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SHORT-TERM FORECASTING OF SLOVAK GDP BASED ON HIGH-FREQUENCY DATA

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Abstract: *The paper compares two forecasts of Slovak GDP, the first with high-frequency data and the second without them. We utilize the last observation from the economic activity index acting as a short-term GDP forecast. We use data from 2000 to 2024 in weekly frequencies and have 27 variables related to different sectors such as: real activity, energy, households, labour, expectations, transport, financial data. We address the problem of Nowcasting of the growth rate of Slovak real GDP using dynamic factor models by incorporating ragged edges in the data. The outcome of the paper is that the model without high-frequency data has better forecasting capabilities and may better forecast economic recessions and growths in the Slovak Republic.*

Keywords: *Nowcasting, GDP, economic activity index, Kalman filter*

JEL Classification: C53, E37, E01

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1 Introduction

Economic activity indices are increasingly being used to measure economic performance. Traditional approaches to compiling these indices are based on quarterly or monthly data, which, although accurate, often have a significant time lag before publication. With growing demand for more timely and flexible indicators, the use of unconventional data sources with higher frequency, such as weekly and daily data, is coming to the fore. These data allow for faster identification of changes in economic activity and can be crucial in monitoring the economic cycle or crisis situations.

The number of studies on nowcasting is growing, but it is still insufficient. Nowcasting is a new field in econometrics and is still evolving. First, although there are many studies on GDP nowcasting, the best method and predictors have not yet been identified, as results vary depending on the region and time of the study. There are only a few studies that compare the accuracy of multiple nowcasting methods. Although the United States is taken as an example, having been the subject of the largest number of studies (59), slightly more than half of the papers (33) focus on nowcasting US GDP, while the other half focus on the labor market, financial and other indicators. In the case of studies focusing on GDP, empirical and methodological studies account for approximately 50%, and just under half of all these studies (15) compare at least two methods. When the euro area is considered (covered by 22 studies), the aim of all of them is to nowcast GDP. Approximately 70% of all these studies are empirical, and half of them compare at least two methods. However, in both the United States and the euro area, the models, and their variants, as well as the approaches chosen by researchers for comparison, differ, and it is not possible to draw conclusions from these studies. Therefore, further research is needed to compare DFM, bridge models, MIDAS models, VAR models, and machine learning methods. The following questions still need to be answered: are the same approaches most suitable for all regions and periods (i.e., phases of the economic cycle), and which model is most suitable for a specific country or region and period (Stundziene et al., 2024). Conventional indicators (hard and soft data) dominate research. There is a wide range of such indicators, and researchers are free to choose the ones that are most suitable for their analysis. Although researchers use many indicators and try to find the best predictors, the results vary. It is likely that the set of best predictors differs across countries and that the predictive power of indicators

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may depend on economic circumstances. Therefore, further research is needed to compare the performance of the best predictors used in previous studies across countries and to verify their predictive abilities over different time periods (Stundziene et al., 2024).

The number of studies examining the performance of unconventional indicators is growing. For example, 24% of the studies examined (47 studies) use data with a frequency higher than one month. However, many of them simply average daily or weekly data and analyse monthly data. In addition, 18% of the papers (34 papers) use alternative indicators, and half of them (16 papers) were published in 2020 or later. The growing popularity of these indicators among researchers suggests that alternative indicators will play a key role in monitoring economies in the future. It should be noted that not only traditional indicators and other macroeconomic indicators are relevant for current GDP forecasts or the display of economic activity; studies have demonstrated the usefulness of real-time alternative indicators (Google trends data, payments, text data, etc.). Future research should therefore include more real-time indicators, new sources of big data, web surveys, electronic transactions, text analysis, etc., which improve the performance of nowcasting (Stundziene et al., 2024).

There is a growing need for regular high-frequency data collection for research purposes. Financial institutions, various economic research institutions, and specialized associations that have real-time data available should provide more opportunities for other researchers to use such data to achieve a breakthrough in this field (Stundziene et al., 2024).

Our work will be based on the methodology developed by Bańbura et al. (2024) and Baumeister et al. (2024), who created a harmonized weekly index of economic activity (hereinafter HaWAI) that uses weekly data, allowing for timely assessment of real economic activity. This framework allows information to be obtained from medium to large data sets in a cost-effective manner and naturally offers a "composite index" in the form of a common factor. The index accurately reflects developments in economic activity in the euro area and in individual countries. Analysis of the factors contributing to these indices and the use of heat maps reveal differences in economic developments within the euro area. These indices are therefore suitable for providing valuable information on real variables on a weekly basis. HaWAI is designed to summarize numerous aspects of economic life that go beyond GDP, yet it tracks its movements accurately. The index captures periods of recession as well as the associated early recovery. In addition, it largely agrees with the extent of fluctuations in economic activity during these periods. For example, HaWAI distinguishes between the sharp decline and subsequent strong recovery during the Great Recession of 2008/9 and the coronavirus pandemic in 2020 from the comparatively milder slowdown and recovery during the recession in early 1992/3 and the eurozone sovereign debt crisis in 2011/12 (Bańbura et al., 2024a). Methodologically, the work of Bańbura et al. (2024) was inspired by the work of Baumeister et al. (2024), whose index is based on a dynamic factor model with mixed frequencies. They demonstrated that there is considerable heterogeneity in the dynamics of the economic cycle at the country level in terms of space and time, except for the economic recession associated with the COVID-19 crisis and the subsequent recovery.

The HaWAI index dataset includes indicators covering various aspects of economic activity, which are monitored on a weekly, monthly, or quarterly basis. The estimation is guided by a Bayesian approach combined with a Kalman filter, which allows for the quantification of various sources of uncertainty and provides a flexible solution to any missing data model. This last feature is particularly important for data sets with mixed frequencies, where indicators are characterized by different publication delays (Bańbura et al., 2024a).

For more detailed information on expert opinions, see, for example, the overview articles (Bańbura et al., 2013). The rest of the paper is structured as follows. Section 2 presents the main objective of the paper. Section 3 describes the methodology and data used in GDP forecasting. Section 4 presents the results of the paper (forecasting ability and comparison of two models), and Section 5 presents the conclusions.

2 Aim of the Paper

The primary objective of this work is to forecast GDP based on high-frequency data. We will examine this objective using dynamic factor models with mixed frequencies in state-space representations using Bayesian methods. A secondary but very important objective for the forecast will be to compile an economic activity index, from which we will then "extract" individual

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forecasts. We will incorporate ragged edges due to situations where data availability is inconsistent across different time periods or sources. We will be primarily inspired by the work of Baumeister, Leiva-León, Sims (2024), using the toolbox of Bańbura, Eraslan, Giammaria, Leiva-León, Paredes (2024).

The individual objectives of our work can be divided and described in more detail as follows:

1. We will create a mixed frequency data set, from which we will then generate 224 data sets, cumulatively adding the number of observations for each variable. We will adjust the number of observations based on ragged edges and add the appropriate number of empty observations (maximum 14 and minimum 12) after the observation in which we would record GDP on a quarterly basis. We will transform the data based on frequency into the appropriate transformation and add it to the appropriate category (real activity, households, expectations, etc.), then standardize it.

2. We employ a Gibbs sampling approach in conjunction with the Kalman filter to estimate parameters within a Bayesian framework. At each iteration of the Gibbs sampler, the Kalman filter is used to generate values for the missing observations. We will monitor how GDP values change based on the cumulative addition of observations, taking the generated values for GDP as a prediction.

3. We will create two forecasts: one with weekly, monthly, and quarterly variables (27 variables) and one with monthly and quarterly variables (17 variables). We will then compare the individual predictions with annual logarithmic GDP differences and evaluate the usefulness of incorporating weekly variables into the model.

3 Methodology, Working Procedures and Data

Dynamic factor models are widely used to construct indices for the timely measurement of real activity. Within dynamic factors, we combine data selected at different frequencies to create a high-frequency indicator of economic activity at the state level. The Bayesian framework allows us to incorporate prior beliefs and hierarchical modelling. Distributions are assigned to model parameters such as factor loadings, factor dynamics, and error variances.

Normal distribution for factor loadings $\Lambda \sim N(0, \sigma^2)$

Inverse-Gamma or Wishart distribution for variance parameters

The posterior distribution is obtained using Bayes' theorem:

$$p(\theta \mid X) \propto p(X \mid \theta) p(\theta)$$

where:

$p(X \mid \theta)$ is the probability of the data given parameters,

$p(\theta)$ is the previous distribution.

The model is estimated for the Slovak Republic. The proposed empirical framework is used to summarize a set of N economic conditions indicators expressed at quarterly, monthly, and weekly frequencies into a single summary index expressed at weekly frequency. We assume that data with lower frequencies, i.e. monthly and quarterly, also have a weekly frequency, but with missing observations. For example, in the case of GDP growth, we assign the quarterly observation to the last week of each quarter and assume that observations for the other weeks are missing. We proceed analogously in the case of monthly variables. Similarly, we allow for missing observations at the end of the sample due to differences in publication delays and at the beginning of the sample, as some series have a relatively short time span (Bańbura et al., 2024b).

3.1 Gibbs sampler

The Gibbs sampler is used to perform Bayesian inference on a linear state space model with errors that may change over time. States are generated efficiently using a Kalman filter (Kim & Nelson, 1999). The model is estimated using Bayesian methods, assuming normal distributions for μ_{0,τ_0} a μ_{1,τ_1}, Beta distributions for p a q and Gamma distributions for σ_ε^2. Inference s_t is performed based on the algorithm implemented in Kim and Nelson (1999), which is an adaptation of the Carter and Kohn (1994) algorithm. For further details on the sampling algorithm, see Leiva-León et al. (2021).

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3.2 Dynamic Factor Models

Let yi, t denote i-th observed indicator, where t = 1..., T are index weeks and T denotes the number of weeks in the sample, and let m = 1..., M be indexing months, where M is the total number of months in the sample. Each week t is associated with month m_t, which includes the Monday of that week, and each month m is associated with the number of weeks, c(m) = 4 or 5, whose Monday falls in month m. Let Y_m be for example industrial production, recorded for month m. We imagine this as the sum of unobserved weekly values Z_t for each week in month m. If week t is the last week in month m_t,

$$Y_{m_t} = Z_t + Z_{t-1} + \cdots + Z_{t-c(m_t)+1}$$

A typical year consists of 52 weeks, so the y-o-y growth rate Y_{m_t} is given by.

$$\begin{aligned} lnY_{m_t} - lnY_{m_t-12} \\ &= \ln c(m_t) - \ln c(m_t - 12) \\ &+ [c(m_t)]^{-1}\left[\ln Z_t + lnZ_{t-1} + \cdots + lnZ_{t-c(m_t)+1}\right] \\ &- [c(m_{t-52})]^{-1}\left[\ln Z_{t-52} + lnZ_{t-53} + \cdots + lnZ_{t-c(m_{t-52})-51}\right] \end{aligned}$$

If a year consists of 53 weeks, then the year-on-year growth rate Y_{m_t} is given by.

$$\begin{aligned} lnY_{m_t} - lnY_{m_t-12} \\ &= \ln c(m_t) - \ln c(m_t - 12) \\ &+ [c(m_t)]^{-1}\left[\ln Z_t + lnZ_{t-1} + \cdots + lnZ_{t-c(m_t)+1}\right] \\ &- [c(m_{t-53})]^{-1}\left[\ln Z_{t-53} + lnZ_{t-54} + \cdots + lnZ_{t-c(m_{t-53})-52}\right] \end{aligned}$$

Similarly, let $q = 1, \ldots, Q$ denote quarters and $d(q)$ the number of weeks in quarter q. $d(q)$ can take the values 12, 13, 14. Let Y_q denote the value of a variable such as real GDP in quarter q a X_t the unobserved weekly level of GDP. We can model the growth rates of Y_q at weekly frequency as:

$$lnY_{q_t} - lnY_{q_{t-4}} = [d(qt)]^{-1}\left(x_t + x_{t-1} + \cdots + x_{t-d(q_t)+1}\right),$$

Where x_t denotes the year-on-year growth rate associated with week t.

It is assumed that yi, t consists of a common and idiosyncratic component. The former is given by the common factor multiplied by the factor loadings. The way in which yi,t is decomposed depends on its frequency, as follows: If $y_{i,t}$ is weekly, then: $y_{i,t} = \lambda_i f_t + u_{i,t}$. If $y_{i,t}$ is monthly, then the following applies: $y_{i,t} = \lambda_i G(f_t) + G(u_{i,t})$. If $y_{i,t}$ is quarterly, then the following applies: $y_{i,t} = \lambda_i H(f_t) + H(u_{i,t})$, for i = 1,...,N, where λi are factor loadings and $G(\cdot)$ and $H(\cdot)$ refer to the respective moving average functions. The common factor, ft, and idiosynkratic component, ui,t, are assumed to have autoregressive dynamics, $f_t = \varphi_1 f_{t-1} + \cdots + \varphi_p f_{t-p} + \epsilon_t$, $u_{i,t} = \psi_{i,1} + \cdots + \psi_{i,q} u_{i,t-q} + \varepsilon_{i,t}$, where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$, $\varepsilon_{i,t} \sim N(0, \sigma_i^2)$, and p is the lag order (Bańbura et al., 2024a).

First, the model elements are estimated using the Bayesian approach. We run the Gibbs sampler, alternately obtaining model parameter draws and factor (time series) draws. For the second case, we use a state-space representation of the model and apply a simulation smoother designed by Carter and Kohn (1994), which can flexibly account for any pattern of missing data. Using this methodology, we can also obtain draws for any missing observations in Yt = [$y1$, t, ..., yN, t] ′, which we denote YtP (Carter & Kohn, 1994). Second, based on the estimates of missing observations in the dataset and the estimates of weights, the harmonized weekly activity index at time t is calculated as,

$$SEAI_t = (\Lambda'\Lambda)^{-1}\Lambda' Y_t^P,$$

where Λ = [$\lambda 1$,...,λN]′ is the median estimate $(n_j \; x \; 1)$ in vector form that collects factor loadings for weekly, monthly, and quarterly variables, and Y_t^P is $(n_j \; x \; T)$ data set, where missing observations for variables with a frequency lower than weekly are replaced by Kalman filter projected values. Such a derivation is very useful at the country level using a cross-sectional dimension, as it provides a more reliable assessment of economic conditions and allows us to study the main determinants of fluctuations in each index (Bańbura et al., 2024a). However, in our work, we abstract from the cross-sectional dimension; we will not compare individual indices between countries but rather evaluate their predictive power for GDP.

3.3 State-Space Representation

Dynamic factor models assume that a set of high-dimensional time series

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datasets, such as hard indicators (GDP, employment, industrial production, etc.), are driven by a small number of unobservable latent factors that evolve over time. These factors capture common trends and dynamics across multiple observed variables. State-space representation provides a structured way to model these hidden factors and estimate them from high-dimensional data that contain random components of the time series u_t. A state-space model consists of two equations:

$$y_t = \Lambda f_t + \varepsilon_t, \varepsilon_t \sim \mathcal{N}(0, R)$$

General measurement equation

Where:

y_t is $N \times 1$ vector observed time series at time t.

Λ is $N \times r$ matrix of factor loadings.

f_t is $r \times 1$ vector of latent factor in time t.

ε_t is vector of white noise.

$$f_t = \Phi f_{t-1} + \eta_t, \eta_t \sim \mathcal{N}(0, Q)$$

State equation

Where:

Φ is $r \times\ r$ state transition matrix.

η_t is $r \times 1$ vector of factor inovation

Q is covariance of factor disturbances

The reason for using state space representations in DFM is that data sets often contain missing values. The Kalman filter is especially useful in this regard because it is used to estimate state-space models. It can seamlessly handle missing data by updating estimates based on available information.

3.4 Kalman filter

The Kalman filter is a recursive algorithm used to estimate hidden (latent) factors of a state-space representation model based on observations with a random component. In addition, it naturally handles missing observations, making it robust in scenarios with incomplete data. The filter also plays a key role in reducing "noise" by distinguishing between actual underlying signals (latent factors) and random components. In addition, it allows for dynamic updating and continuous refinement of factor estimates as new data become available. It consists of two main steps:

Prediction: Based on the previous estimate $\hat{f}_{t-1|t-1}$ and its covariance $P_{t-1|t-1}$

Prediction of factor dynamics: $\hat{f}_{t|t-1} = A\hat{f}_{t-1|\,t-1}$

Prediction of covariance: $P_{t|t-1} = AP_{t-1|t-1}A' + Q$, this step creates estimates of factors ahead of time.

Update: After observing y_t, we update the factor estimates

Calculation of forecast error: $v_t = \ y_t - \Lambda\hat{f}_{t|t-1}$

Calculation of innovation covariance: $S_t = \Lambda P_{t|t-1}\Lambda' + R$

Calculation of Kalman gain: $K_t = \ P_{t|t-1}\Lambda' S_t^{-1}$

Update of factor estimate: $\hat{f}_{t|t-1} + K_t V_t$

Update of covariance: $P_{t|t} = (I - K_t\Lambda)P_{t|t-1}$, this step corrects the prediction based on added information from y_t.

The Kalman smoother is often used after filtering to obtain smoothed estimates of factors by including both past and future information. Using backward recursion: $\hat{f}_{t|T} = \hat{f}_{t|t} + J_t\left(\hat{f}_{t+1|T} - \hat{f}_{t+1|t}\right)$, where $J_t = P_{t|t}A' P_{t+1|t}^{-1}$. This achieves more accurate factor estimates by utilizing the entire data set.

With the state-space representation model, we use a Kalman filter and Kalman smoother to obtain optimal extraction of the latent state of actual activity. As is standard in classical estimation, we initialize the Kalman filter using the unconditional mean and covariance matrix of the state vector. For more detailed information on expert opinions (see, for example, articles by Aruoba

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et al., 2009; Bańbura et al., 2024b; Baumeister et al., 2024; Camacho & Perez-Quiros, 2010; Mariano & Murasawa, 2003).

3.5 Data Selection

As regards individual data, we selected 27 variables with weekly, monthly, and quarterly frequencies. We have 10 variables with weekly frequencies, 11 variables with monthly frequencies, and 6 variables with quarterly frequencies. For more detailed information, see Table 2. We also performed an ADF (Augmented Dickey-Fuller) test for the given variables. The H0 hypothesis states that the time series is non-stationary, while the alternative hypothesis states that the given time series is stationary. If MacKinnon's approximate p-value is less than 0.05, we reject hypothesis H0, the alternative hypothesis applies, and thus the time series is stationary. Of the 27 variables, 8 were found to be non-stationary, see Table 1. Bayesian estimation allows for flexible parameter priors, which can help stabilize the estimate even if some variables are not stationary. A Bayesian structural time series model (e.g., using a Kalman filter or Gibbs sampler) can explicitly separate: Trend components (which may be non-stationary) and cyclical components (which are stationary). This allows for correct derivation without enforcing stationarity, i.e., it is not necessary to ensure the stationarity of the data.

Table 1: Augmented Dickey-Fuller Test of Stationarity for Individual Time Series

	Variable	P-value	Stationarity
Augmented Dickey-Fuller Test	Slovak stock index	0.2575103	No
	VSAX60SD	1.96e-05	Yes
	Electricity consumption	2.69e-07	Yes
	Number of flights	0.1962852	No
	dYC3-1	0.2189721	No
	OECD google tracker	1.88e-09	Yes
	Price of petrol	0.2516854	No
	Toll in euros	4.41e-26	Yes
	Toll in km	1.75e-25	Yes
	E-cash register sales	6.26e-08	Yes
	Industrial production	3.51e-05	Yes
	Export	4.98e-05	Yes
	Retail turnover	2.16e-08	Yes

Augmented Dickey-Fuller Test	Registration of personal vehicles	1.62e-14	Yes
	Unemployment	0.4226395	No
	Consumer confidence	0.0166981	Yes
	Industry confidence indicator	1.51e-08	Yes
	Confidence indicator in services	0.0442012	Yes
	Accommodation occupancy of Facilities	0.0001051	Yes
	Financial stress	2.27e-10	Yes
	Import crude	0.0014921	Yes
	Building permits	6.24e-06	Yes
	Real GDP	0.0047086	Yes
	Employment	0.1313314	No
	Property prices	0.7062518	No
	Greenhouse gas emissions	0.1913413	No
	Capacity utilization	0.0018959	Yes

Source: own processing.

Table 2: Data Included in the Model, Categorized with Transformation Codes and Frequencies

Category	Variables	Freq.	First obs.	Transformation code	Source	SA
Real activity	Industrial production	M	1.5.2000	Annual log difference (monthly)	Eurostat	Yes
	Export	M	1.5.2000	Annual log difference (monthly)	Eurostat	Yes
	real GDP	Q	26.6.2000	Annual log difference (quarterly)	SOSR	Yes
	Capacity utilization	Q	26.6.2000	Level	DG ECFIN	Yes
Energy	Electricity consumption	W	22.12.2014	Annual log difference (weekly)	SOSR	No
	Import of crude	M	27.1.2003	Annual log difference (monthly)	SOSR	No
	Green house gases	Q	29.3.2010	Log-Level	Eurostat	No
House-holds	OECD google tracker	W	5.1.2004	Annual log difference (weekly)	OECD	No
	E-cash register sales	W	3.2.2020	Log-Level	FA SR	No
	Retail turnover	M	29.1.2001	Annual log difference (monthly)	SOSR	No
	Property prices	Q	28.3.2005	Annual log difference (quarterly)	NBS	No

Labour	Unemployment	M	1.5.2000	Annual difference (monthly)	SOSR	Yes
	Accomodation occupancy of Facilities	M	27.1.2003	Annual log difference (monthly)	Eurostat	No
	Employment	Q	26.6.2000	Annual log difference (quarterly)	Eurostat	Yes
Expect.	Consumer confidence	M	1.5.2000	Level	DG ECFIN	Yes
	The Services Confidence Indicator	M	1.5.2000	Level	SOSR	Yes
	Industrial confidence indicator	M	1.5.2000	Level	SOSR	Yes
	Building permits	Q	31.3.2003	Annual log difference (quarterly)	Eurostat	No
Transport	Number of flights	W	7.1.2019	Log-Level	Eurocontrol	No
	Price of petrol	W	24.5.2004	Log-Level	SOSR	No
	Toll in km	W	6.1.2014	Log-Level	Skytoll	No
	Toll in euros	W	6.1.2014	Log-Level	Skytoll	No
	Registration of personal vehicles	M	27.1.2003	Log-Level	ACEA	No
Financial indicators	Slovak stock index	W	3.4.2000	Log-Level	BSSE	No
	VSAX60SD	W	3.4.2000	Log-Level	BSSE	No
	dYC3-1	W	3.4.2000	Level	NBS	No
	Financial stress	M	1.5.2000	Level	ECB	No

Source: own processing.

3.6 Mixed Frequency and Ragged Edges

This paper deals with the problem of mixing weekly, monthly, and quarterly data frequencies. The basic frequency of the mixed-frequency data set was set to weekly. Monthly data are recorded every fourth or fifth week, and quarterly data every twelfth, thirteenth, or fourteenth week, with other observations being treated as empty. The problem with accurately combining individual frequencies into a single data set is that it is not entirely clear how individual observations of variables with the relevant frequency repeat themselves, and the recording of individual data with the relevant observation does not always fall on the same date. The latter was solved by unifying the date on which individual frequencies are "recorded." In our work, this day is Monday. This modification allows individual observations to be recorded on the same date without deviations. Thus, the date for quarterly and monthly variables is always shifted to Monday. The problem of repeating the distance (in weeks) between the recording of new monthly and quarterly data compared to the last recorded observation can be solved easily. When compiling a dataset with mixed frequencies, it is necessary to compile separate datasets for weekly, monthly, and quarterly data. For each of these sets, a variable indicating the frequency must be generated, i.e., for quarterly data in our case, quarterly = 1 for each quarterly observation, for monthly data, monthly = 1 for each monthly observation, and for weekly data, weekly = 1 in the same way.

Table 3: Publication Delays for Individual Variables

	Variable	Publication Delays
Publication Delays	Slovak stock index	D+1
	Electricity consumption	D+1
	Number of flights	D+1
	dYC3-1	W+1,D1
	OECD google tracker	W+1,D1
	Toll in euros	W+1,D1
	Toll in km	W+1,D1
	Price of petrol	W+1,D1
	E-cash register sales	W+1,D1
	Industrial production	M+2,D13-15
	Export	M+2,D16
	Retail turnover	M+2,D4-6
	Registration of personal vehicles	M+1,D20
	Unemployment	M+1,D20
	Consumer confidence	M0,D23-27
	Industry confidence indicator	M0,D23-27
	Confidence indicator in services	M0,D23-27
	Accomodation occupancy of Facilities	M+2,D24
	Financial stress	M+1,D28
	Import crude	M+2,D7
	Building permits	M+1,D3
	real GDP	M+2,D15
	Employment	M+2,D7
	Property prices	M+2,D9
	Greenhouse gas emissions	M+5,D22
	Capacity utilization	M-1,D29

Source: own processing.

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Subsequently, when merging individual files into one large file, the date variable is used as a common "key" for successful pairing of the relevant variables so that observations between individual frequencies are harmonized. In addition to missing observations resulting from the presence of mixed frequencies, missing data are also the result of uneven data margins at the end of the sample due to asynchronous data release timing, occasional incomplete reports or data entry errors, and data series which are only available for part of the sample period (Baumeister et al., 2024). As can be seen from Table 3, some data are also recorded daily, namely SAX, electricity consumption, and number of flights. We aggregated these variables on a weekly basis: $collapse\ (mean) sax\ electricity\ dyc31\ (sum) flights, by(date)$.

3.7 Creating Mixed Frequency Data Sets

After combining the weekly, monthly, and quarterly data sets, we have a finalized mixed frequency data set. We will use data from April 3, 2000, to July 8, 2024. We will create 1,267 data sets that will grow cumulatively. This means that each subsequent file will have one additional observation based on the nearest quarter.

Methodologically, we did this by creating a backup file from which we left the first 14 observations for each variable, then deleting the last 13 observations and applying ragged edges rules, which deleted observations that we would not have had available at that time. We deleted the last 13 observations because we wanted to extend the sample by one quarter ahead. We did not want the observations to contain values because the Kalman filter can handle this and because the creation of another file cumulatively fills these gaps until the space between the first observation and the next quarter is empty, at which point the data set is again extended by another 13 empty observations. Space between the first observation and the next quarter is empty, then the data set is expanded again by another 13 empty observations. This process is used for nowcasting, where the gradual reduction of the data set simulates the availability of historical data.

At the beginning, it was appropriate for us to combine our mixed-frequency dataset with ragged edges rules. We did this by joining both datasets via a "key," i.e., a date variable. We then defined pairs, i.e., for each variable, its "rule" variable, which carried information about when the variable was published, while deleting observations that should not have been available in a given period from the last observations, simply by using: $replace\,`main\_var' = .\,if\ date > `check\_var'[\_N - 12]$ After creating these 1,267 data sets, we will keep the 1,044th to 1,267th sets, as we are interested in nowcasting the period from the beginning of Covid-19 to the present.

4 Results

As already mentioned in the objectives of our work, we will deal with short-term forecasting of Slovak GDP based on high-frequency data. We will compare two mixed-frequency models. One with monthly and quarterly frequency of variables and the other with weekly, monthly and quarterly frequency. We will also compare them with a naive AR1 forecast. We will evaluate individual forecasts by testing the accuracy of predictions based on standard metrics. We will calculate MAE (Mean Absolute Error, hereinafter MAE), MFE (Mean Forecast Error, hereinafter MFE), MSE (Mean Squared Error, hereinafter MSE), RMSE (Root Mean Squared Error, hereinafter RMSE). If necessary, we will try to fine-tune the individual forecasts based on Bridge equations to improve the 'performance' of the individual forecasts. We will not fine-tune the AR1 forecast as it will serve as a reference value for comparing a relatively simple method with a more complex forecasting method. As we are nowcasting the past, we will evaluate our forecasts against the annual logarithmic difference in Slovakia's GDP. We will forecast 17 quarters from 30 March 2020 to 1 April 2024.

Between 2020 and 2024, there were quite a few economic milestones. The year 2020 and the start of the Covid-19 pandemic caused a decline in GDP. In 2021, economic recovery began. In 2022, energy prices rose due to Russia's invasion of Ukraine. The year 2023 was marked by low economic growth and rising prices. In 2024, more modest economic growth was observed, with certain challenges for the consolidation of public finances. We will look at these individual periods and try to show whether the data we have and the model we have worked with can predict these periods and how accurately they can be forecasted.

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4.1 Forecast Comparison Metrics and AR(1) Autoregressive Model

We will compare our forecasts with the annual logarithmic difference in GDP. We will calculate the MAE, MFE, MSE, RMSE and MAPE statistics.

MAE measures the average size of errors between actual and predicted values without considering the direction. The smaller the value, the better the accuracy of the prediction. The formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MFE measures the average difference between actual values and predicted values with respect to direction. A positive MFE means that forecasts tend to underestimate, while a negative MFE means overestimation. Given formula:

$$MFE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$$

MSE measures the average square differences between actual and predicted values. It penalises large errors more than small errors. Given formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

RMSE is the square root of MSE; it provides a metric of error in the same units as the data. Lower values indicate better model performance. The formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

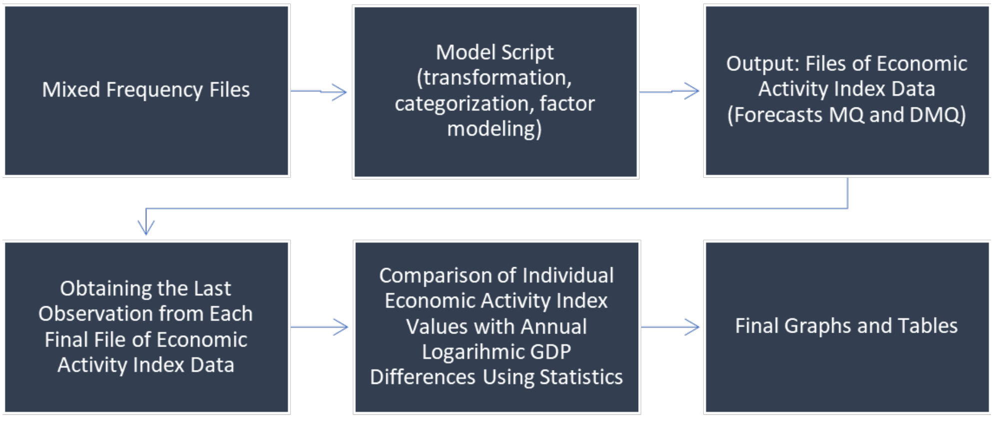
MAPE Mean absolute percentage error is a metric used in forecasting to measure the accuracy of predictions. It indicates how much the predicted values differ from the actual values, expressed as a percentage.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100$$

We calculate individual metrics for all types of forecasts and then provide tables with the results.

4.2 Results of the MQ Model (monthly and quarterly data)

Diagram 1: Procedure for Obtaining Individual Forecasts for a Mixed Freequency Set



Source: own processing.

We will use the above-mentioned 224 data sets to create an economic activity index. For each variable in a single data set, we will perform a time series transformation and categorisation of individual variables, as shown in Table 1. We will then use a Gibbs sampler to estimate parameters in a Bayesian framework. We will select a common factor from the data set for the forecast and then calculate the economic activity index. This entire process is iterative, and we run it three thousand times for one mixed-frequency data set. We then store the results in a single file for each input file. We perform the described process for all 224 so-called vintage data sets. From the resulting files, we obtain the last observation of the activity index, which we assign to the date when we record the annual logarithmic difference of Slovak GDP (hereinafter ALD GDP). We then evaluate the individual forecasts. The reason why the forecast is compiled from vintage data files is that we are trying to ensure that information that was not published at the time does not enter the forecast and

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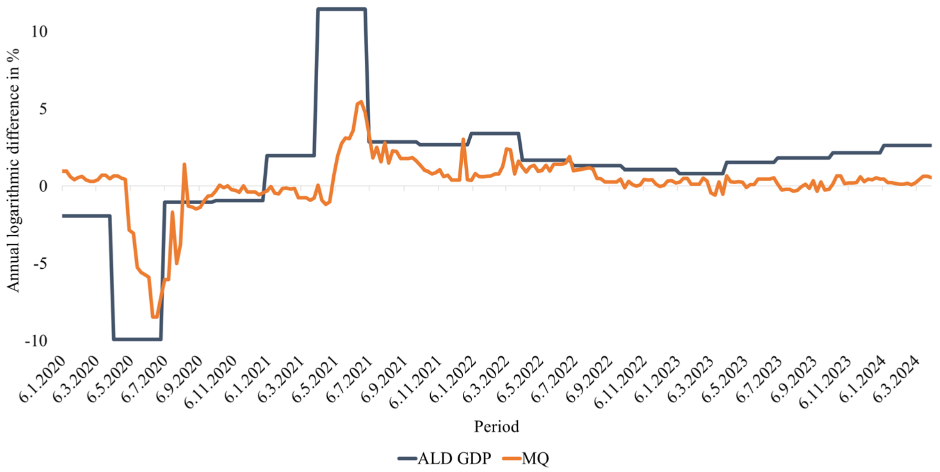
thus does not influence the calculated prediction.

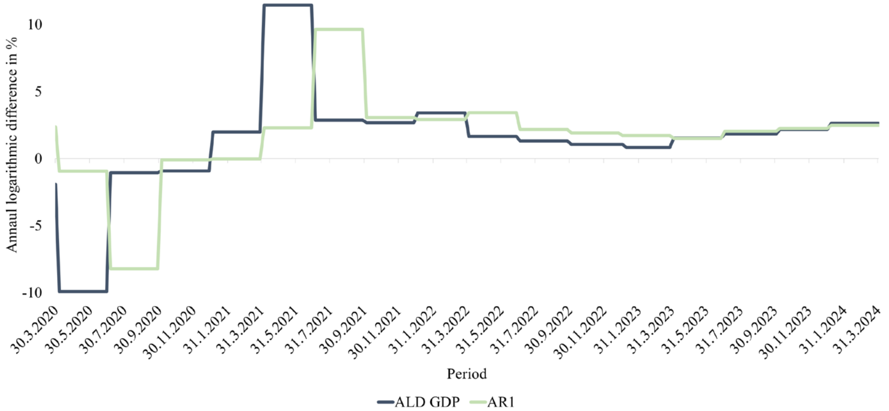
Figure 1: Comparison of MQ Forecast with ALD GDP



Source: own processing.

The initial results of the economic activity index for the weekly framework indicate that the model's forecasts have significant errors. The MAE values differ by an average of approximately 2.21 units. The reason why we record the same value for ALD GDP for 13 weeks in the weekly framework is that the actual value is only recorded in 1 week, but if we want to calculate statistics for each week, we have added the same value for the given weeks.

Figure 2: Comparison of the Naive AR1 Forecast with ALD GDP



Source: own processing.

The bias (MFE) is 1.09, with the model tending to underestimate the results, see Figure 1, orange solid line compared to the dark blue line. We also compared the MQ forecast with the naive AR1 forecast, see Figure 2. This forecast shows worse results, with MFE coming out negative close to zero (-0.40), which indicates an overestimation of the forecast compared to reality. The reason why we call the AR1 forecast naive is that it cannot correctly predict uctuations because it is based on the past, in this case □ − 1. Based on Table 4, we can see that the MQ forecast is better in individual statistics, except for the MFE statistic, which indicates other directions of bias. However, neither forecast is considered to accurately reflect reality, as the MAPE statistic remains relatively high for MQ (81.95) and AR1 (111.35).

Table 4: Statistics of MQ and AR1 Forecasts with Their Difference

	MQ	AR1	MQ - AR1
MAE	2.21	2.63	-0.42
MFE	1.09	-0.40	1.49
MSE	10.86	17.00	-6.14
RMSE	3.30	4.12	-0.83
MAPE	81.95	111.35	-29.40

Source: own processing.

4.3 Bridge Equations

Since the forecast had significant errors, we decided to use Bridge equations, a type of econometric model that combines high-frequency data with lower-frequency data. It is commonly used for nowcasting or forecasting economic indicators when complete data sets are not yet available (Huček et al., 2015). General formula for Bridge equations:

$$Y_t = \alpha + \sum_{i=1}^{n} \beta_i x_{t-i} + \epsilon_t$$

We will use the least squares method to estimate the relationship between ALD GDP (dependent variable) and MQ (independent variable). Bridge equations will be performed on our results (from 224 data sets), whereby it is necessary to delete the last observation for ALD GDP from each vintage data set, as it would affect the forecast by introducing unavailable information. A new MQ

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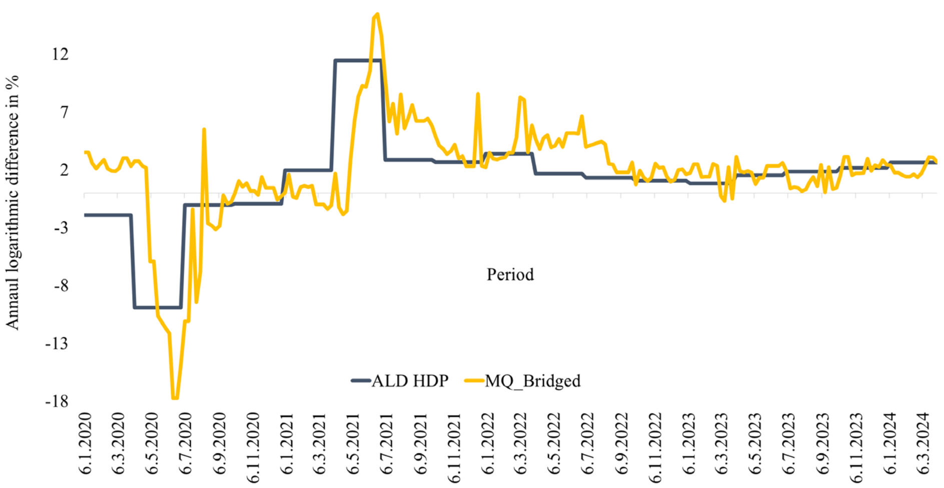
(MQ_Bridged, hereinafter MQ_Bridged) is then estimated for all data sets, the last observation of MQ_Bridged is stored for the relevant quarter, and a new data set is then compiled from the latest MQ_Bridged predictions. Such a data set can be used for comparison with ALD GDP. Our index did not contain autocorrelation, so it was not necessary to include the AR1 term in the Bridge equations. We performed the autocorrelation test using the Breusch-Godfrey LM test, see Table 5. If the p-value is greater than 0.05, the H0 hypothesis cannot be rejected, and therefore there is no autocorrelation in the model.

Table 5: The Breusch-Godfrey Autocorrelation Test

Breusch-Godfrey LM test for autocorrelation			
lags(p)	Prob>chi2	lags(p)	Prob>chi2
1	0.9962	6	0.217
2	0.9827	7	0.3056
3	0.9463	8	0.39
4	0.6574	9	0.4869
5	0.1802	10	0.4764
H0: no serial correlation			

Source: own processing.

Figure 3: Comparison of MQ_Bridged with ALD GDP



Source: own processing.

Based on Figure 3, we can see that the MQ_Bridged forecast overestimates individual fluctuations, while the initial MQ forecast insufficiently explains individual periods. Overall, MQ_Bridged is a better forecast than AR1, as its MAE, MFE, MSE, RMSE and MAPE are smaller (see Table 6), but its values are closer to AR1 than to the initial MQ forecast, which makes it a worse alternative to the latter.

Table 6: Statistics of MQ and MQ_Bridged Forecasts Compared to AR1 Forecast

	MQ	MQ_B	AR1	MQ - AR1	MQ_B - AR1
MAE	2.21	2.38	2.63	-0.42	-0.25
MFE	1.09	-0.54	-0.40	1.49	-0.14
MSE	10.86	12.90	17.00	-6.14	-4.09
RMSE	3.30	3.59	4.12	-0.83	-0.53
MAPE	81.95	108.77	111.35	-29.4	-2.58

Source: own processing.

4.4 DMQ Model Results (weekly, monthly, quarterly data)

The DMQ forecast is an extension of the MQ forecast, which contained 17 time series of monthly and quarterly frequency. DMQ contains 27 variables of weekly, monthly and quarterly frequency. The autocorrelation test showed that there is no autocorrelation in the model (see Table 7).

Table 7: The Breusch-Godfrey Autocorrelation Test

Breusch-Godfrey LM test for autocorrelation			
lags(p)	Prob>chi2	lags(p)	Prob>chi2
1	0.2088	6	0.4753
2	0.4533	7	0.5849
3	0.6614	8	0.6116
4	0.2617	9	0.6975
5	0.3532	10	0.7714
H0: no serial correlation			

Source: own processing.

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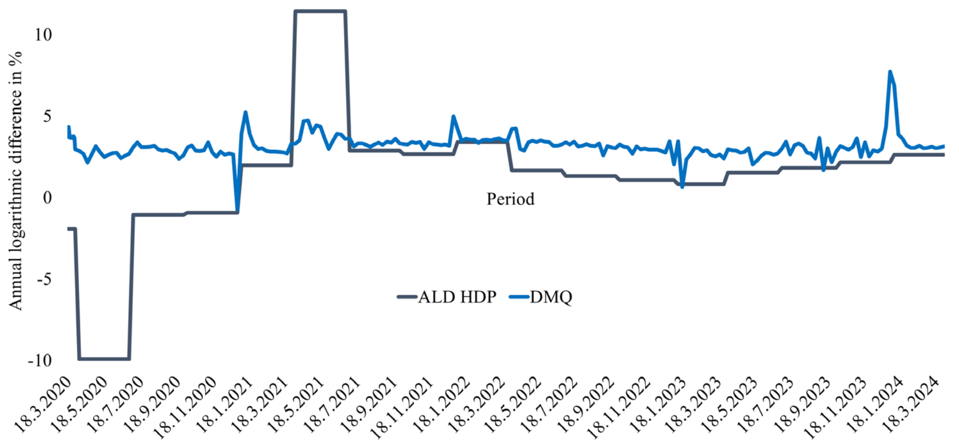
Figure 4: Comparison of DMQ Forecast with ALD GDP



Source: own processing.

Figure 4 show that the forecast was not sufficiently effective in predicting ALD GDP values. It did not capture the Covid-19 pandemic during 2020 and next year's increase in 2021. In general, the 'calm' periods of 2022 and 2024 were not significantly different from reality, but the peak in January 2024 again failed to provide information about the state of GDP. The bridge equations for ALD GDP did not help to clarify the period between the "Covid" decline and 'post-pandemic' growth. The forecast remained virtually unchanged, see Table 8 and 9. Over the entire forecast horizon, we see slight changes between the original results and the 'bridged' ones.

Table 8: Statistics of DMQ and DMQ_Bridged Forecasts Compared to MQ and MQ_Bridged Forecast

	DMQ	DMQ_B	MQ	MQ_B	DMQ - MQ	DMQ_B - MQ_B
MAE	2.79	2.79	2.21	2.38	0.58	0.41
MFE	-1.90	-1.90	1.09	-0.54	-2.99	-1.36
MSE	17.68	17.53	10.86	12.90	6.82	4.63
RMSE	4.20	4.19	3.30	3.59	0.91	0.60
MAPE	130.11	129.85	81.95	108.77	48.16	21.8

Source: own processing.

The AR1 forecast proved to be a better forecast than the DMQ forecasts. See the last two columns of Table 8.

Table 9: Statistics of DMQ and DMQ_Bridged Forecasts Compared to AR1 Forecast

	DMQ	DMQ_B	AR1	DMQ - AR1	DMQ_B - AR1
MAE	2.79	2.79	2.63	0.17	0.16
MFE	-1.90	-1.90	-0.40	-1.50	-1.50
MSE	17.68	17.53	17.00	0.68	0.54
RMSE	4.20	4.19	4.12	0.08	0.06
MAPE	130.11	129.85	111.35	18.76	18.49

Source: own processing.

A comparison of the MQ forecast with the DMQ forecast (see Table 8) showed that the MQ has a lower MAE, which means that the forecasts are on average closer to the actual values. MQ has a small positive deviation (MFE), while DMQ has a larger negative deviation, which means that DMQ tends to overestimate values more significantly. Since MSE penalises larger errors more heavily, the much higher MSE for DMQ indicates that it makes larger errors more frequently. MQ is a better predictor in every metric, indicating that it makes more accurate and reliable predictions, but its lack of timeliness prevents it from observing GDP developments more frequently. DMQ has much higher errors (especially in MSE and RMSE), which means that it has problems with large deviations.

4.4 Aggregation of the DMQ Model, AG_DMQ

Due to the considerable inaccuracy of the DMQ forecast, we aggregated the variables observed on a weekly basis to a monthly frequency. All variables except the number of flights were aggregated into a monthly average, while the number of flights was aggregated into a sum.

Table 10: Correlation between GDP and Relevant Variables of Weekly Frequency Aggregated to Monthly Frequency

Slovak stock index	VSAX60SD	dYC3-1	OECD google tracker	Toll in km
0.49	-0.30	-0.18	0.99	0.63
Electricity consumption	Number of flights	Price of petrol	Toll in euros	E-cash register sales
-0.18	0.40	0.70	0.38	0.70

Source: own processing.

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We decided to exclude several variables based on the correlation value between GDP and the relevant variable. We decided to set the correlation threshold at a value greater than or equal to 0.45. See Table 10. Based on this rule, we decided to exclude the volatility index of the Slovak stock index (vsax60sd), the difference between the 3-year and 1-year yield curves of Slovak government bonds (dYC3-1), electricity consumption, the number of flights and tolls expressed in euros. We decided to retain the other monthly and quarterly variables, as the MQ model forecasts captured the individual forecast periods relatively well. See Table 11 for the variables used in the modified DMQ forecast.

Table 11: Variables Used in the Modified DMQ Forecast

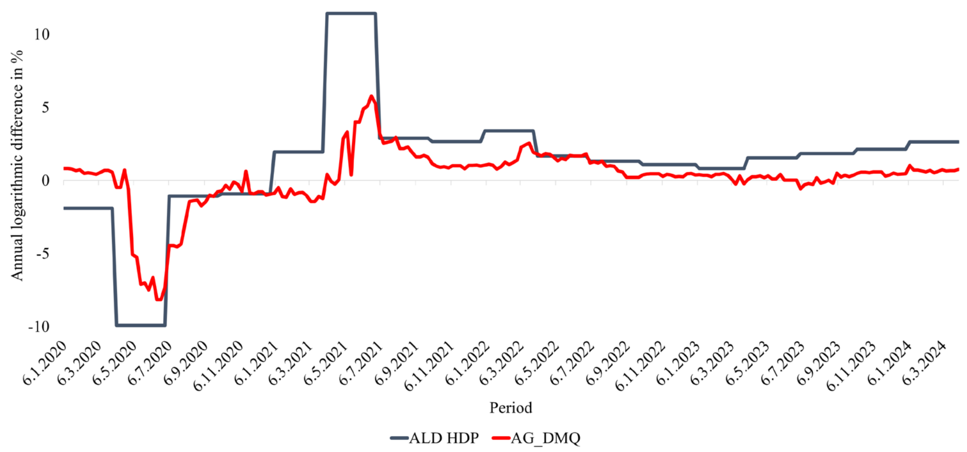
Category	Variables	Freq.	First obs.	Transformation code	Source	SA
Real activity	Industrial production	M	1.5.2000	Annual log difference (monthly)	Eurostat	Yes
	Export	M	1.5.2000	Annual log difference (monthly)	Eurostat	Yes
	real GDP	Q	26.6.2000	Annual log difference (quarterly)	SOSR	Yes
	Capacity utilization	Q	26.6.2000	Level	DG ECFIN	Yes
Energy	Import of crude	M	27.1.2003	Annual log difference (monthly)	SOSR	No
	Green house gases	Q	29.3.2010	Log-Level	Eurostat	No
House-holds	OECD google tracker	W	5.1.2004	Annual log difference (weekly)	OECD	No
	E-cash register sales	W	3.2.2020	Log-Level	FA SR	No
	Retail turnover	M	29.1.2001	Annual log difference (monthly)	SOSR	No
	Property prices	Q	28.3.2005	Annual log difference (quarterly)	NBS	No
Labour	Unemployment	M	1.5.2000	Annual difference (monthly)	SOSR	Yes
	Accomodation occupancy of Facilities	M	27.1.2003	Annual log difference (monthly)	Eurostat	No
	Employment	Q	26.6.2000	Annual log difference (quarterly)	Eurostat	Yes

Expect.	Consumer confidence	M	1.5.2000	Level	DG ECFIN	Yes
	The Services Confidence Indicator	M	1.5.2000	Level	SOSR	Yes
	Industrial confidence indicator	M	1.5.2000	Level	SOSR	Yes
	Building permits	Q	31.3.2003	Annual log difference (quarterly)	Eurostat	No
Transport	Price of petrol	W	24.5.2004	Log-Level	SOSR	No
	Toll in km	W	6.1.2014	Log-Level	Skytoll	No
	Registration of personal vehicles	M	27.1.2003	Log-Level	ACEA	No
Financial indicators	Slovak stock index	W	3.4.2000	Log-Level	BSSE	No
	Financial stress	M	1.5.2000	Level	ECB	No

Source: own processing.

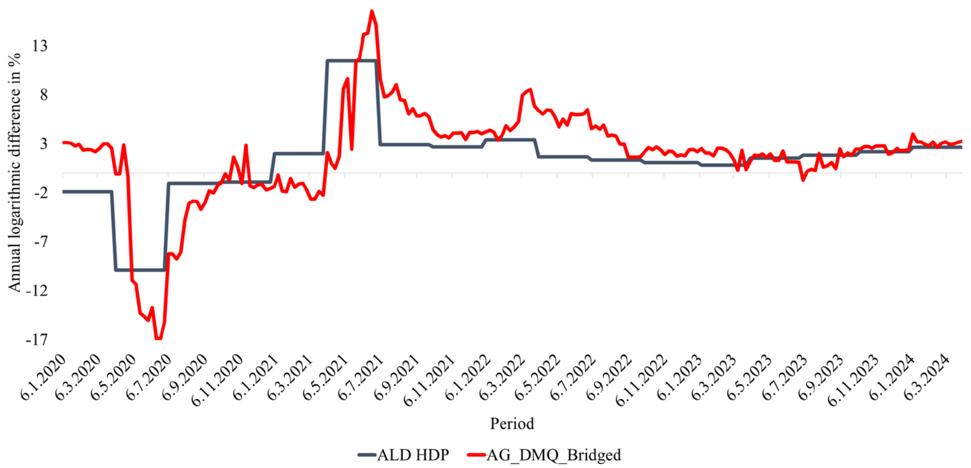
The initial estimate of the modified forecast showed considerable similarity to the MQ forecast, with relatively small deviations (see Figure 1 and 5). Like the initial forecast, the modified forecast underestimated reality across the entire forecast horizon (17 quarters). For this reason, we decided to adjust the AG_DMQ forecast using Bridge equations to estimate ALD GDP using the OLS method. Based on Graph 6, we can see that the forecast significantly overestimated the initial decline recorded in 2020 and slightly overestimated the subsequent growth. The period after growth until September 2022 was relatively poorly estimated, but we did not register any significant deviations from reality in the subsequent period from September 2022 to March 2024.

Figure 5: Comparison of AG_DMQ Forecast with ALD GDP



Source: own processing.

Figure 6: Comparison of AG_DMQ Bridged Forecast with ALD GDP



Source: own processing.

A comparison of aggregated DMQ forecasts with AR1 forecasts shows that Bridge equations did not help improve forecasting ability, see Table 12. The AG_DMQ forecast proved to have the best results among all forecasts, see Tables 13 and 15.

The Bridge forecast overestimated the MFE (-0.65) over the entire forecast horizon. Meanwhile, AG_DMQ underestimated the MFE (1.06). However, it is important to note that, compared to the naive AR1 forecast, forecasts based on dynamic factor models proved useful in identifying significant impulses in the economy. Although the initial DMQ model failed to capture individual crises, its aggregation made it possible to capture significant impulses. Overall, this forecast had the smallest MAPE, although it was still relatively high.

Table 12: Statistics of AG_DMQ and AG_DMQ_Bridged Forecasts Compared to MQ and MQ_Bridged Forecasts

	AG_DMQ	AG_DMQ_B	MQ	MQ_B	AG_DMQ - MQ	AG_DMQ_B - MQ_B
MAE	2.00	2.49	2.21	2.38	-0.20	0.11
MFE	1.06	-0.65	1.09	-0.54	-0.03	-0.10
MSE	9.21	12.12	10.86	12.90	-1.65	-0.78
RMSE	3.03	3.48	3.30	3.59	-0.26	-0.11
MAPE	73.63	115.90	81.95	108.77	-8.32	7.13

Source: own processing.

Table 13: Statistics of AG_DMQ and AG_DMQ_Bridged Forecasts Compared to MQ and MQ_Bridged Forecasts

	AG_DMQ	AG_DMQ_B	AR1	AG_DMQ - AR1	AG_DMQ_B - AR1
MAE	2.0	2.49	2.63	-0.62	-0.14
MFE	1.6	-0.65	-0.4	1.46	-0.24
MSE	9.21	12.12	17.0	-7.79	-4.87
RMSE	3.3	3.48	4.12	-1.09	-0.64
MAPE	73.63	115.9	111.35	-37.73	4.55

Source: own processing.

Table 14 shows the p-values of the Diebold-Mariano test for pairwise comparisons of forecast accuracy in different models based on MSE. We also provide average values in Table 15, with the model interpretation being: The AR1 forecast achieves an MSE that is on average 6.14 units higher than the MQ forecast, with this difference being statistically significant at the 1% significance level. Statistical significance is indicated using standard significance levels (* for $p < 0.1$, ** for $p < 0.05$, *** for $p < 0.01$). The results show that MQ significantly outperforms AR1 ($p = 0.0001$ **) and MQ_B also shows a statistically significant improvement over AR1 ($p = 0.0257$ **). Conversely, high p-values for DMQ and DMQ_B compared to AR1 (p = 0.686

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and 0.7467) do not indicate any significant difference in predictive accuracy. When comparing MQ and MQ_B, the p-value (0.0967 *) indicates weak evidence of a difference. The aggregated models AG_DMQ and AG_DMQ_B consistently outperform other specifications, with several results being highly significant - for example, AG_DMQ compared to AR1 (p = 0.0000 ***), MQ (p = 0.0005 ***) and MQ_B (p = 0.0048 ***). Similarly, AG_DMQ_B shows high performance, significantly outperforming AR1 (p = 0.0021 ***), DMQ (p = 0.0119 **) and DMQ_B (p = 0.0137 **). These findings suggest that aggregation-based forecasting methods show statistically higher prediction accuracy in several cases compared to other models.

Table 14: Diebold-Mariano Test for Comparing Individual Forecasts Based on P-value

Diebold-Mariano test	AR1	MQ	MQ_B	DMQ	DMQ_B	AG_DMQ	AG_DMQ_B
AR1	-	0.0001 ***	0.0257 **	0.686	0.7467	0 ***	0.0021 ***
MQ	0.0001 ***	-	0.0967 *	0.002 ***	0.0024 ***	0.0005 ***	0.3218
MQ_B	0.0257 **	0.0967 *	-	0.0429 **	0.049 **	0.0048 ***	0.4466
DMQ	0.686	0.002 ***	0.0429 **	-	0 ***	0.0002 ***	0.0119 **
DMQ_B	0.7467	0.0024 ***	0.049 **	0 ***	-	0.0002 ***	0.0137 **
AG_DMQ	0 ***	0.0005 ***	0.0048 ***	0.0002 ***	0.0002 ***	-	0.0059 ***
AG_DMQ_B	0.0021 ***	0.3218	0.4466	0.0119 **	0.0137 **	0.0059 ***	-

Source: own processing.

Table 15: Diebold-Mariano Test for Comparing Individual Forecasts Based on the Average Value

Diebold-Mariano test	AR1	MQ	MQ_B	DMQ	DMQ_B	AG_DMQ	AG_DMQ_B
AR1	-	-6.14 ***	-4.09 **	0.68	0.54	-7.79 ***	-4.87 ***
MQ	6.14 ***	-	2.04 *	6.82 ***	6.67 ***	-1.65 ***	1.26
MQ_B	4.09 **	-2.04 *	-	4.77 ***	4.63 ***	-3.69 ***	-0.78
DMQ	-0.68	-6.82 ***	-4.77 ***	-	-0.14 ***	-8.47 ***	-5.55 **
DMQ_B	-0.54	-6.67 ***	-4.63 ***	0.14 ***	-	-8.33 ***	-5.41 **
AG_DMQ	7.79 ***	1.65 ***	3.69 ***	8.47 ***	8.33 ***	-	2.92 ***
AG_DMQ_B	4.87 ***	-1.26	0.78	5.55 **	5.41 **	-2.92 ***	-

Source: own processing.

5 Conclusion

Based on Figure 1 and 4, we can see that the MQ model is better at predicting recessions and subsequent recoveries, while it has greater difficulty in periods of calm. Conversely, the initial DMQ model was practically unable to capture the Covid-19 recession and next year's recovery in any way, but periods of relative calm were estimated relatively well. This may raise the question of what such a model is useful for if it can forecast GDP well in periods of relative calm but fails to capture significant impulses in more chaotic times. Based on this logic, we believe that the AG_DMQ model proved to be the most suitable tool, as it was able to capture individual shocks in the economy relatively well. The individual statistics MAE, MFE, MSE, RMSE, and MAPE also prove this in comparison with the initial DMQ and MQ models.

However, it should be noted that the primary objective of creating a high-frequency index of economic activity is to monitor the real economy in a timely manner, which lower frequencies are unable to do. The results of the AG_DMQ forecast, see Figure 5 and Tables 12 and 13 and 14 show an improvement in forecasting ability compared to the MQ forecast. We admit that setting the correlation threshold for excluding variables was to some extent ad hoc, but the main goal was to retain those variables that show a stronger correlation with GDP. This analysis therefore requires a more sophisticated approach and further research into the selection of the most appropriate high-frequency indicators.

It is also important to note that significant deviations of the forecast from reality may be caused by inappropriate adjustments, the introduction of overly volatile data into the model, and the removal of seasonal patterns, calendar effects, and holiday effects (Wegmüller et al., 2023).

Although DFMs can use many observed variables to extract a small number of latent factors that govern the system, and thus more variables can help improve the estimation of common factors and reduce noise, too many variables with poorly transformed data can, on the contrary, introduce unnecessary noise and increase computational complexity if not handled correctly.

However, it should be noted that DMQ, MQ, and AG_DMQ forecasts are more indicative of broader economic activity than of timely weekly changes. In other words, the methodology was not designed to provide the most accurate

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current forecast of GDP growth (Bańbura et al., 2024b).

For future research, we would recommend placing greater emphasis on the issue of ragged edges, supplemented with information on possible data revisions by statistical offices. Furthermore, we recommend a more detailed examination of the issue of selecting appropriate priors in Bayesian estimation, which can change and influence the results of individual forecasts as they affect how the Kalman filter fills gaps in the mixed-frequency data set. It would also be useful to examine how alternative data transformations or other aggregation methods could lead to improved forecast results or use other methods for forecasting GDP based on high-frequency data, such as machine learning methods.

REFERENCES

[1] Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business and Economic Statistics*, *27*(4), 417–427. https://doi.org/10.1198/jbes.2009.07205

[2] Bańbura, M., Eraslan, S., Giammaria, A., Leiva-León, D., & Paredes, J. (2024). Introducing HaWAI - harmonised weekly activity index for the euro area and its member states. *European Central Bank*.

[3] Bańbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). Now-casting and the real-time data flow. In *Handbook of Economic Forecasting* (Vol. 2, pp. 195–237). Elsevier B.V. https://doi.org/10.1016/B978-0-444-53683-9.00004-9

[4] Baumeister, C., Leiva-León, D., & Sims, E. (2024). Tracking weekly state-level economic conditions. *Review of Economics and Statistics*, *106*(2), 483–504. https://doi.org/https://doi.org/10.1162/rest_a_01171

[5] Camacho, M., & Perez-Quiros, G. (2010). Introducing the Euro-sting: Short-term indicator of Euro area growth. *Journal of Applied Econometrics*, *25*(4), 663–694. https://doi.org/10.1002/jae.1174

[6] Carter, C. K., & Kohn, R. (1994). On Gibbs sampling for state space models. In *Biometrika* (Vol. 81, Issue 3). https://doi.org/10.1093/biomet/81.3.541

[7] Huček, J., Huček, H., Kař, A., Mari´ Mari´an, M., & Avra, V. ´. (2015). *SHORT-TERM FORECASTING OF REAL GDP USING MONTHLY DATA*. www.nbs.sk

[8] Kim, C.-J., & Nelson, C. R. (1999). State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications, volume 1 of MIT Press Books. *MIT Press*. https://doi.org/10.7551/mitpress/6444.001.0001

[9] Mariano, R. S., & Murasawa, Y. (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics*, *18*(4), 427–443. https://doi.org/10.1002/jae.695

[10] Stundziene, A., Pilinkiene, V., Bruneckiene, J., Grybauskas, A., Lukauskas, M., & Pekarskiene, I. (2024). Future directions in nowcasting economic activity: A systematic literature review. *Journal of Economic Surveys*, *38*(4), 1199–1233. https://doi.org/10.1111/joes.12579

[11] Wegmüller, P., Glocker, C., & Guggia, V. (2023). Weekly economic activity: Measurement and informational content. *International Journal of Forecasting*, *39*(1), 228–243. https://doi.org/10.1016/j.ijforecast.2021.10.010