Improving Forecasts of Turnover Indices Using Tax Data

Why are we doing this?

In 2020 Quarterly National Accounts (QNA) have been integrated at Statistics Austria (STAT). The integration gives compilers at STAT access to a more detailed data basis and synergy benefits within the statistical institute. Setting up the compilation from scratch gave the opportunity to tackle existing issues, improve estimation and incorporate state-of-the art econometric techniques.
Short term Statistics (STS) turnover indices are one of the main data sources in QNA. However, the last month of turnover indices is not available in time for the first release of QNA and thus has to be forecasted. Previously this has been done by using a univariate ARIMA model.

Using Tax Data

The integration within the directorate of macroeconomic statistics gives QNA early access to turnover tax data (UVA). Preliminary results can be used in time for the first release of a new quarter. This additional data source is subject to limitations as it is not checked for plausibility on an individual level. On an aggregated level STS turnover indices and UVA follow a similar trajectory, see Figure I. This will add information to make predictions more accurate.

Figure I: Trajectory of tax data (UVA) and STS turnover indices

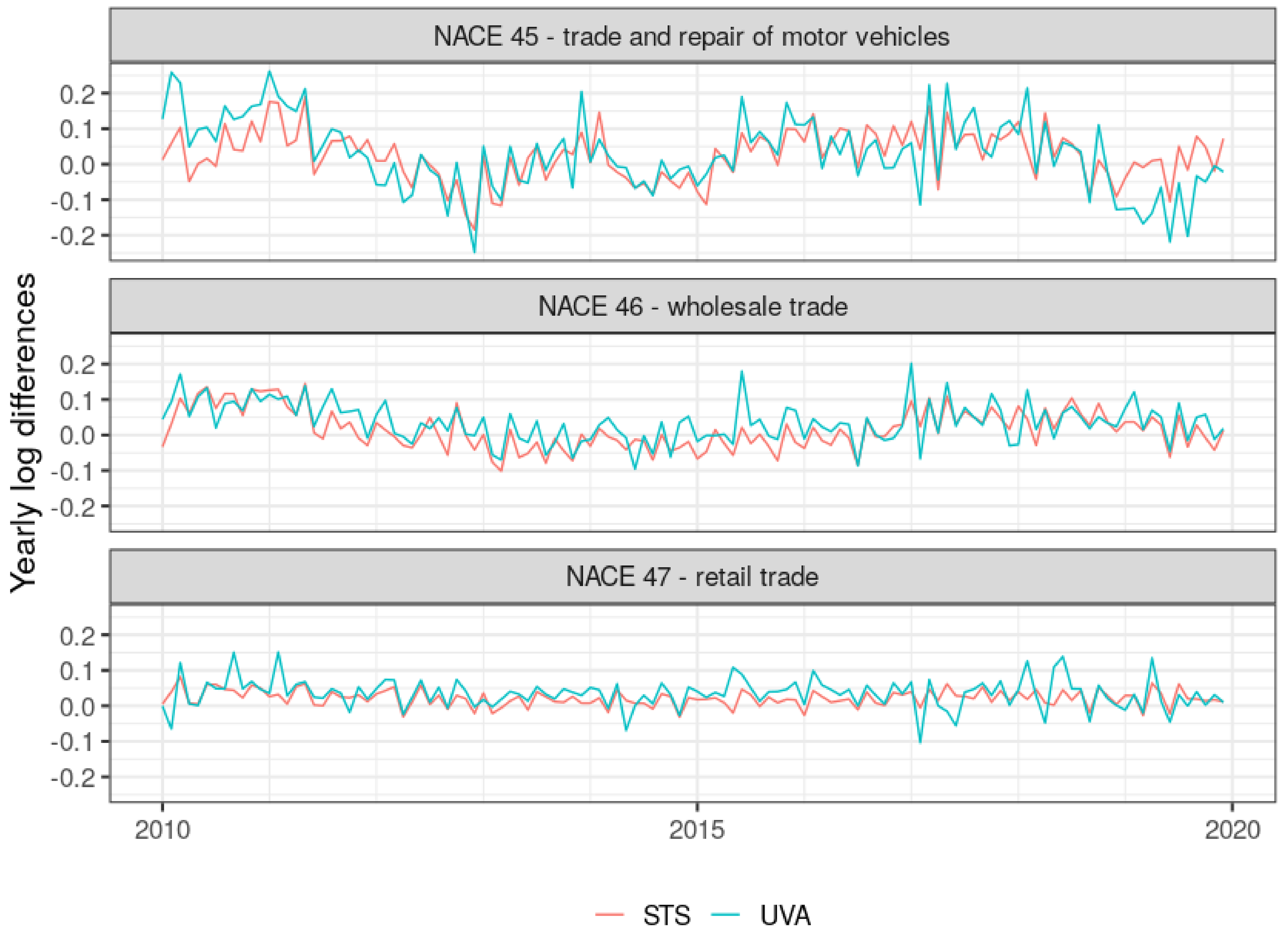
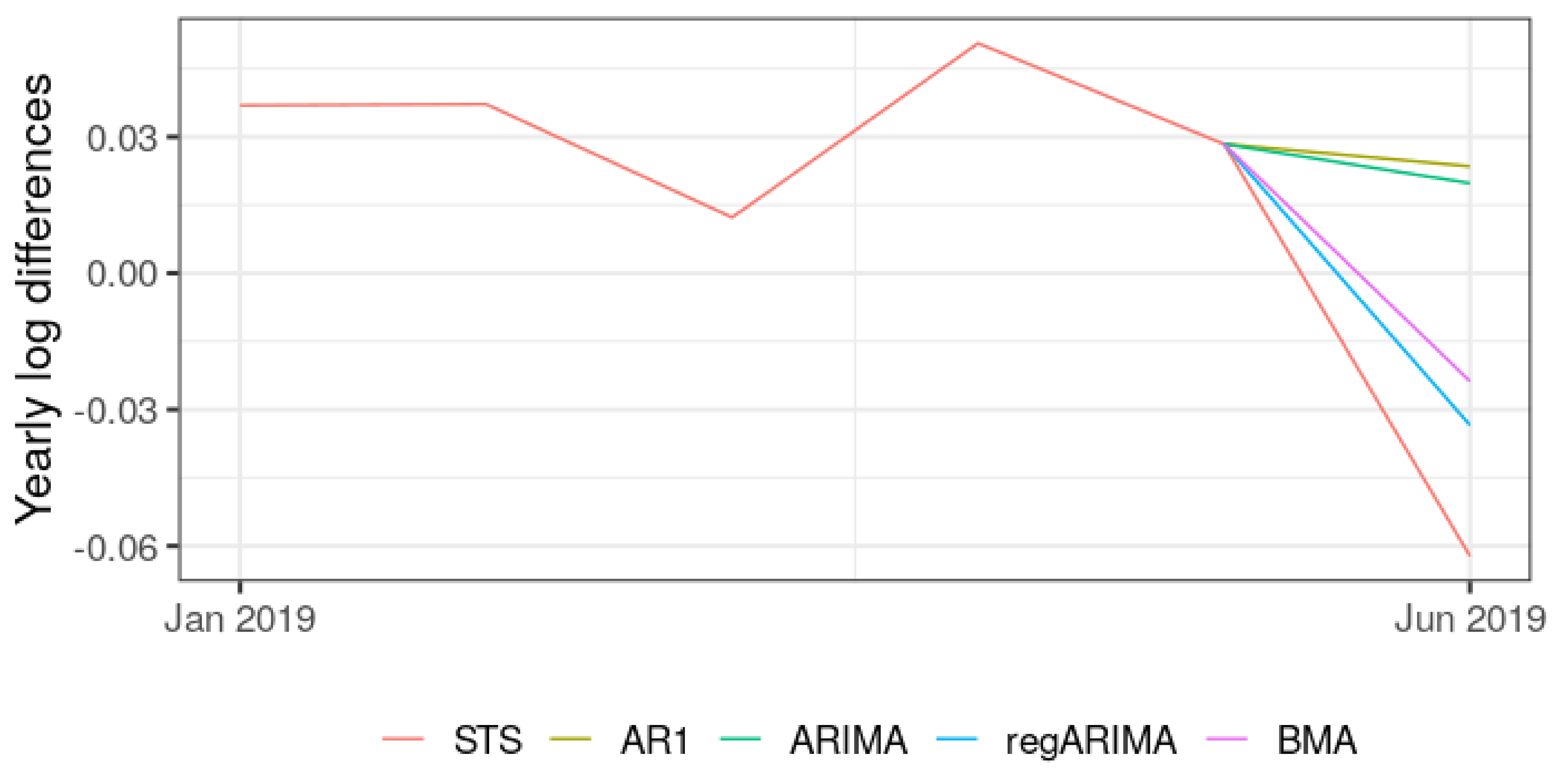


Figure II: Forecasts for NACE 46 – wholesale trade – June 2019



Methods

We propose to forecast the turnover indices using Bayesian Model Averaging (BMA) with an Autoregressive Distributed Lags (ADL) model. In an ADL setting several lags of the variable of interest as well as other variables and their lags are implemented as regressors. BMA is a widely used approach in the empirical literature to deal with the problem of model uncertainty as one cannot determine the true data generating process. The literature shows that a combination of models improves the forecast quality. The BMA algorithm selects various combinations of $i \in [1,p]$ $j \in [0,p], k \in [0,K]$ where p is the maximum number of lags and K is the number of additional regressors and weights the models based on their marginal likelihood.

$$y_t = \alpha + \sum_i \beta_i y_{t-i} + \sum_{k,j} \delta_j x_{k,t-j} + \varepsilon_t$$

To test whether BMA improves the forecast we compare it to three benchmark models:

- AR1, autoregressive of order 1: the classic benchmark
- ARIMA , univariate: standard approach in QNA for missing data
- regARIMA: ARIMA with external regressor

The criteria to asses model performance are

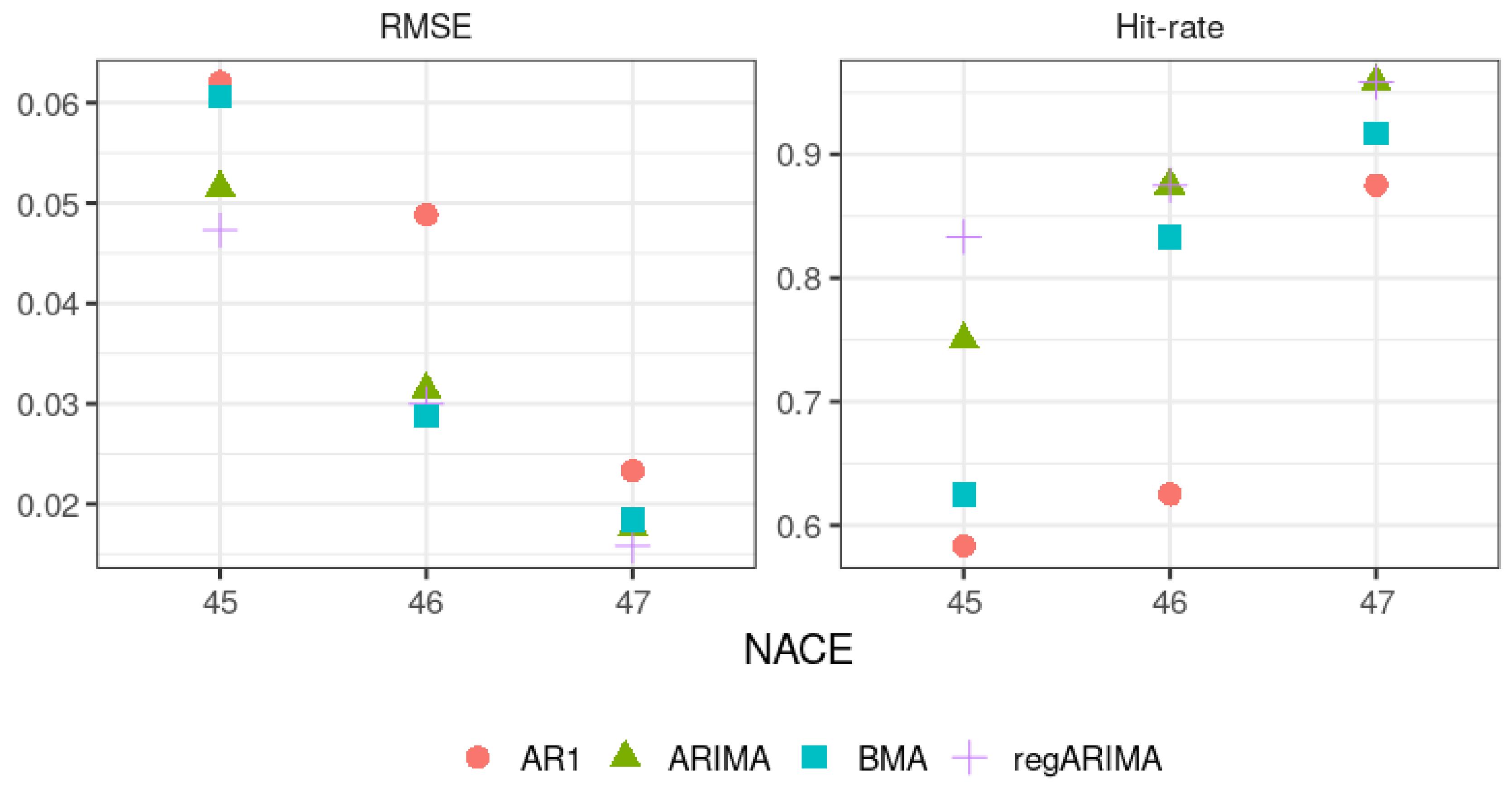
- Root Mean Squared Error (RMSE): $\sqrt{(\hat{y} - y)^2}$
- Hit rate to predict the right sign (direction of change)

So far we look at data up to 2019. The testing period for the models are the years 2018 and 2019 (24 months).

Preliminary Results

Figure II on the left shows the forecast of NACE 46 (wholesale trade) for July 2019 as an example. One sees that the models that consider information for the last month are much more likely to account for the drop, albeit no model catches the full extent. Over the test period no model continuously dominates all other models. However, it becomes clear that the use of UVA data improves forecast on average. Figure III below shows RMSE (left panel) and the hit rate (right panel) for each type of model. The AR1 model is clearly outperformed by all other models. But the BMA does not beat the univariate ARIMA and the regARIMA. Although the levels of RMSE vary across industries, the regARIMA has the lowest RMSE in all cases considered. The hit rate shows a similar picture. The share of correctly forecasted signs is highest for the regARIMA models. In wholesale and retail trade the univariate ARIMA performs equally well. BMA only beats the AR1 forecast.

Figure III: RMSE (left) and Hit rate (right) o different forecast approaches



Next Steps

The improvement of QNA and its input indicators is constant work in progress. The presented approach suggests that the used ARIMA models are already good candidates that are not easy to beat. It also shows that the inclusion of new data for the current period improves forecasts.
In a next step we will explore different ways of model averaging and further refine models. We are also applying these experiments to service industries, as there are similar issues in these industries.
An interesting question that arises from these results is whether model averaging can adopt faster to a shock like the current pandemic. The empirical literature suggests that a BMA approach is more likely to react to structural breaks. This is something we are currently evaluating.

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