Lessons from Implementing a QNA Framework at Statistics Austria

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Abstract

In Austria Quarterly National Accounts (QNA) are currently not compiled by the NSI (Statistics Austria - STAT) but by the Austrian Institute of Economic Research (WIFO). This is about to change as QNA will be compiled and published by STAT from 2020 onwards in order to be stronger interlinked with Annual National Accounts (ANA).

The integration of QNA enables us to revise the compilation process in two ways. Firstly, we can review indicators in detail and connect QNA and ANA stronger. Changes in methods mainly occur on the expenditure side, as preliminary data on CPA-6-digits-level is available in-house. Using detailed information on quarterly supply of goods we can use the same framework as the yearly commodity flow to destine goods to final use categories. A similar advantage arises in the extension of the price data base with quarterly price indices. The additional use of micro data from tax- and social insurance statistics makes the income approach more coherent to ANA.

Secondly, we are implementing the whole compilation process in R. At Statistics Austria R is becoming a broadly used tool, as the Methods Unit is maintaining a well-functioning server environment for R. For temporal disaggregation we are using the tempdisagg package by Sax and Steiner (2013) for Seasonal Adjustment JDemetra +, RJDemetra and the new Package Persephone are used.

As this project is work in progress impact is hard to be measured exactly. Trial compilations indicate that changes and adaptations in either ANA or QNA are better communicated between teams and are integrated faster in the corresponding frameworks. This lowers overall revision.

Introduction

The integration of QNA gave us the opportunity to revise the technical framework and to adjust methods. The process of implementation is still ongoing; we can, however, draw some first conclusions. Due to the long-standing arrangement of outsourcing QNA to WIFO, one major challenge arose from the fact that there was not much in-house expertise on QNA at STAT. Know-how had to be built up from scratch with the help of the ESS community.

This paper reflects on the first one-and-a-half years of implementation and draws conclusions that might help other NSIs when setting up a new framework for QNA, changing organisational structures or improving compilation techniques. We start with some background information on the handover process. In the following we outline several difficulties we encountered. We will show how we dealt with issues and reflect on ongoing problems. Generally, our lessons learned can be divided in three main topics: (i) organisational, (ii) methodological, and (iii) technical lessons.

Background Information and Timeline

In order to increase efficiency and collaboration between QNA and ANA it has been decided to integrate compilation QNA at STAT. The project required two new employees that were hired in early 2018. They were mainly chosen by their expertise on time series analysis and programming experience. The new core - team of three full-time employees is responsible for the output and expenditure approach. They are implementing the framework in close collaboration with the Methods Unit and ANA teams. The income approach and labour QNA were integrated in the existing ANA income team, consisting of 2.5 full-time equivalents.

The QNA team is part of the department of national accounts, which in turn is part of the directorate of macroeconomic statistics. The national accounts department consists of several teams, of which the teams responsible for the output and expenditure approach in ANA are our closest cooperation partners. The Methods Unit supports all directorates in methodical questions, hosts the R-server environment and is responsible for seasonal adjustment in QNA.

The first year of the project was a so-called `implementation phase'. The focus was on researching appropriate tools and methods as well as acquiring sub-annual data. To become familiar with the methods, requirements and challenges of QNA compilation we took advantage of the European Statistical Training Programme[1] (ESTP) and visited the QNA team of DESTATIS in Germany in April 2018.

In the second year of implementation the focus lies on analysing parallel computations and fine-tuning results to improve methods and models. The first parallel QNA compilation was for the first quarter of 2019. We got a first feedback on our organisational timeline and saw the benefits of standardised programmes and processes.

Organisational Lessons

The implementation of several parts of National Accounts (NA) (e.g. Regional Accounts, Input-Output (IO)-Tables, Sector Accounts) is usually a long lasting process of trial and error. Methods and techniques mainly depend on the available data and the continuous improvement of technical

[1] Time Series Econometrics and Temporal Disaggregation

support. Therefore, they are always subject to changes, even when there is no revision of legal frameworks (ESA in particular) or classifications (e.g. NACE). In contrast, the transfer of QNA has to be managed within two years, which is quite challenging considering that we had no experience in implementing a whole part of NA from scratch. In this process we took full advantage of handbooks (in particular the Handbook of Quarterly National Accounts: European Union 2013) and method inventories from other countries, as well as of the expertise of the ANA-teams within STAT.

One of the first challenges was dividing responsibilities within the QNA-team. During the process of implementation, responsibilities changed according to the task in focus.

Phase I - Assessing and collecting basic data

A special aspect of NA is that it uses data from almost every organisational unit of STAT as well as administrative data from other organisational units. During the first months we worked on getting an overview of available data. The basic requirements for our purposes are monthly or quarterly data that are available at least at t+58 days. After identifying appropriate source data, each team member was responsible for getting detailed information about several data sources. This involved reading standard documentations to learn more about definitions and survey techniques and assessing the appropriateness for QNA purposes. In this phase we strongly cooperated with data suppliers, who were invited to meetings in order to explain compilation methods, possible restrictions and transmission modalities.

Considering the process of accessing source data we faced several challenges. Firstly, due to different workflows and software use in different directorates there is no unique way of data transmission. Since there is no central data warehouse at STAT we get different files (e.g. xlsx, sas) in different ways (e.g. e-mail attachments, common folder access). A central system for data inputs, as used for example at ISTAT (Giancarlo Bruno et al. 2019) would facilitate the process. Due to these circumstances an additional step was to organise data in a way that it is useful for QNA purposes.

Another constraint concerned financial issues. Since the implementation process has to be cost-neutral we cannot access fee-based data from other institutions. The budgetary constraints applied also within STAT, i.e. specific data processing for particular QNA purposes by experienced staff in other organisational units was not always feasible.

Despite the mentioned challenges we can profit from the production of the main basic data within STAT. It allows us to get preliminary data earlier and to get information on metadata and on recent revisions informally. Moreover, we can immediately give feedback on unusual developments or outliers.

Phase II - Estimating aggregates

After collecting and adapting source data for QNA purposes we started the next phase, which was actual compilation and estimation of aggregates. At first, the strategy was to divide the responsibilities alongside the QNA approaches (i.e. output and expenditure approach) and aggregates accordingly, as it is the case in ANA. But we realised that it is more efficient to allocate responsibilities according to underlying input data and methods. This allocation has several advantages. Firstly, each of us already had specific knowledge of input data from researching data in Phase I. Deep knowledge of data is crucial for its use as indicators. Secondly, the allocation along data sources facilitates basic consistency checks during compilation, which in turn reduces workload during balancing. And thirdly, a more personal point of contact for providers of input-data facilitates informal communication on the latest information about data limitations.

To maximise cooperation with ANA teams we were eager to integrate them from the very beginning of our implementation process. In a first meeting we presented our transmission programme (TP), methodical differences between QNA and ANA and our implementation timetable. We started with the output side as its concept and source data are more comprehensive. So, in a first step all members of the ANA output approach team presented their compilation methods and gave advice on appropriate input data for the according quarterly aggregates. From this basic structure we started our quarterly estimations. In a feedback-loop we compared our estimates with published QNA data and discussed differences with ANA experts until we reached sound results. This process took about three to four months. We proceeded in the same way with the expenditure approach aggregates. This was, however, not as straightforward as estimating the aggregates of the output approach. The expenditure approach of GDP is more heterogeneous than the output approach and there is fewer quarterly data. The expertise of the ANA expenditure side team proved to be very helpful at that stage. They presented us their ideas and reflections on appropriate quarterly input data for all aggregates. Due to this very intensive cooperation we were able to adapt their programmes and in some cases to use the same level of detail as in ANA. For example, we compiled a quarterly commodity flow with goods at CPA-6-digit level in the same way as it is used in ANA to estimate quarterly investment.

The quarterly aggregates of the income approach are compiled by the respective ANA team. Team members are compiling the same aggregates quarterly and annually. The QNA team also includes the team lead of the ANA income approach team to ensure full integration in the implementation and compilation process. The same applies for the integration of seasonal adjustment. One team member from Methods Unit brings in longstanding expertise with time series and seasonal adjustment.

In weekly QNA meetings current matters are discussed with all team members. Topics range from new developments in accounting aggregates to methodological issues. Depending on topics, annual accountants or colleagues from other units at STAT take part to discuss issues. The Jour Fixe is institutionalised in a way that topics and attendees (apart from QNA core team) are flexible. During the implementation phase this proved to be a good way to communicate latest progress, discuss estimation problems and agree on timetables. We plan to maintain this procedure also after the implementation process.

Challenges we still face concern an effective personnel backup system and lack of experience concerning the best way to integrate ANA-teams in regular QNA compilation. The implementation of QNA is creating new workflows in ANA Teams. The chronological order is revised in a way that difficult sub-annual aggregates are calculated first. Difficult in this context means, that either the underlying sub-annual data is weak or aggregates are subject to high revisions. By calculating these aggregates first the latest information on annual development and structural changes can be used in QNA already for the publication of Q4 or the first revision when publishing Q1. Constant Feedback loops between QNA and ANA Teams should ensure that the two frameworks are synchronised. It will, however, take time to institutionalise the new procedures.

Implementing a well-working backup system is an ongoing challenge. Across all organisational units staff is facing shortage of time resources with their current workload. We aim to include at least two additional colleagues who can step in when there is an unexpected shortfall in the QNA team e.g. due to illness.

The responsibilities during the regular QNA compilation are allocated flexibly, i.e. each team member has access to basic data and can run the programmes to estimate the aggregates. We are aware of the fact that knowledge and experience in analysing the results is to a certain extent a question of time. The open structure in compilation and joint efforts in the analysis of results are breaking down barriers to step in for a colleague.

We use *Confluence* to document workflows and progress. *Confluence* is a commercial tool for a wiki style documentation and communication platform. This also helps staff that is not part of the core QNA team to understand our compilation process. In case of unexpected personnel shortfalls someone with basic knowledge of our framework should be able to perform the calculations with the manuals on *Confluence*.

Methodical Lessons

Estimating QNA consists of two main tasks, namely distributing annual values to quarters and estimating the quarters for which there are no ANA benchmark values. In most cases the method of choice is the temporal disaggregation approach by Chow and Lin (1971), to disaggregate and extrapolate series. The Chow-Lin Method is recommended by EUROSTAT (see European Union 2018). It is a statistical method that is based on a linear regression between the annual benchmark values and the sub-annual indicator. The crucial part is to use a suitable indicator. This indicator should follow a similar yearly trajectory as the annual benchmark value and describe a related variable, for example using sub-annual turnover to disaggregate production. We faced different challenges when looking for appropriate indicators. Depending on aggregates and industries issues ranked from timely availability to inconsistencies with the annual benchmark values. The following sections will highlight some of these issues with concrete examples.

Finding a suitable indicator

Construction is a significant part of economic production, accounting for 6.4% of value added (ANA, 2017). Construction in Austria is characterised by small firms, many of which operate only for a short period of time. This makes it extremely difficult for any statistic to capture these industries correctly, in particular NACE 43 (Specialised Construction Activities). Monthly short term business statistics calculate turnover indices (TOI) and production indices (PI) based on cut-off surveys. Unfortunately, these indices do not correspond very well to yearly production from ANA. When disaggregating and extrapolating the series with the method of Chow and Lin (1971) we found a systemic upward bias (compared to ANA results).

So far, we tried three different indicators: TOI, PI and the value of sold production. The production index performs best with respect to the reflection of the seasonal pattern and growth. We do, however, need to account for systematic biases. Hence, the search for a better indicator goes on. It should improve the parameters within the disaggregation model, i.e. have a similar trajectory as the structural data used in ANA. Further, coordination and communication with the corresponding ANA team and the Directorate of Business Statistics is necessary to improve current indicators and to have coherent calculations in ANA and QNA.

Predicting indicators

Turnover indices from short-term business statistics are crucial index series for various aggregates on the production side and for private consumption. The problem is that the indices for trade and services are not compiled in time to be used in QNA. To get an accurate estimation of GDP we need to forecast the missing month of turnover indices.

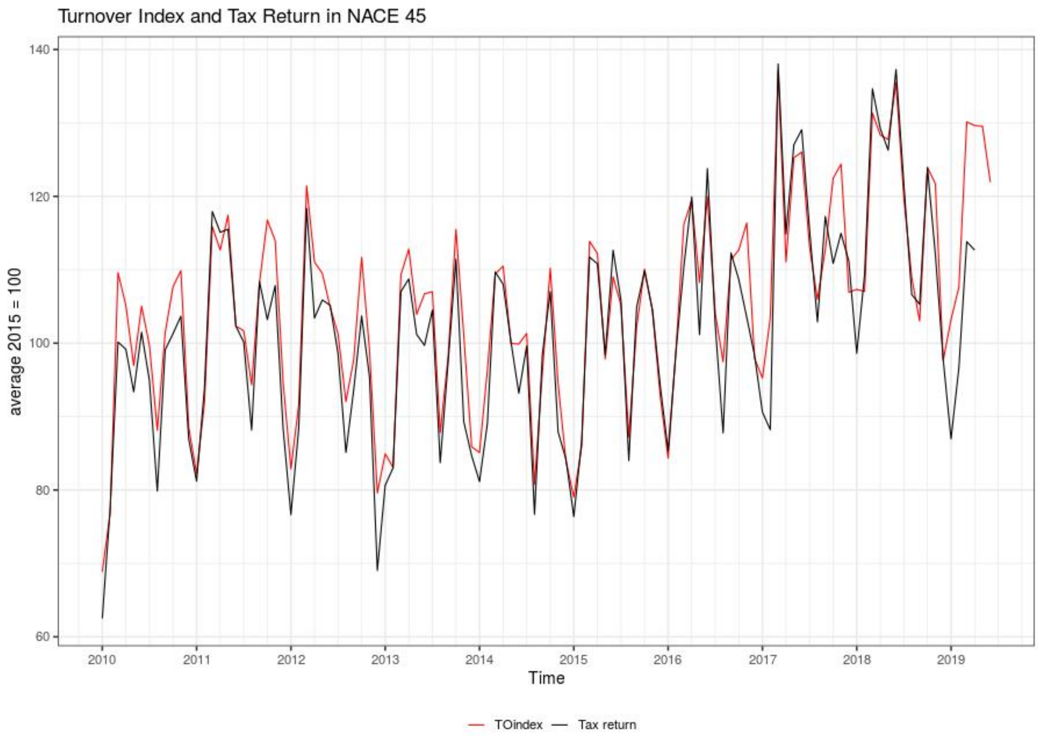

Figure 1 Turnover Index and Advance tax return (Source: Statistics Austria)

Turnover indices mainly use *advance return of sales tax* and cut-off-surveys on turnover. These values are checked for plausibility and correctness before the index is calculated. To forecast the index we will use a seasonal ARIMA model with unprocessed advance tax return as regressor as in equation 1.

$$\boldsymbol{\Phi_p(B)\,\Phi_P(B^{12})(1-B^d)(1-B^{D12})kjh_t = \mu + \theta_q(B)\,\Theta_Q(B^{12})\,\varepsilon_t + \beta\,uva_t} \quad (1)$$

Where kjh_t is the turnover index at time t, uva_t the advance return of sales tax at time t with the respective coefficient β. B denotes the Backshift operator, Φ_p, Φ_P, θ_q and $\Theta_Q$represent the AR and MA polynomials of a $(p,d,q)(P,D,Q)_{12}$ seasonal ARIMA. The mean is denoted by μ and ε_t is a random error term with white noise.

This model has been tested against a seasonal ARIMA without considering advance return as indicator (see equation 2) as well against a simple regression model of differenced in tax return on differenced TOI (equation 3).

$$\boldsymbol{\Phi_p(B)\,\Phi_P(B^{12})(1-B^d)(1-B^{D12})kjh_t = \mu + \theta_q(B)\,\Theta_Q(B^{12})\,\varepsilon_t} \quad (2)$$

$$(1 - B)kjh_t = \mu + \beta\,(1 - B)uva_t + \varepsilon_t \qquad (3)$$

Preliminary results show that the inclusion of advance returns in the ARIMA model is lowering forecast errors in some industries. This improves QNA estimates as advance returns have previously not been available to QNA compilers.

Finding suitable reference groups for indicators

Private consumption of households is a very complex and heterogeneous aggregate. But it is also one of the biggest with substantial public interest. Because of its importance we chose a very detailed approach for disaggregation that is strongly connected to ANA compilation.

In Austria 45 % of private consumption relates to goods. It is assumed that private consumption of goods develops with retail trade in the corresponding NACE sub-class (5-digit), taken from short-term business statistics and advance tax returns. In ANA consumption of goods is compiled in a very detailed framework at CPA-6-digit level. To disaggregate these annual benchmark values we use short term indices.

As it isn’t possible to soundly infer the sub-annual development goods in a single CPA sub-category (6 digits) we constructed new bundles of commodities by grouping them according to their retail NACE sub-class. To give an illustrating example: there are forty-three different CPA sub-categories for clothing, differentiating between type of garment and material. Not every single one of them will follow the seasonal pattern of retail sale of clothing, think winter coats or shorts. But the bundle of all clothing items is showing similar developments as retail sale. Similarly, there are 121 different goods that are typically bought in supermarkets; food, drinks, spices. Figure 2 illustrates the development of the turnover index for supermarkets and compares it to the development of annual consumption of all *supermarket-goods,* and the three most-consumed goods within this group: fresh fruits, fresh vegetables and wine.

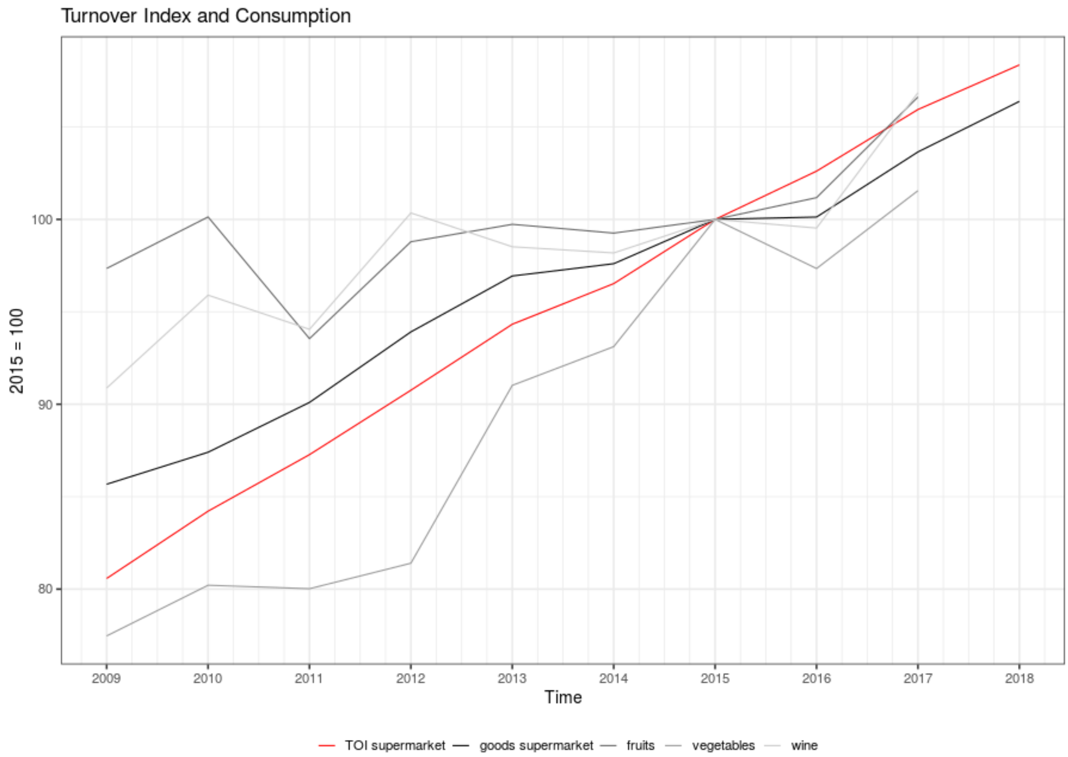

Figure 2 Development of yearly turnover index, consumption of supermarket goods and the most common goods bought in supermarkets: fruits, vegetables and wine. 2015 is set to 100 to account for different magnitudes. (Source: Statistics Austria)

As Figure 2 illustrates, single CPA-6-digit goods do not follow the same yearly trajectory as the aggregated TOI for supermarkets. The group of all supermarket goods, however, does show a similar development. This is also reflected by a statically significant coefficient of the index (p-value < 0.001) and a stationary error-term.

Dealing with prices and chain-linked volumes

For most aggregates on the production side of GDP the annual production value is disaggregated and extrapolated with indicators from short-term business statistics. To get from production (P1) to value added (B1) we use input-output ratios from ANA. In ANA input-output ratios result from IO and structural business statistics. For the most recent year intermediate consumption is assumed to change at the same rate as production. So the input-output ratio at previous year prices (pyp) is assumed to equal the input-output ratio at current prices (cup) from the year before.

$$\frac{B1_{t-1}^{cup}}{P1_{t-1}^{cup}} = \frac{B1_t^{pyp}}{P1_t^{pyp}}$$

This works well in ANA, where each year is calculated separately. In QNA we look at time series, so in order to infer a steady relation between input and output we have to look at chain-linked volumes (clv). The first step is to get the chain linked input–output ratio from ANA. This can either be obtained by chain-linking the input-output ratio at current and previous year prices or taking the ratio of value added and production (see Appendix, page 15). Figure 3 shows workflow from production at current prices to value added. Production at cup is deflated using detailed price indices from our price data base. The price data base consists of weighted Laspeyers price indices with weights from IO-Tables and ANA. Production at cup and pyp is chained with the annual overlap method (IMF 2017, chapter

8). Via input-output ratios we get to chain-linked value added. Using the information from ANA, we get to value added at pyp via inverse annual overlap. We use an implicit price index from our price data base to attain value added at cup.

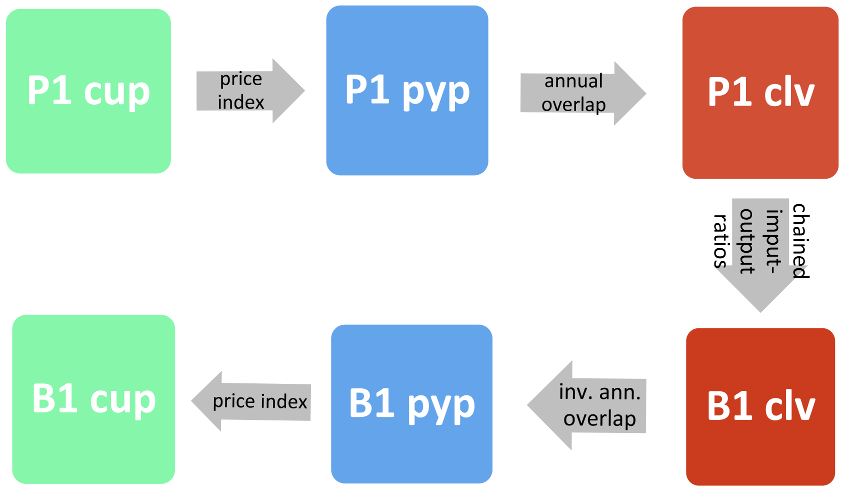

Figure 3 getting from cup production values to value added.

We follow this rather complex workflow to not violate the time series consistency when keeping the input-output ratio of the last year constant. In the compilation of the price data base and in the set-up of the framework many details need to be considered to not violate ESA regulations and to stay consistent with ANA and IO statistics. Hence, this is one of the most fragile parts in compilation and changes in any other part of the national accounts framework affect our volume measurements. The presented procedure is still subject to evaluation to ensure methodical correctness.

Updating the time series

To avoid time series breaks all series will be updated with the first publication in 2020. The transmission programme of ESA 2010 requires member states to provide consistent data from 1995 onwards. Updating the time series opens two fields of problems; firstly, the level of detail and concepts as well as surveyed activities in business and price statistics changed (e.g. NACE Revisions 2003 and 2008, ESA 2010, changing from full samples to cut-off samples in business statistics). Secondly, the question of how to communicate changes in seasonal patterns arises. As stated in the introduction, there are cases were differences cannot be traced back straightforwardly, but some can be identified. This section will illustrate how we are dealing with those problems.

Connecting different data sources

The available level of detail of price indices differs a lot over time. The Consumer Price Index (CPI), for example, is only available on CPA-6-digit-level after 2011. For the years before 2000 there is only one overall CPI with no further differentiation available. Similar availability issues apply to all price indices. To get a time consistent price index for NA aggregates prices are weighted using IO structures and are benchmarked to implicit ANA deflators.

Even stronger data restrictions appear in all aggregates concerning the service sector. Business statistics do not cover services in Austria before 2003. Even now, some areas that are not surveyed (this will change with FRIBS, Framework Regulation Integrating Business Statistics). Statistically white areas have to be tackled individually, sometimes one has to go to a next-higher level or to interpolate and back cast data with the help of administrative data such as number of employees or declared taxes. This is an ongoing issue as, so far, not all series are updated back until 1995.

Explaining new patterns in the updated series

GDP will have a different seasonal pattern when the series are updated in 2020. Figure 4 gives a first impression of the different patterns. This is, of course, still subject to change, as there are about nine months left to our publication. The majority of the production side of GDP is based on strong data sources, which provide suitable, well-fitting indicators. Some are still up for discussion as an optimal solution is yet to be found.

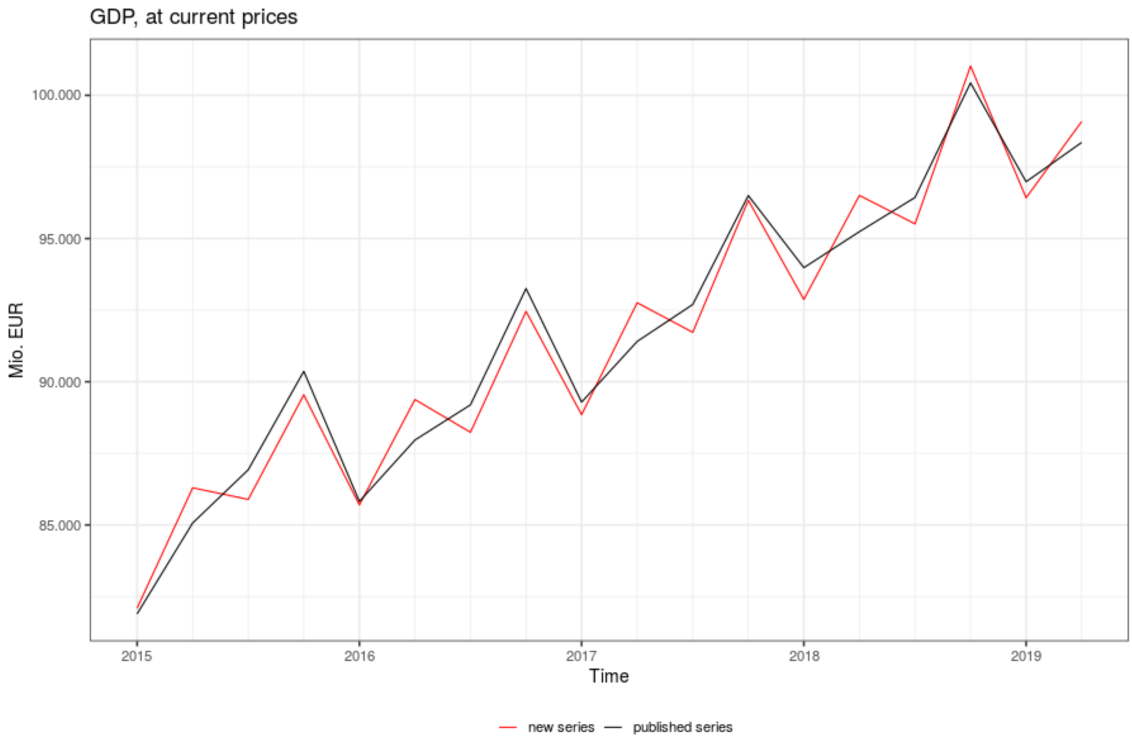

Figure 4 Differences in seasonal patterns between currently published GDP and the new series published in 2020 (Source: Statistics Austria)

The main reason for the differences in Figure 4 actually lies in the different estimation methods on the income side of GDP that affects value added in NACE activities O to U. Series of the income approach are disaggregated using the Denton (1971) benchmarking method. This is the appropriate method as the high frequency input data describes the same low-frequency variable and is measured in the same unit. Nevertheless, as the data are preliminary and adjustments have to be made for ANA, the time series need to be benchmarked.

Wages and salaries (D11), which result from the income approach, are used to disaggregate value added of non-market producers in NACE activities O to U. As value added of non-market producers is measured on the basis of occurring costs *wages and salaries* is an appropriate indicator. In Austria a special case arises; most workers get paid 14 times a year. Additional salaries are paid in June ("Holiday bonus") and December ("Christmas bonus"). ESA 2010 requires us to account for these extra payments in the respective quarters. The share of non-market producers is considerably high in NACE activities O to U, therefore these different patterns arise.

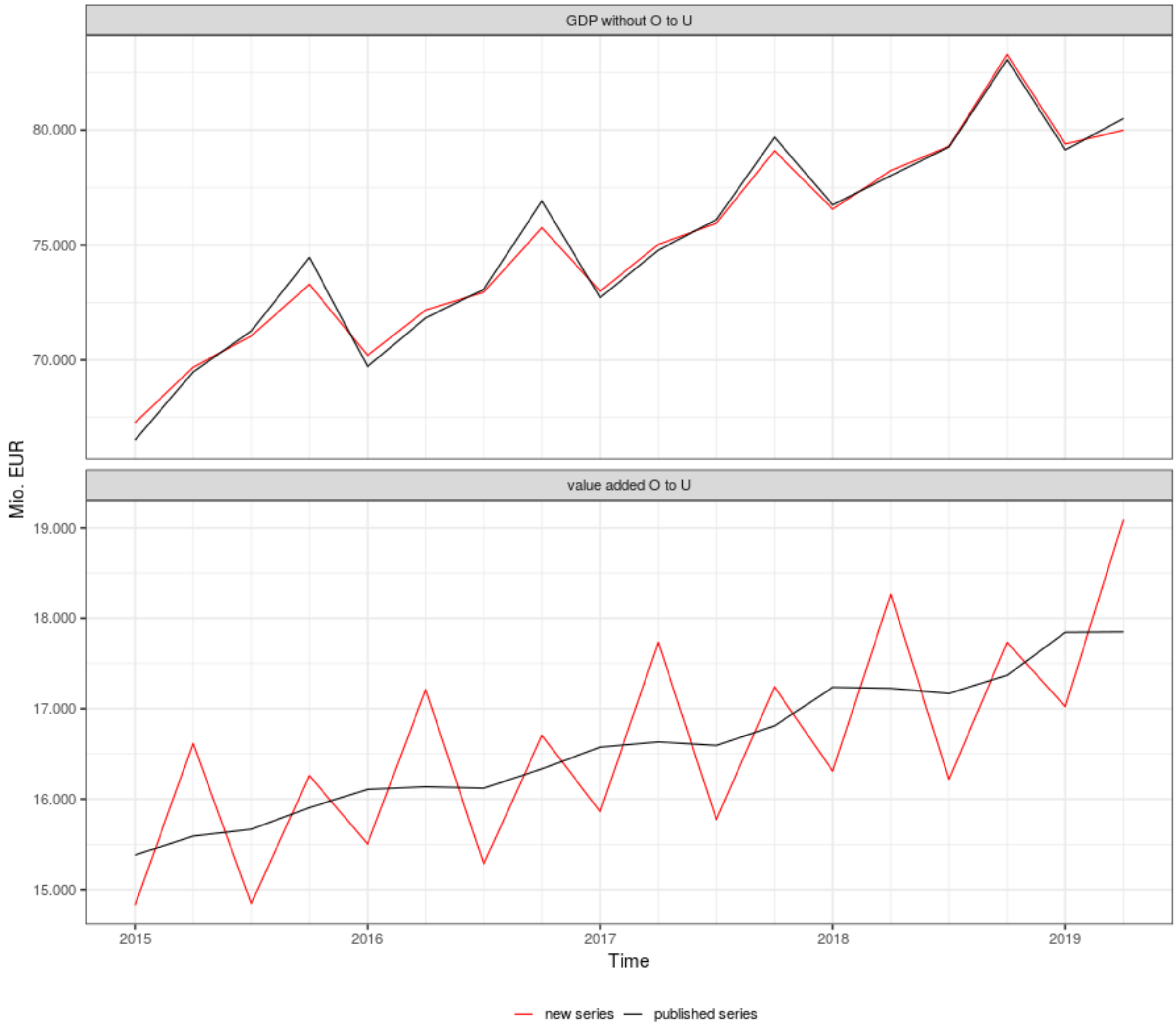

Figure 5 Separate seasonal patterns for GDP without NACE devisions O to U and value added of those activities. (Source. Statistics Austria)

In terms of volume these patterns should not show. We therefore need to find an appropriate method to correctly represent economic reality. We are currently discussing different approaches suggested in the EUROSTAT Handbook on QNA (European Union 2013, 2.38).

Technical Lessons

Our aim was to create a flexible and intuitive compilation framework. Based on our experience and resources we chose *R* as default environment. Whenever possible, existing programmes from ANA have been adapted for quarterly purposes in SAS (ANA is based on SAS programmes). As a result, some data processing steps are technically quite fragmented. One example is the quarterly commodity flow. Data sources like PRODCOM statistics and foreign trade statistics are stored in SAS files. The structural information on use categories of goods are taken from ANA and stored as Excel files. The compilation of the quarterly commodity flow is based on a SAS programme. The results are further processed to disaggregate annual values in R.

Individual technical solutions resulted from specific conditions and circumstances during the implementation process, rather than following a previously set plan. Decisions were made according to programming experience of staff members, existing programmes for ANA, time resources and user demands. After the implementation phase - when there will be more time resources – all programmes will be transferred to R to ensure a homogeneous framework.

The diversity of source files did not cause major problems. With *R haven* and *openxlsx* one can read a variety of data formats. However, the technical fragmentation requires detailed documentation to retrace every step. This is particularly important for our personnel backup to be able to fill in for QNA members immediately when necessary. In some cases the use of different programmes is a result of tight time resources in the implementation process. Whenever possible and appropriate, existing ANA programmes were adopted for quarterly purposes in SAS. They will, however, be transferred to an R environment after the implementation phase.

Processing data and compiling results

R is becoming a commonly used tool at STAT. The Methods Unit is maintaining the server environment for R and manages internal packages. The advantage of the use of *R* is the fact that it is a free, open source software. It is intuitive and widely used in the academic community, which facilitates transition processes. To integrate R to the existing IT environment the Methods Unit launched several internal packages. These packages connect shared drives to the server, access data bases and generate slides in corporate design. Within directorate of macroeconomic statistics we wrote a package that includes commonly used functions and frequent calculations, such processing input data, generating chain-linked volumes or export to our data base. Apart from the internal package we frequently use *haven* and *openxlsx* to import data. To process, manipulate and analyse data we use *dplyr*, *reshape2*, *tseries*, *forecast*, *urca* and *ggplot2*. For the actual disaggregation and benchmarking the *tempdisagg* package by Sax and Steiner (2013) is necessary. *RJDemetra* and *Persephone* are essential for seasonal adjustment.

Our framework is structured in modules. There are individual R projects for aggregates that are compiled together, for example output of all manufacturing activities, or private consumption of goods. The results are stored in the data base, where they are further processed, aggregated to publication levels and chain-linked.

Storage and balancing

Within the directorate of macroeconomic statistics we use a Db2 database, version 11.1. For each use case within the directorate there is a *schema*, e.g. for balance of payments, national accounts. The base table stores all variables at compilation level and their properties (seasonal adjustment information, prices, whether there have been other adjustments). In the R environment one sees previously defined views, such as ESA 2010 TP tables or a lower aggregation for plausibility checks. Those views are saved to retrace publications and revisions at any point in time. In the data base only the authentic data at the latest state is stored.

We are currently developing an *R shiny app* for balancing. The shiny app should replace Excel outputs to view results. Individual adjustments made during the balancing process will then be stored in the data base with the according flag that is has been adapted. This reduces effort to document reconciliation adjustments in an already tight time frame before publication.

Finding practical and effective technical solutions is an ongoing process. Usually several requirements, like programmers' and users' preferences have to be considered. The DB2 database is a good tool for this purpose, since data can be processed and read out in different formats. For now this seems to us the best solution, however, we are aware of the fact that this is also a question of experience and that we have to be flexible with technical solutions.

Conclusions

From 2020 onwards QNA will be compiled by Statistics Austria. The implementation started in 2018 and is a challenging process, since a whole set of national accounts aggregates has to be set up within a short period of time. This article sums up our main experiences, problems and learnings so far and might help other national statistic institutes when reorganising parts of QNA regarding methods, technical support or institutional arrangements.

Concerning institutional arrangements we found that the most effective way to allocate responsibilities among the QNA team is based on familiarity with basic data as well as on methodical and programming skills. This differs from ANA, where responsibilities refer to the three approaches of NA (i.e. production, expenditure and income accounts). Apart from this, we profited from the experience and know-how of annual national accountants, who supported us during the whole process and are also integrated in actual quarterly compilations by checking the plausibility of our results. Moreover, we saw the importance of intense cooperation with basic data providers, since the quality of our results highly depends on information concerning the indicators we use to estimate the aggregates.

After 18 months of implementation the general framework is set. We found suitable solutions for most problems, such as forecasting indicators that are not available on time or finding appropriate levels of detail for disaggregation. In some cases, however, we are still looking for an optimal way to generate consistent time series or find better indicators. In the analysis of our results from parallel compilations we identified possible reasons for revised seasonal pattern, which seems to come from different indicators on the income side of GDP.

One of the biggest novelties in our approach is the technical framework. We took the opportunity to set up everything in R. In our case this is the best solution as it is a flexible environment that can easily be extended. The use of an R shiny app and the db2 database facilitates the further use of our results for those who do not have programming skills in R or prefer other environments.

The Austrian situation is quite unique as it does not happen on a regular basis that a whole new part of National Accounts is implemented at once. Nonetheless, our lessons learned show other providers of official data the challenges and benefits of our approaches. The open discussion about methods and technical solutions helps to make the compilation of official data more transparent and comparable for users.

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List of Acronyms

ANA	Annual National Accounts
B1	Value Added
clv	Chain-linked Volumes
CPA	Statistical Classification of Products by Activity
CPI	Consumer Price Index
cup	Current prices
D11	Wages and salaries
DESTATIS	Statistisches Bundesamt (German NSI)
ESS	European Statistical System
ESTP	European Statistical Training Programme
IO	Input-Output Statistics
ISTAT	Instituto Nazionale di Statistica (Italian NSI)
NACE	Statistical classification of economic activities
NSI	National Statistical Institute
P1	Production value
PI	Production Index
pyp	Previous year prices
QNA	Quarterly National Accounts
STAT	Statistics Austria (Austrian NSI)
TOI	Turnover index
TP	Transmission programme
WIFO	Austrian Institute of Economic Research

APPENDIX

b ...value added

p ...production

r ...input-output ratio

^{cup} ...current prices

^{pyp} ...previous year prices

^{clv} ...chain-linked

1. $b_t^{clv} = \frac{b_t^{pyp}}{b_{t-1}^{cup}} * b_{t-1}^{clv}$
2. $p_t^{clv} = \frac{p_t^{pyp}}{p_{t-1}^{cup}} * p_{t-1}^{clv}$

$$\rightarrow \qquad \frac{b_t^{clv}}{p_t^{clv}} = \frac{b_t^{pyp} * b_{t-1}^{clv}}{b_{t-1}^{cup}} * \frac{p_{t-1}^{cup}}{p_t^{pyp} * p_{t-1}^{clv}}$$

$$= \frac{b_t^{pyp}}{p_t^{pyp}} * \frac{p_{t-1}^{cup}}{b_{t-1}^{cup}} * \frac{b_{t-1}^{clv}}{p_{t-1}^{clv}}$$

$$= \frac{r_t^{pyp}}{r_{t-1}^{pyp}} * \frac{b_{t-1}^{clv}}{p_{t-1}^{clv}}$$

$$= \frac{r_t^{pyp}}{r_{t-1}^{cup}} * r_{t-1}^{clv}$$

→ the ratio of chain-linked value added and chain-linked production equals the chain-linked input-output ratio.