Improving Forecasts of Turnover Indices Using Tax Data

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1. INTRODUCTION

QNA offer a broad picture of economic development in the short term. They build the basis for assessing recent economic performance and forecasting the near future [1,2]. The growth rate of GDP is of great public interest, especially in times of crisis. Policy-makers and researchers look for a comprehensive data set that allows to identify current developments and determine business cycles. To provide this information in the short term QNA combine high-frequency indicators with the detailed framework of National Accounts (NA) [2].

QNA are balancing between timelier estimates and data quality, two demands that have increased over the years [1,3]. To meet these demands compilers have to adopt new data sources and methods. The challenge is the availability of high-quality input data. Reliable data for the current quarter lowers revisions. Lower revisions in turn increase reliability of the results and support trust in data.

In 2020 QNA have been integrated at our National Statistical Institute (NSI). Part of this process was to review methods and input data and identify methodological issues. The integration gives compilers at the NSI access to a more detailed data base 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.

Estimation of output in QNA depends on turnover in the respective industry. In trade and service industries turnover is measured by turnover indices (TOI) from Short Term Business Statistics (STS). The index for the last month of the quarter is, however, not available in time to be used in QNA. Hence, the missing quarter of turnover indices has to be forecasted in order to get an accurate estimation of output in these industries. In the past this has been done using a univariate seasonal ARIMA.

The quality of forecasts based on the univariate ARIMA varies between industries, Table 1 shows the Percentage Forecast Errors (PFE), which is $\frac{y-\hat{y}}{y} * 100$. Forecasts are made for the following quarter, considering the TOI up to the respective quarter.

The high minimal PFE are striking. Most of them are in the second quarter 2020. Across all industries turnover went down as businesses closed due to the COVID-19 pandemic. This abrupt fall could not have been anticipated based on the history of each series. In the most affected industries accommodation and food services (NACE I), air transportation (NACE 51) and administrative and support services (NACE N) the estimates TOI would have been very far off the actual TOI. But even without considering the year 2020 and the pandemic the standard deviation of PFE is high. Lower variance in the forecast error would also lower revisions of QNA production.

To improve forecasts and to be able to catch unforeseen breaks we include data from advance return of sales tax (UVA). This data set contains monthly turnover values reported to tax authorities. It is also the main source for the compilation of STS turnover indices [4].

Table 1 Percentage Forecast Errors of TOI by Industry

NACE	Min.	1st.Qu.	Median	Mean	3rd.Qu.	Max.	SD	Mean (without 2020)	SD (without 2020)
45	-23,5[a]	-1,8	-0,2	-2,0	3,5	8,1	9,2	1,3	3,9
46	-14,4[b]	-1,6	0,2	-0,7	1,8	6,5	4,7	0,6	2,8
49	-26,2[b]	-1,1	0,9	-1,3	1,7	5,6	7,6	1,1	1,9
50	-184,1[b]	-14,5	-1,0	-15,4	6,1	29,3	51,2	0,7	13,0
51	-330,4[b]	-4,6	0,1	-27,2	1,1	12,8	89,0	0,8	7,4
52	-19,3[b]	-0,9	-0,4	-1,4	1,5	3,0	5,6	0,4	1,6
53	-5,9[a]	-2,2	-0,6	-0,5	0,5	5,8	2,9	-0,0	2,7
I	-150,4[b]	-0,8	-0,5	-11,9	1,0	3,7	40,2	0,3	1,7
62	-11,0[b]	-0,9	0,9	0,4	2,7	6,8	4,2	0,3	2,8
63	-6,2	-1,7	1,3	0,6	3,2	5,9	3,5	0,9	3,3
M	-19,6[b]	-0,7	0,5	-0,9	1,3	4,2	5,7	0,9	1,5
N	-53,9[b]	-2,3	-1,6	-4,3	1,2	7,9	15,0	0,4	3,7

Source: STS Turnover indices; Forecasts: Own Calculations
Indices are quarterly the test period is 14 observations starting in Q1 2017;
Forecasts are for the following quarter i.e. h = 1
[a] 1st Quarter 2020. [b] 2nd Quarter 2020

For the regular payment of sales-tax firms are supposed to report their turnover within 45 days1 after the end of each month. 92.5 % of firms report in time which covers 82.9 % of total turnover [5]. In time response rate and coverage varies between industries (in the considered industries coverage[2] ranges between 94% and 103% [5])and can also be affected by external factors or pubic holidays.

For the compilation of turnover indices STS cleans the data on firm level in order to adjust implausible or not reported turnover [4]. These data processing steps are necessary to get a reliable value for official statistics. Nevertheless, unprocessed UVA data has a very similar trajectory to STS-turnover indices in most industries. It adds information and improves forecast accuracy.

2. METHODS

Modern time series econometrics offer a broad tool box to use this information. One way is to include UVA as regressor in the ARIMA Model. Another possibility is to use an Autoregressive Distributed Lag (ADL) Model, which combines the past information from the index and UVA.

Empirical literature [6–8] shows that a combination or pooling of forecasts often outperforms the best individual forecast. The idea is to combine different models in order to diversify forecast errors as one can never determine the true data generating process. Models can differ in a sense that they either take different sources of information into account (i.e. different variables) or by making different assumptions on the relationship between variables; i.e. different model specifications [9].

In empirical examples the true data generating process cannot be determined. Therefore, models are incomplete and forecasts may be biased. Combining models can offset biases

[1] The 15th of the second-following month (§21 Abs. 1 UStG); i.e. 15th of March for January

[2] Coverage as percentage of the final yearly taxable turnover. Can be >100% due to various reason, e.g. financial years differ from calendar years or incorrect reporting during the year.

and reduce variances and thus improve forecasts. Especially in non-stationary time series and time series with breaks combinations are likely to outperform individual forecasts [6].

To check whether this improves the forecast, results are compared to out of sample forecasts of the univariate ARIMA and the actual STS turnover index.

In the case of forecasting the turnover index for the use in QNA, it is obvious that the model used is not the true data generating process and not all information can be used due to time constraints. The business cycle and external shocks cause location shifts and breaks in the time series. Forecasts that rely on a single model may not be able to react to unexpected shocks in the same way as a combination of models. To evaluate models and see if they are statistically different from each other one can use the MCS from [10]. The MCS is similar to a confidence interval for a parameter, it acknowledges data limitations and gives a set of models which includes the best one with a given confidence.

3. RESULTS

Preliminary results show that the inclusion of UVA improves forecasts. Table 2 shows the Mean Squared Forecast Error (MSFE, $\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2$) of the univariate ARIMA, the regARIMA containing UVA as regressor and the ADL Model.

Table 2 Mean Squared Forecast Error by Model and Industry

NACE	univaritate ARIMA	regARIMA	ADL
45	76,54	33,72	39,58
45	81,4	36,1	42,4
46	20,8	8,8	4,2
49	41,8	13,2	12,8
50	560,7	464,7	443,7
51	393,5	291,3	238,1
52	26,9	21,4	27,3
53	9,0	11,3	10,4
I	315,9	43,7	37,1
62	21,2	20,2	20,8
63	14,4	17,9	18,8
M	30,9	27,1	26,2
N	128,4	90,8	96,6

In most industries the inclusion of UVA improves forecasts. In some industries like wholesale trade (NACE 46) or accommodation and food services (NACE I) MSE is reduced to 20% and 11 % of the univariate ARIMA MSE, respectively. In order to correctly evaluate these results, models need to be refined and checked for robustness. The current state of work only allows for a general overview of the models.

4. CONCLUSIONS

Increasing the accuracy of forecasts and reducing the variance improves the quality at the first release of QNA. To do so compilers depend on shortly available and reliable input data. This work explores the use of administrative tax data on turnover to improve forecasts of STS turnover indices used in QNA. In a first step we find that forecasts errors are a lot smaller in models that consider information for the current quarter. In a next step preliminary models will be refined and tested against each other. We will further evaluate the benefits of pooling forecasts and quantify the effect on revisions in QNA. Nevertheless, the use of current data in the forecast will help to catch unforeseen developments in the economic environment.

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