase	no	0
205	CHINOGA	Total industry: business climate	no	0
206	TRADE	Exports - Total	yes	1
207	TRADE	Exports: Raw materials and intermediate goods	yes	1
208	TRADE	Exports: Raw materials	yes	1
209	TRADE	Exports: Raw materials for industrial processing	yes	1
210	TRADE	Exports: Organic raw materials for industrial processing	yes	1
211	TRADE	Exports: Animal raw materials for industrial processing	yes	1
212	TRADE	Exports: Mining raw materials for industrial processing	yes	1
213	TRADE	Exports: Intermediate and semi-finished goods	yes	1
214	TRADE	Exports: Intermediate goods for the nutrition industry	yes	1
215	TRADE	Exports: Intermediate goods for food production	yes	1
216	TRADE	Exports: Intermediate goods for feeding stuff production	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
217	TRADE	Exports: Intermediate goods for the industry (excluding nutrition)	yes	1
218	TRADE	Exports: Intermediate goods for the textile and clothing industry	yes	1
219	TRADE	Exports: Intermediate goods made out of paper	yes	1
220	TRADE	Exports: Intermediate goods made out of leather and fur	yes	1
221	TRADE	Exports: Intermediate goods made out of wood and cork	yes	1
222	TRADE	Exports: Intermediate goods made out of plastics	yes	1
223	TRADE	Exports: Intermediate goods made out of rubber	yes	1
224	TRADE	Exports: Chemical intermediate goods	yes	1
225	TRADE	Exports: Chemical raw materials	yes	1
226	TRADE	Exports: Chemical semi-finished goods for industrial use	yes	1
227	TRADE	Exports: Intermediate goods for construction as well as glass and ceramics	yes	1
228	TRADE	Exports: Intermediate goods for construction	yes	1
229	TRADE	Exports: Intermediate goods made out of glass, ceramics and soil	yes	1
230	TRADE	Exports: Intermediate goods made out of metal	yes	1
231	TRADE	Exports: Basic products made out of metal in pure form	yes	1
232	TRADE	Exports: Intermediate and finished goods made out of metal	yes	1
233	TRADE	Exports: Electrical and electronic intermediate goods	yes	1
234	TRADE	Exports: Intermediate goods for machines and appliances	yes	1
235	TRADE	Exports: Watch parts	yes	1
236	TRADE	Exports: Intermediate goods for vehicle construction	yes	1
237	TRADE	Exports: Commodities for public needs	yes	1
238	TRADE	Exports: Energy sources	yes	1
239	TRADE	Exports: Crude oil and basic products	yes	1
240	TRADE	Exports: Fuels	yes	1
241	TRADE	Exports: Fuels, petroleum-based	yes	1
242	TRADE	Exports: Capital goods	yes	1
243	TRADE	Exports: Machinery and instruments	yes	1
244	TRADE	Exports: Power generation and transmission machinery (less vehicle engines)	yes	1
245	TRADE	Exports: Electrical power generation and transmission machinery	yes	1
246	TRADE	Exports: Non-electrical power generation and transmission machinery	yes	1
247	TRADE	Exports: Replacement parts for power generation and transmission machinery	yes	1
248	TRADE	Exports: Manufacturing machinery	yes	1
249	TRADE	Exports: Mechanical design and processing machinery	yes	1
250	TRADE	Exports: Machines for thermal processing of fabrics	yes	1
251	TRADE	Exports: Design and processing machinery (excluding mechanical and thermal)	yes	1
252	TRADE	Exports: Replacement parts for manufacturing machinery	yes	1
253	TRADE	Exports: Machines and equipment	yes	1
254	TRADE	Exports: Building and agricultural machinery	yes	1
255	TRADE	Exports: Chop-, cut- and distributing machines	yes	1
256	TRADE	Exports: Machines for movement of goods	yes	1
257	TRADE	Exports: Optical- and precision instruments	yes	1
258	TRADE	Exports: Tools and equipment	yes	1
259	TRADE	Exports: Measure-, test-, control and operating equipment	yes	1
260	TRADE	Exports: Replacement parts for machines	yes	1
261	TRADE	Exports: Machines and tools for equipment of buildings	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
262	TRADE	Exports: Heating and air conditioning	yes	1
263	TRADE	Exports: Technical equipment and appliances for buildings	yes	1
264	TRADE	Exports: Parts for technical equipment and appliances for buildings	yes	1
265	TRADE	Exports: Machines and equipment for the service industry	yes	1
266	TRADE	Exports: Office equipment	yes	1
267	TRADE	Exports: Data processing equipment	yes	1
268	TRADE	Exports: Office equipment (excluding data processing equipment)	yes	1
269	TRADE	Exports: Software	yes	1
270	TRADE	Exports: Printing machinery	yes	1
271	TRADE	Exports: Delivery devices and installations	yes	1
272	TRADE	Exports: Storage and transport containers	yes	1
273	TRADE	Exports: Hospital- and healtcare equipment	yes	1
274	TRADE	Exports: Machine parts for the service industry	yes	1
275	TRADE	Exports: Commercial vehicles	yes	1
276	TRADE	Exports: Road vehicle	yes	1
277	TRADE	Exports: Replacement parts for commercial vehicles	yes	1
278	TRADE	Exports: Building materials	yes	1
279	TRADE	Exports: Goods for construction above ground	yes	1
280	TRADE	Exports: Goods for construction above ground (excluding prefabricated construction)	yes	1
281	TRADE	Exports: Goods for construction below ground	yes	1
282	TRADE	Exports: Consumer goods	yes	1
283	TRADE	Exports: Food and non-essential food items	yes	1
284	TRADE	Exports: Food	yes	1
285	TRADE	Exports: Non-essential food items	yes	1
286	TRADE	Exports: Animal food	yes	1
287	TRADE	Exports: Non-durable consumer goods (excluding foodstuffs)	yes	1
288	TRADE	Exports: Ready-made goods	yes	1
289	TRADE	Exports: Clothing and footware	yes	1
290	TRADE	Exports: Bed linen and household linen	yes	1
291	TRADE	Exports: Body care-, cosmetical and pharmaceutical products	yes	1
292	TRADE	Exports: Body care and cleaning products	yes	1
293	TRADE	Exports: Cosmetics, perfume and body care products	yes	1
294	TRADE	Exports: Pharmaceutical products (including sanitary products)	yes	1
295	TRADE	Exports: Handicraft materials like dyes, glue and yarn	yes	1
296	TRADE	Exports: Other household non-durable goods	yes	1
297	TRADE	Exports: Miscellaneous non-durable goods	yes	1
298	TRADE	Exports: Printed matter	yes	1
299	TRADE	Exports: Books, newspapers, magazines	yes	1
300	TRADE	Exports: Printed matter like notes, cards and advertising material	yes	1
301	TRADE	Exports: Durable consumer goods	yes	1
302	TRADE	Exports: Home facilities	yes	1
303	TRADE	Exports: Furniture and do-it-yourself products	yes	1
304	TRADE	Exports: Flooring, curtains and decoration	yes	1
305	TRADE	Exports: Lighting, ornamental decoration etc.	yes	1
306	TRADE	Exports: Household utensils	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
307	TRADE	Exports: Tableware and cutlery	yes	1
308	TRADE	Exports: Household utensils (excluding tableware and cutlery)	yes	1
309	TRADE	Exports: Household appliances	yes	1
310	TRADE	Exports: Entertainment electronics	yes	1
311	TRADE	Exports: Radio-, TV- and video equipment	yes	1
312	TRADE	Exports: Photo and movie devices	yes	1
313	TRADE	Exports: Hi-Fi equipment	yes	1
314	TRADE	Exports: Play-, Sport- and recreational equipment	yes	1
315	TRADE	Exports: Vehicles, like private cars and motorcycles	yes	1
316	TRADE	Exports: Private cars	yes	1
317	TRADE	Exports: Motorcycles and bicycles	yes	1
318	TRADE	Exports: Accessories to private cars and motorcycles	yes	1
319	TRADE	Exports: Watches, jewellery and optics	yes	1
320	TRADE	Exports: Watches	yes	1
321	TRADE	Exports: Jewellery	yes	1
322	TRADE	Exports: Glasses, contact lenses and binoculars	yes	1
323	TRADE	Exports: Musical instruments and accessories	yes	1
324	TRADE	Imports - Total	yes	1
325	TRADE	Imports: Raw materials and intermediate goods	yes	1
326	TRADE	Imports: Raw materials	yes	1
327	TRADE	Imports: Raw materials for agriculture	yes	1
328	TRADE	Imports: Organic raw materials for agriculture	yes	1
329	TRADE	Imports: Animal raw materials for agriculture	yes	1
330	TRADE	Imports: Raw materials for food production	yes	1
331	TRADE	Imports: Organic raw materials for food production	yes	1
332	TRADE	Imports: Animal raw materials for food production	yes	1
333	TRADE	Imports: Raw materials for industrial processing	yes	1
334	TRADE	Imports: Organic raw materials for industrial processing	yes	1
335	TRADE	Imports: Animal raw materials for industrial processing	yes	1
336	TRADE	Imports: Mining raw materials for industrial processing	yes	1
337	TRADE	Imports: Intermediate and semi-finished goods	yes	1
338	TRADE	Imports: Intermediate goods for the nutrition industry	yes	1
339	TRADE	Imports: Intermediate goods for food production	yes	1
340	TRADE	Imports: Intermediate goods for feeding stuff production	yes	1
341	TRADE	Imports: Intermediate goods for the industry (less nutrition)	yes	1
342	TRADE	Imports: Intermediate goods for the textile and clothing industry	yes	1
343	TRADE	Imports: Intermediate goods made out of paper	yes	1
344	TRADE	Imports: Intermediate goods made out of leather and fur	yes	1
345	TRADE	Imports: Intermediate goods made out of wood and cork	yes	1
346	TRADE	Imports: Intermediate goods made out of plastics	yes	1
347	TRADE	Imports: Intermediate goods made out of rubber	yes	1
348	TRADE	Imports: Chemical intermediate goods	yes	1
349	TRADE	Imports: Chemical raw materials	yes	1
350	TRADE	Imports: Chemical semi-finished goods for industrial use	yes	1
351	TRADE	Imports: Intermediate goods for construction as well as glass and ceramics	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
352	TRADE	Imports: Intermediate goods for construction	yes	1
353	TRADE	Imports: Intermediate goods made out of glass, ceramics and soil	yes	1
354	TRADE	Imports: Intermediate goods made out of metal	yes	1
355	TRADE	Imports: Basic manufactures made out of metal in pure form	yes	1
356	TRADE	Imports: Intermediate and finished goods made out of metal	yes	1
357	TRADE	Imports: Electrical and electronic intermediate goods	yes	1
358	TRADE	Imports: Intermediate goods for machines and appliances	yes	1
359	TRADE	Imports: Watch parts	yes	1
360	TRADE	Imports: Intermediate goods for vehicle construction	yes	1
361	TRADE	Imports: Commodities for public needs	yes	1
362	TRADE	Imports: Energy sources	yes	1
363	TRADE	Imports: Crude oil and basic products	yes	1
364	TRADE	Imports: Power fuels	yes	1
365	TRADE	Imports: Power fuels, petroleum-based	yes	1
366	TRADE	Imports: Power fuels from natural gas and hydrocarbon	yes	1
367	TRADE	Imports: Fuels	yes	1
368	TRADE	Imports: Fuels, petroleum-based	yes	1
369	TRADE	Imports: Fuels from coal, coke, wood etc.	yes	1
370	TRADE	Imports: Capital goods	yes	1
371	TRADE	Imports: Machinery and instruments	yes	1
372	TRADE	Imports: Power generation and transmission machinery (excluding vehicle engines)	yes	1
373	TRADE	Imports: Electrical power generation and transmission machinery	yes	1
374	TRADE	Imports: Non-electrical power generation and transmission machinery	yes	1
375	TRADE	Imports: Replacement parts for power generation and transmission machinery	yes	1
376	TRADE	Imports: Manufacturing machinery	yes	1
377	TRADE	Imports: Mechanical design and processing machinery	yes	1
378	TRADE	Imports: Machines for thermal processing of fabrics	yes	1
379	TRADE	Imports: Design and processing machinery (excluding mechanical and thermal)	yes	1
380	TRADE	Imports: Replacement parts for manufacturing machinery	yes	1
381	TRADE	Imports: Machines and equipment	yes	1
382	TRADE	Imports: Building and agricultural machinery	yes	1
383	TRADE	Imports: Chop-, cut- and distributing machines	yes	1
384	TRADE	Imports: Machines for movement of goods	yes	1
385	TRADE	Imports: Optical- and precision instruments	yes	1
386	TRADE	Imports: Tools and machines	yes	1
387	TRADE	Imports: Measure-, test-, control and operating equipment	yes	1
388	TRADE	Imports: Replacement parts for machines	yes	1
389	TRADE	Imports: Machines and equipment for equipment of buildings	yes	1
390	TRADE	Imports: Heating and air conditioning	yes	1
391	TRADE	Imports: Technical equipment and appliances for buildings	yes	1
392	TRADE	Imports: Parts for technical equipment and appliances for buildings	yes	1
393	TRADE	Imports: Machines and equipment for the service industry	yes	1
394	TRADE	Imports: Office equipment	yes	1
395	TRADE	Imports: Data processing equipment	yes	1
396	TRADE	Imports: Office equipment (excluding data processing equipment)	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
397	TRADE	Imports: Software	yes	1
398	TRADE	Imports: Printing machinery	yes	1
399	TRADE	Imports: Delivery devices and installations	yes	1
400	TRADE	Imports: Storage and transport containers	yes	1
401	TRADE	Imports: Recording-, projection and presentation equipment	yes	1
402	TRADE	Imports: Hospital- and healtcare equipment	yes	1
403	TRADE	Imports: Machine parts for the service industry	yes	1
404	TRADE	Imports: Commercial vehicles	yes	1
405	TRADE	Imports: Road vehicle	yes	1
406	TRADE	Imports: Stationary equipment for commercial vehicles	yes	1
407	TRADE	Imports: Replacement parts for commercial vehicles	yes	1
408	TRADE	Imports: Building materials	yes	1
409	TRADE	Imports: Goods for construction above ground	yes	1
410	TRADE	Imports: Prefabricated construction and components	yes	1
411	TRADE	Imports: Construction above ground (excluding prefabricated construction)	yes	1
412	TRADE	Imports: Goods for construction below ground	yes	1
413	TRADE	Imports: Consumer goods	yes	1
414	TRADE	Imports: Food and non-essential food items	yes	1
415	TRADE	Imports: Food	yes	1
416	TRADE	Imports: Non-essential food items	yes	1
417	TRADE	Imports: Animal food	yes	1
418	TRADE	Imports: Non-durable consumer goods (excluding food)	yes	1
419	TRADE	Imports: Ready-made goods	yes	1
420	TRADE	Imports: Clothing and footwear	yes	1
421	TRADE	Imports: Bed linen and household linen	yes	1
422	TRADE	Imports: Body care-, cosmetic and pharmaceutical products	yes	1
423	TRADE	Imports: Body care and cleaning products	yes	1
424	TRADE	Imports: Cosmetics, perfume and body care products	yes	1
425	TRADE	Imports: Pharmaceutical products (including sanitary products)	yes	1
426	TRADE	Imports: Handicraft materials like dyes, glue and yarn	yes	1
427	TRADE	Imports: Other household non-durable goods	yes	1
428	TRADE	Imports: Miscellaneous non-durable goods	yes	1
429	TRADE	Imports: Printed matter	yes	1
430	TRADE	Imports: Books, newspapers, magazines	yes	1
431	TRADE	Imports: Printed matter like notes, cards and advertising material	yes	1
432	TRADE	Imports: Durable consumer goods	yes	1
433	TRADE	Imports: Home facilities	yes	1
434	TRADE	Imports: Furniture and do-it-yourself products	yes	1
435	TRADE	Imports: Flooring, curtains and decoration	yes	1
436	TRADE	Imports: Lighting, ornamental decoration etc.	yes	1
437	TRADE	Imports: Household utensils	yes	1
438	TRADE	Imports: Tableware and cutlery	yes	1
439	TRADE	Imports: Household utensils (excluding tableware and cutlery)	yes	1
440	TRADE	Imports: Household appliances	yes	1
441	TRADE	Imports: Entertainment electronics	yes	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
442	TRADE	Imports: Radio-, TV- and video equipment	yes	1
443	TRADE	Imports: Photo and video devices	yes	1
444	TRADE	Imports: Hi-Fi equipment	yes	1
445	TRADE	Imports: Play-, sport- and recreational equipment	yes	1
446	TRADE	Imports: Vehicles, like private cars and motorcycles	yes	1
447	TRADE	Imports: Private cars	yes	1
448	TRADE	Imports: Motorcycles and bicycles	yes	1
449	TRADE	Imports: Accessories to private cars and motorcycles	yes	1
450	TRADE	Imports: Watches, jewellery and optics	yes	1
451	TRADE	Imports: Watches	yes	1
452	TRADE	Imports: Jewellery	yes	1
453	TRADE	Imports: Glasses, contact lenses and binoculars	yes	1
454	TRADE	Imports: Musical instruments and accessories	yes	1
455	STOCK	SWITZ-DS Alt. Electricity - PRICE INDEX	no	1
456	STOCK	SWITZ-DS Asset Managers - PRICE INDEX	no	1
457	STOCK	SWITZ-DS Banks - PRICE INDEX	no	1
458	STOCK	SWITZ-DS Basic Mats - PRICE INDEX	no	1
459	STOCK	SWITZ-DS Build Mat/Fixt - PRICE INDEX	no	1
460	STOCK	SWITZ-DS Basic Resource - PRICE INDEX	no	1
461	STOCK	SWITZ-DS Bus Trn/Emp Ag - PRICE INDEX	no	1
462	STOCK	SWITZ-DS Bus Sup Svs - PRICE INDEX	no	1
463	STOCK	SWITZ-DS Chemicals - PRICE INDEX	no	1
464	STOCK	SWITZ-DS Spec Chem - PRICE INDEX	no	1
465	STOCK	SWITZ-DS Cloth & Access - PRICE INDEX	no	1
466	STOCK	SWITZ-DS CONS.DISCRETNRY. - PRICE INDEX	no	1
467	STOCK	SWITZ-DS Consumer goods - PRICE INDEX	no	1
468	STOCK	SWITZ-DS Consumer services - PRICE INDEX	no	1
469	STOCK	SWITZ-DS Consumer staples - PRICE INDEX	no	1
470	STOCK	SWITZ-DS Con & Mat - PRICE INDEX	no	1
471	STOCK	SWITZ-DS Con. Electricity - PRICE INDEX	no	1
472	STOCK	SWITZ-DS Coml Veh/Truck - PRICE INDEX	no	1
473	STOCK	SWITZ-DS Computer Hardware - PRICE INDEX	no	1
474	STOCK	SWITZ-DS Cont & Pack - PRICE INDEX	no	1
475	STOCK	SWITZ-DS Delivery services - PRICE INDEX	no	1
476	STOCK	SWITZ-DS Drug Retailers - PRICE INDEX	no	1
477	STOCK	SWITZ-DS Div Inds - PRICE INDEX	no	1
478	STOCK	SWITZ-DS Dur Hh Prd - PRICE INDEX	no	1
479	STOCK	SWITZ-DS Electricity - PRICE INDEX	no	1
480	STOCK	SWITZ-DS Elec Compo/Eq - PRICE INDEX	no	1
481	STOCK	SWITZ-DS Eltro Eq - PRICE INDEX	no	1
482	STOCK	SWITZ-DS Eltro/Elec Eq - PRICE INDEX	no	1
483	STOCK	SWITZ-DS Eqt Ivst Ins - PRICE INDEX	no	1
484	STOCK	SWITZ-DS Food and beverages - PRICE INDEX	no	1
485	STOCK	SWITZ-DS Fd Rtl & W - PRICE INDEX	no	1

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Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
486	STOCK	SWITZ-DS Fd & Drug Rtl - PRICE INDEX	no	1
487	STOCK	SWITZ-DS Financials - PRICE INDEX	no	1
488	STOCK	SWITZ-DS Financial Svs(3) - PRICE INDEX	no	1
489	STOCK	SWITZ-DS Full Lin Insur - PRICE INDEX	no	1
490	STOCK	SWITZ-DS Financial Svs(4) - PRICE INDEX	no	1
491	STOCK	SWITZ-DS Fd Producers - PRICE INDEX	no	1
492	STOCK	SWITZ-DS Forestry and paper - PRICE INDEX	no	1
493	STOCK	SWITZ-DS General industry - PRICE INDEX	no	1
494	STOCK	SWITZ-DS General retailers - PRICE INDEX	no	1
495	STOCK	SWITZ-DS H/C Eq & Svs - PRICE INDEX	no	1
496	STOCK	SWITZ-DS H/H Gds,Home Con - PRICE INDEX	no	1
497	STOCK	SWITZ-DS Health Care - PRICE INDEX	no	1
498	STOCK	SWITZ-DS Heavy Con - PRICE INDEX	no	1
499	STOCK	SWITZ-DS Inds Machinery - PRICE INDEX	no	1
500	STOCK	SWITZ-DS Inds Eng - PRICE INDEX	no	1
501	STOCK	SWITZ-DS Inds Gds & Svs - PRICE INDEX	no	1
502	STOCK	SWITZ-DS Ind. Met & Mines - PRICE INDEX	no	1
503	STOCK	SWITZ-DS Inds Transpt - PRICE INDEX	no	1
504	STOCK	SWITZ-DS Industrials - PRICE INDEX	no	1
505	STOCK	SWITZ-DS Insurance - PRICE INDEX	no	1
506	STOCK	SWITZ-DS Investment Cos. - PRICE INDEX	no	1
507	STOCK	SWITZ-DS Life Insurance - PRICE INDEX	no	1
508	STOCK	SWITZ-DS Marine Transpt - PRICE INDEX	no	1
509	STOCK	SWITZ-DS Media Agencies - PRICE INDEX	no	1
510	STOCK	SWITZ-DS Medical Eq - PRICE INDEX	no	1
511	STOCK	SWITZ-DS Media - PRICE INDEX	no	1
512	STOCK	SWITZ-DS Nonlife Insur - PRICE INDEX	no	1
513	STOCK	SWITZ-DS Paper - PRICE INDEX	no	1
514	STOCK	SWITZ-DS Pers & H/H Gds - PRICE INDEX	no	1
515	STOCK	SWITZ-DS Personal Goods - PRICE INDEX	no	1
516	STOCK	SWITZ-DS Pharmaceuticals and biotechnology - PRICE INDEX	no	1
517	STOCK	SWITZ-DS Pharmaceuticals - PRICE INDEX	no	1
518	STOCK	SWITZ-DS Reinsurance - PRICE INDEX	no	1
519	STOCK	SWITZ-DS Retail - PRICE INDEX	no	1
520	STOCK	SWITZ-DS Speciality Fin - PRICE INDEX	no	1
521	STOCK	SWITZ-DS Iron and steel - PRICE INDEX	no	1
522	STOCK	SWITZ-DS Support Services - PRICE INDEX	no	1
523	STOCK	SWITZ-DS Tch H/W & Eq - PRICE INDEX	no	1
524	STOCK	SWITZ-DS Technology - PRICE INDEX	no	1
525	STOCK	SWITZ-DS Telecom Eq - PRICE INDEX	no	1
526	STOCK	SWITZ-DS Telecom, media, IT - PRICE INDEX	no	1
527	STOCK	SWITZ-DS Non-financial - PRICE INDEX	no	1
528	STOCK	SWITZ-DS Market - PRICE INDEX	no	1
529	STOCK	SWITZ-DS DS-MARKET EX RES - PRICE INDEX	no	1
530	STOCK	SWITZ-DS DS-MARKET EX TMT - PRICE INDEX	no	1

Continued on next page

Table A-1 – continued from previous page

Nr.	Block	Indicator	Seas. Adjustment	Transformation
531	STOCK	SWITZ-DS Travl and Tourism - PRICE INDEX	no	1
532	STOCK	SWITZ-DS Travel & Leisure - PRICE INDEX	no	1
533	STOCK	SWITZ-DS Transport services - PRICE INDEX	no	1
534	STOCK	SWITZ-DS Utilities - PRICE INDEX	no	1
535	INTEREST	SWISS 3 MONTH LIBOR (SNB) - MIDDLE RATE	no	2
536	INTEREST	SWISS CONFEDERATION BOND 1 YEAR - RED. YIELD	no	2
537	INTEREST	SWISS CONFEDERATION BOND 2 YEAR - RED. YIELD	no	2
538	INTEREST	SWISS CONFEDERATION BOND 3 YEAR - RED. YIELD	no	2
539	INTEREST	SWISS CONFEDERATION BOND 4 YEAR - RED. YIELD	no	2
540	INTEREST	SWISS CONFEDERATION BOND 5 YEAR - RED. YIELD	no	2
541	INTEREST	SWISS CONFEDERATION BOND 6 YEAR - RED. YIELD	no	2
542	INTEREST	SWISS CONFEDERATION BOND 7 YEAR - RED. YIELD	no	2
543	INTEREST	SWISS CONFEDERATION BOND 8 YEAR - RED. YIELD	no	2
544	INTEREST	SWISS CONFEDERATION BOND 9 YEAR - RED. YIELD	no	2
545	INTEREST	SWISS CONFEDERATION BOND 10 YEAR - RED. YIELD	no	2
546	INTEREST	SWISS CONFEDERATION BOND 15 YEAR - RED. YIELD	no	2
547	INTEREST	SWISS CONFEDERATION BOND 20 YEAR - RED. YIELD	no	2
548	INTEREST	SWISS CONFEDERATION BOND 30 YEAR - RED. YIELD	no	2
549	INTEREST	SWISS INTERBANK 1M (ZRC:SNB) - BID RATE	no	2
550	INTEREST	SWISS INTERBANK 1Y (ZRC:SNB) - BID RATE	no	2
551	INTEREST	SWISS INTERBANK 2M (ZRC:SNB) - BID RATE	no	2
552	INTEREST	SWISS INTERBANK 3M (ZRC:SNB) - BID RATE	no	2
553	INTEREST	SWISS INTERBANK 6M (ZRC:SNB) - BID RATE	no	2
554	INTEREST	SWISS LIQ.FINANCING RATE (SNB) - MIDDLE RATE	no	2
555	INTEREST	SWISS INTERBANK 7 DAYS (ZRC : SNB)	no	2
556	INTEREST	SWISS INTERBANK TOMORROW NEXT (ZRC : SNB)	no	2
557	CURRENCY	Swiss franc to Euro (WMR) - Exchange rate	no	1
558	CURRENCY	Swiss franc to UK (WMR) - Exchange rate	no	1
559	CURRENCY	Swiss franc to US $ (WMR) - Exchange rate	no	1

Transformation to stationarity: 0 – none; 1 – monthly growth rate; 2 – monthly difference