How bad are fiscal revisions in the euro area?

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Abstract

We investigate the properties of fiscal revisions in the euro area by contrasting them with macro revisions. To this end, we construct a fiscal real-time dataset containing quarterly releases of Government Finance Statistics, which is supplemented by macro variables from Main National Accounts. Fiscal revisions, like macro revisions, do not satisfy desirable properties expected from well-behaved revisions. In particular, they tend to have positive mean, are non-negligible in size and are predictable. With our investigation we contradict the often heard view that fiscal data are subject to extraordinarily sizeable revisions. While it was the case some years ago since 2014 the revisions for the main fiscal categories are in the same ballpark as the revisions for the main macroeconomic series. In general, properties of fiscal and macro revisions are quite similar since the introduction of ESA 2010 in 2014.

Keywords: Fiscal policy, real-time data, data revisions

Contents

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1. Introduction

Most macroeconomic data are revised after the initial release. Revisions originate from various sources with new information becoming available by the time of subsequent releases being the most obvious cause. Conceptual changes to statistical definitions and to compilation and estimation methods constitute another reason. In the case of intra-annual statistics that require seasonal adjustment the revisions may also originate from a re-estimation of seasonal factors. Finally, simple correction of errors and elimination of omissions that take place in the context of a data production process may also lead to data revisions.[1]

Whatever the source of the revisions given their common existence they should be taken as a fact of life. In this context, researchers and policy-makers have no choice rather than understanding them. Only a proper recognition of revisions enables the application of optimal statistical methods that lead to sound analytical conclusions.[2] In the same vein, an acknowledgement of revisions is necessary to place an adequate trust in data available at the time when a policy decision is formed.[3]

This paper analyses revisions to quarterly fiscal data in the euro area. Its main objective is to determine how well-behaved fiscal revisions are, especially by contrasting them with macro revisions. To this end, we check to which extent the properties of well-behaved revisions, as outlined by Aruoba (2008), are fulfilled. The criteria are based on the following three characteristics: (1) zero bias, (2) little dispersion and (3) unpredictability given the information available at the time of the initial announcement.

The main contribution of this paper is to deliver a comprehensive analysis of revisions to quarterly fiscal data in the euro area. The literature studying revisions to quarterly macroeconomic data has been growing for decades and by now it is very rich (see a literature survey in Croushore (2011)). A large bulk of the literature, like Mankiw and Shapiro (1986), concentrates on the primary indicator of economic activity, which is GDP or GNP. Other papers suggest extensions along various dimensions. Shrestha and Marini (2013), for example, investigate whether the magnitude of revisions to GDP differs during crisis episodes. Also, there are studies analysing revisions to a broader set of economic indicators going beyond the measures of output (see, e.g. Aruoba (2008) for the US, Branchi et al. (2007) for the euro area, Faust et al. (2005)} for G7 economies).

According to our best knowledge, no study exists that analyses revisions to the euro area quarterly fiscal data in a comprehensive way. The literature on revisions to fiscal statistics established so far concentrates on annual data often with a view to shedding light on fiscal discipline and budgetary frameworks. De Castro et al. (2013) use real-time vintages of annual budget balance to evaluate the quality of initial data releases, on the basis of which compliance with the fiscal rules is assessed. Maurer and Keweloh (2017) attempt to answer the question whether the quality of annual fiscal data provided in the context of the Excessive deficit procedure (EDP) improved over time in the EU. As far as we are aware, Asimakopoulos et al. (2020) demonstrating usefulness of real-time fiscal data for forecasting purposes, is the only study that provides some limited characteristics of revisions to quarterly fiscal series for the biggest four euro area economies (i.e. Germany, France, Italy and Spain). As concluded in the literature survey on real-time data and fiscal policy analysis in Cimadomo (2016), "more work is needed in this field". With our analysis we try to fill the gap.

Another significant contribution of our study is the creation a real-time fiscal quarterly dataset for the euro area countries. The ability of researchers to conduct real-time analysis depends on real-time datasets, which collect in one place data available at any point in the past. In the US two comprehensive real-time datasets exist next to each other, namely Real-Time Data Set for Macroeconomists by Federal Reserve Bank

[1] Carson et al. (2004) provides many useful clarifications on statistical revisions, including on typology and terminology.

[2] Multiple studies underline the usefulness of real-time fiscal data for fiscal forecasting, budgetary surveillance or identification of fiscal shocks (see, e.g. Pedregal and Pérez (2010), Asimakopoulos et al. (2020) and Cimadomo (2016)).

[3] Orphanides (2001) in its seminal contribution demonstrates the complexity of policy decision-making in real time. Most notably, the study emphasizes that policy recommendations obtained with real-time data are considerably different from these based on ex-post revised figures.

of Philadelphia (see Croushore and Stark (2001)) and ArchivaL Federal Reserve Economic Data (ALFRED) by the Federal Reserve Bank of St. Louis (see Stierholz). Also, significant efforts have been made to establish a real-time dataset for the euro area (see Giannone et al. (2010)). We contribute to this work by collecting all vintages of Government Finance Statistics for the euro area countries since their publication started in mid-2000s.

To answer our research question, we derive a broad set of statistics that allow us to assess all three requirements for well-behaved revisions. To this end, by calculating the mean of revisions we check the degree of a bias across fiscal variables. Moreover, we assess the extent of dispersion in revisions using several indicators. Finally, by running a set of regression models we verify whether revisions are predictable given available information at the time of the initial release. To put the results into perspective, we contrast fiscal revisions with macro revisions, which are significantly better understood in the economic literature.

Our investigation first concludes that fiscal revisions, like macro revisions, do not satisfy desirable properties expected from well-behaved revisions. This finding is not only relevant for final revisions but it also holds for intermediate revisions. Fiscal variables exhibit a positive bias since most of them grows in annual terms by 0.1-0.3 percentage points more compared to what is published initially. Given the average growth in the sample of around 4% the value of the bias is non-negligible.

Second, the dispersion of fiscal revisions tends to be relatively sizable. Mean absolute revision - our most intuitive summary statistic - amounts to around 1 percentage point for the annual growth in the biggest and most stable categories. It reaches significantly higher values for small and volatile items, most notably government investment. Our analysis also indicates that fiscal revisions became significantly smaller since 2014, which is the moment of the ESA 2010 introduction. While the mean absolute revision for the biggest and most stable categories considerably exceeds 1 percentage point in the first subsample (up to 2014Q2) it is significantly lower than 1 percentage point in the second subsample.

Third, fiscal revisions are in general predictable. While the degree of predictability varies significantly across the variables it is substantial for many of them. The conditional mean with respect to the information available at the time of the initial release is statistically different from zero. As such, revisions do not only reflect new incoming information but also the information known at the time of the initial publication. This feature also speaks in favour of treating fiscal revisions as 'badly' behaved.

When contrasted with macro revisions, fiscal revisions are quite comparable. Both fiscal and macro revisions are associated with a positive bias of a similar order. At first sight, fiscal revisions appear to be significantly more dispersed than macro revisions, as measured by the mean absolute revision, for instance. We document, however, that since 2014, when the magnitude of fiscal revisions narrowed down considerably, both types are revisions are in the same ballpark. Also, the degree of predictability does not appear to differ between the two types of variables. In this context, we contradict the often heard view that fiscal data in general are subject to particularly large revisions (see, e.g. Cimadomo (2016)).

The paper is organised as follows. Section 2 describes the construction of the real-time quarterly fiscal database, which constitutes the basis for the analysis. Section 3 analyses unconditional properties of final revisions, which enables to assess the bias and dispersion. Section 4, in turn, investigates the degree of predictability of the revisions, which completes the assessment of the three criteria for well-behaved revisions. Any additional information contained in the intermediate revisions is discussed in Section 5. Finally, Section 6 concludes.

2. Real-time quarterly fiscal dataset

Fundamental to our analysis is the construction of a real-time quarterly fiscal dataset, which will serve as a basis for calculating the revisions. The dataset primarily relies on quarterly Government Finance Statistics

(GFS) published by Eurostat.[4] GFS data provide information on economic activities of governments in a harmonised and country-comparable manner.[5] [6] While the data spreads over both non-financial (i.e. revenue and expenditure) and financial (i.e. borrowing and lending) activities of the governments in the paper we only cover the former.

In addition, the dataset is supplemented with a limited set of variables from Main National Accounts (MNA) dataset, which are labelled as 'macro variables'. They are used as a reference to assess the relative properties of the fiscal revisions. The MNA vintages take due consideration of the timing of the GFS vintages, even if the releases of the two datasets do not coincide. This means that to determine a relevant vintage of the MNA dataset we use only the information available at the time of the corresponding GFS data release.

2.1. Structure of the real-time dataset

The structure of our real-time dataset follows a typical set-up, as presented in Diebold and Rudebusch (1991) and as embedded in ECB's Statistical Data Warehouse (SDW) (see a demonstration in Table 1). Each column represents a data release, which in the case of GFS data takes place four times per year (in January, April, July and October).[7] Each row, in turn, represents a quarter for which the economic activity is measured. Data releases for a given quarter can be traced from left to right within the corresponding row. Differences between releases constitute intermediate revisions, which then make up final revisions (i.e. a difference between the final release and the first release).

[4]A section dedicated to government finance statistics is available on Eurostat's website (https://ec.europa.eu/eurostat/web/government-finance-statistics).

[5]European GFS are conceptually consistent with the European system of national and regional accounts in the European Union (referred to as ESA 2010). In fact, the GFS compilation is based on re-arranging transactions recorded in the various ESA accounts that are relevant for the government sector.

[6]In addition to the ESA 2010 accounting framework published in the Official Journal on 26 June 2013 (https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-02-13-269) and implemented in September 2014, Eurostat publishes the Manual on Government Deficit and Debt — ESA Implementation (the latest 2019 edition: https://ec.europa.eu/eurostat/documents/3859598/10042108/KS-GQ-19-007-EN-N.pdf/5d6fc8f4-58e3-4354-acd3-a29a66f2e00c). The manual constitutes a complement to ESA 2010 by providing specific guidance on the treatment of statistical issues regarding government finance statistics.

[7]The data for a given quarter are compiled for the first time 90 days after the end of the quarter and are published after validation around 110 days after the end of the quarter.

Table 1: Timing of the revisions and underlying releases

		Release time					
		Jul (T)	Oct (T)	Jan (T+1)	Apr (T+1) (1st annual release)	Jul (T+1)	Oct (T+1) (2nd annual release)
Observation quarter	Q1(T)	1st release	2nd release	3rd release	4th release	5th release	6th release **(final)**
			1st *interm.* revision	2nd *interm.* revision	3rd *interm.* revision	4th *interm.* revision	5th *interm.* revision
			final revision				
	Q2(T)		1st release	2nd release	3rd release	4th release	5th release **(final)**
				1st *interm.* revision	2nd *interm.* revision	3rd *interm.* revision	4th *interm.* revision
				final revision			
	Q3(T)			1st release	2nd release	3rd release	4th release **(final)**
					1st *interm.* revision	2nd *interm.* revision	3rd *interm.* revision
					final revision		
	Q4(T)				1st release	2nd release	3rd release **(final)**
						1st *interm.* revision	2nd *interm.* revision
						final revision	

To define revisions it is necessary to take a stance which release constitutes a final value for a certain quarter. Treating the most recent available observations as final releases may be suboptimal because of benchmark revisions, which take place every several years and lead to revisions of not only the most recent quarters but also remote ones.[8] Against this background, the selection of a final value becomes a delicate balancing act between two objectives. On the one hand, there is a desire to incorporate as many releases as possible to reflect any new incoming information since the moment of the initial release. On the other hand, one should limit the number of releases to avoid as much as possible the undesirable contamination of the dataset with benchmark revisions. The notion of a final value in this situation becomes necessarily arbitrary. In addition, it should be recognised that fiscal data even though reported at quarterly frequency carry some characteristics of annual data, which reflects the annual nature of budgeting and reporting in the public sector.

In this paper we define the final value for any quarter of year T by the value released in October of the subsequent year $T{+}1$. The main motivation for our choice is to duly recognise that quarterly fiscal data are, at least to some degree, annual in nature. As documented in Section 5, quarterly fiscal figures are revised mainly at the time of annual data releases (i.e. in April and October). In this context, we regard as final

[8] Statistical agencies occasionally adjust their methodologies, which leads to revisions of entire time series — the so-called benchmark revisions. In the European Union a harmonised European revision policy was put in place to ensure coordinated and consistent revisions (see Eurostat (2019)). According to this policy, benchmark revisions should take place each five years, with implementation years ending with '4' and '9'. Consequently, benchmark revisions for ESA 2010, which govern both GFS and MNA, were supposed to be implemented in 2014 (at the time of the ESA 2010 introduction) and 5 years later in 2019. In practice, however, not all countries followed the recommendations. Some Member States carried out benchmark revisions outside the benchmark years — before, after or even each year including during the benchmark years. The lack of regularity makes controlling for benchmark revisions in practice extremely challenging.

values the outcomes of the second annual EDP (Excessive deficit procedure) release.[9] At the same time, by keeping a limited distance between a first and a final release we make the dataset as much as possible unaffected by benchmark revisions.

The set-up implies that different quarters within a year have a varying number of releases before the final value is determined (see Table 1). Q1 figures require six releases until they become final while Q4 only three. In other words, while for Q1 observations it takes 1 1/4 years to determine its final values it lasts only 1/2 year for Q4 observations. The property equally applies to all variables considered in the analysis therefore it does not affect comparability between them in any way.

To analyse the revisions we transform the GFS data, expressed in EUR millions, into growth rates.[10] In particular, we calculate annual growth rates with respect to the same quarter of a preceding year. By calculating this way, rather than with respect to a preceding quarter, we avoid a need for seasonal adjustment, which in the presence of updates to seasonal factors would add another source of revisions. Also, considering growth rates makes the analysis more robust to benchmark revisions than it would be the case for levels. Benchmark revisions often lead to level shift adjustments of all quarters, even those reaching far into the past, but leave the growth profile still largely unaffected. The average growth for most of the fiscal and macro series in the sample oscillates around 4% (see Figure B.22 in Section B of the online appendix).

2.2. Final and intermediate revisions

Final revisions are calculated as a difference between the final release (x_t^f) for quarter t and the first release (x_t^1) for the same quarter t following the below equation:

$$r_t^f = x_t^f - x_t^1$$

The definition implies that a positive value is associated with an underestimation of a first release and the other way around (see the left-hand-side chart of Figure 1 for illustration).

Intermediate revisions are calculated as a difference between directly succeeding data releases as follows:

$$r_t^i = x_t^{i+1} - x_t^i$$

where x_t^i is an i-th release for quarter t.

The sum of intermediate revisions to a given quarterly value amounts to a final revision (see Table 1 and the right-hand-side chart of Figure 1 for illustration). In this context, intermediate revisions can be used to decompose final revisions — the aspect we explore in Section 5. The varying distance between final and initial releases results in a different number of intermediate revisions depending on a quarter (see again Table 1 for illustration).

2.3. Data scope

Our real-time fiscal dataset contains all main categories provided in the GFS datasest. We look closely at the following 9 fiscal variables.

- Total revenue
  - Direct taxes
  - Indirect taxes
  - Social contributions

[9]As a part of the Excessive deficit procedure all EU member states are obliged to report their annual fiscal outturns before 1 April and 1 October each year.

[10]To be precise, we approximate growth rates by log differences. The approximation leaves ordinary changes over time largely unaffected. However, it diminishes extraordinarily huge changes compared to the standard growth rate calculation.

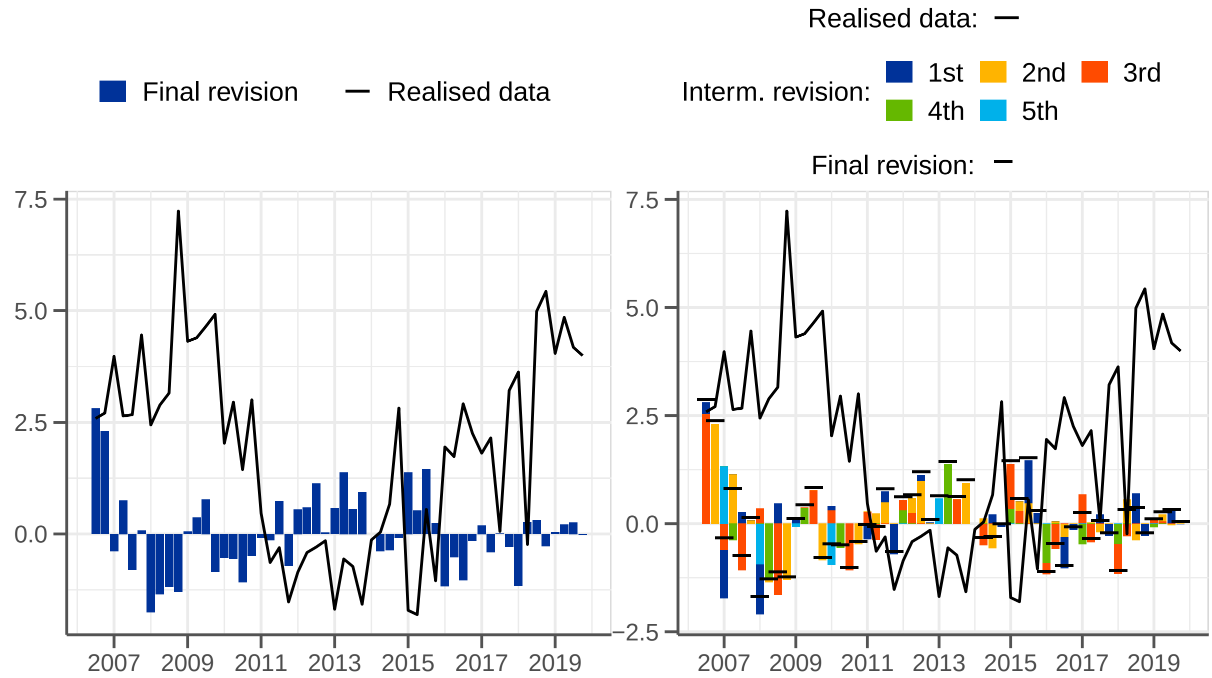


Figure 1: Revisions to the growth rate of gov. compensation in the Netherlands

- Total expenditure
  - Social transfers
  - Purchases
  - Gov. compensation
  - Gov. investment

The set includes total revenue and total expenditure, as well as their main components. Table D.2 in the online appendix gives an overview of all variables together with their full statistical names and with series keys needed to download the data.[11]

We do not explicitly investigate minor fiscal categories, like capital revenue or subsides, on account of their extraordinary volatility. The only exception we make is government investment, which belongs to our particular interests as an important fiscal policy instrument and as a direct demand component. The excluded variables account only for a limited share of gov. revenue and expenditure, and as such, they are usually unable to drive the general picture on fiscal policy. Concretely, the minor items comprise 10% of total revenue and 7% of total spending in our dataset (see Figure B.21). At the same time, they are very volatile (see standard deviation in Figure B.22) and they come with very large revisions (see Figure 2 and Figures A.5, A.6, A.10, A.12, A.14 in the online appendix). Notwithstanding this, the minor variables are captured in the analysis by being a part of total revenue and total expenditure. Consequently, they play a fair role in the analysis even without being considered individually.

The dataset is supplemented with the selected following items from the MNA dataset.[12]

- GDP

[11] Only around 2/3 of the vintages in our real-time fiscal dataset are available through ECB's SDW. Vintages published before 2010 even though public, have not been disseminated to SDW and they are based on snapshots of Eurostat data releases.
[12] To ensure comparability with fiscal data all macroeconomic variables are expressed in nominal terms, therefore they also contain the price component.

- Private consumption
- Total investment
- Export
- Gov. consumption
- Wages and salaries

We regard this set of variables as a reliable benchmark for assessing fiscal revisions. Similarly to the fiscal variables, the series keys needed for data retrieval are specified in the online appendix in Table D.3.

Regarding the country coverage, the dataset underlying the paper includes all 19 countries comprising currently the EMU, as well as the euro area aggregate.[13] For the purpose of our analysis, however, we consider individually only 9 biggest (in terms government size as measured by total expenditure) countries. The remaining 10 countries account for only around 5.5% of the euro area government expenditure (see Figure B.23) but exhibit extraordinarily high revisions (see Figure 3). Moreover, as can be seen in the single-variable revision plots (Figures A.1 - A.12), there are instances when fiscal data for some of these small countries are not subject to any revisions. Zero revisions in these cases should not support a view about high data accuracy but rather raise concerns regarding the data quality.

Giving the small and volatile countries a prominent role in forming conclusions on the euro area fiscal data would be misleading. The volatility and incompleteness exhibited by these countries does not influence the big picture on fiscal policy in the euro area simply because of the small size. For this reason we group the small volatile 10 countries into one geographical unit — the rest of the euro area (REA). By doing so we reduce the weight of these countries in the analysis even though we still cover them. In addition, we occasionally look at the euro area aggregate, especially with a view to putting the country fiscal data into perspective.

Our dataset consists of 59 quarterly GFS vintages taking place since January 2007 to July 2021. The selection of the first vintage is dictated by the moment in which quarterly GFS data started being stored in an organised and complete manner.[14] Admittedly, it took until October 2014 before the reporting of the GFS data became compulsory and complete. Notwithstanding this, even well before October 2014 the GFS data were published regularly by most of the euro area countries on voluntary basis.[15] The last vintage is simply the release containing final values for 2019, which is the last year unaffected by the COVID-19 crisis.

A look at the data over time reveals that the dispersion of the fiscal revisions dropped significantly in 2014. Figure 4 illustrates that the 5-95% interval calculated for each year narrows down noticeably in 2014 for total revenue and total expenditure. The shrinkage clearly stands out when the two fiscal variables are compared to GDP. The width of the interval for the latter stays remarkably constant over the entire period 2007-19 except for 2015 influenced by the extraordinarily high revisions to Irish GDP. By contrast, the width of the interval for the fiscal series has been exceeding the one of GDP by a wide margin only until 2014. After 2014, however, the bands of the fiscal series become much more aligned compared to GDP. The change could be related to the introduction of ESA 2010 in October 2014 and to the fact that the reporting of the quarterly fiscal data became compulsory at the time. While determining the exact reason is outside the scope of our paper we will bear this fact in mind when analysing the data.

[13]With the intention of saving space the following country abbreviations are used throughout the paper: BE (Belgium), DE (Germany), EE (Estonia), IE (Ireland), GR (Greece), ES (Spain), FR (France), IT (Italy), CY (Cyprus), LV (Latvia), LT (Lithuania), LU (Luxembourg), MT (Malta), NL (the Netherlands), AT (Austria), PT (Portugal), SI (Slovenia), SK (Slovakia), FI (Finland) and EA (the euro area).

[14]The development work on Government Finance Statistics took place since 2002. Only in 2007 the data were considered to be of sufficient quality and complete enough to be used in economic analysis at the ECB.

[15]Our fiscal real-time dataset contains some missing values due to data unavailability before October 2014. Most notably, Germany and France published the GFS data only in October once per year rather than on quarterly basis.

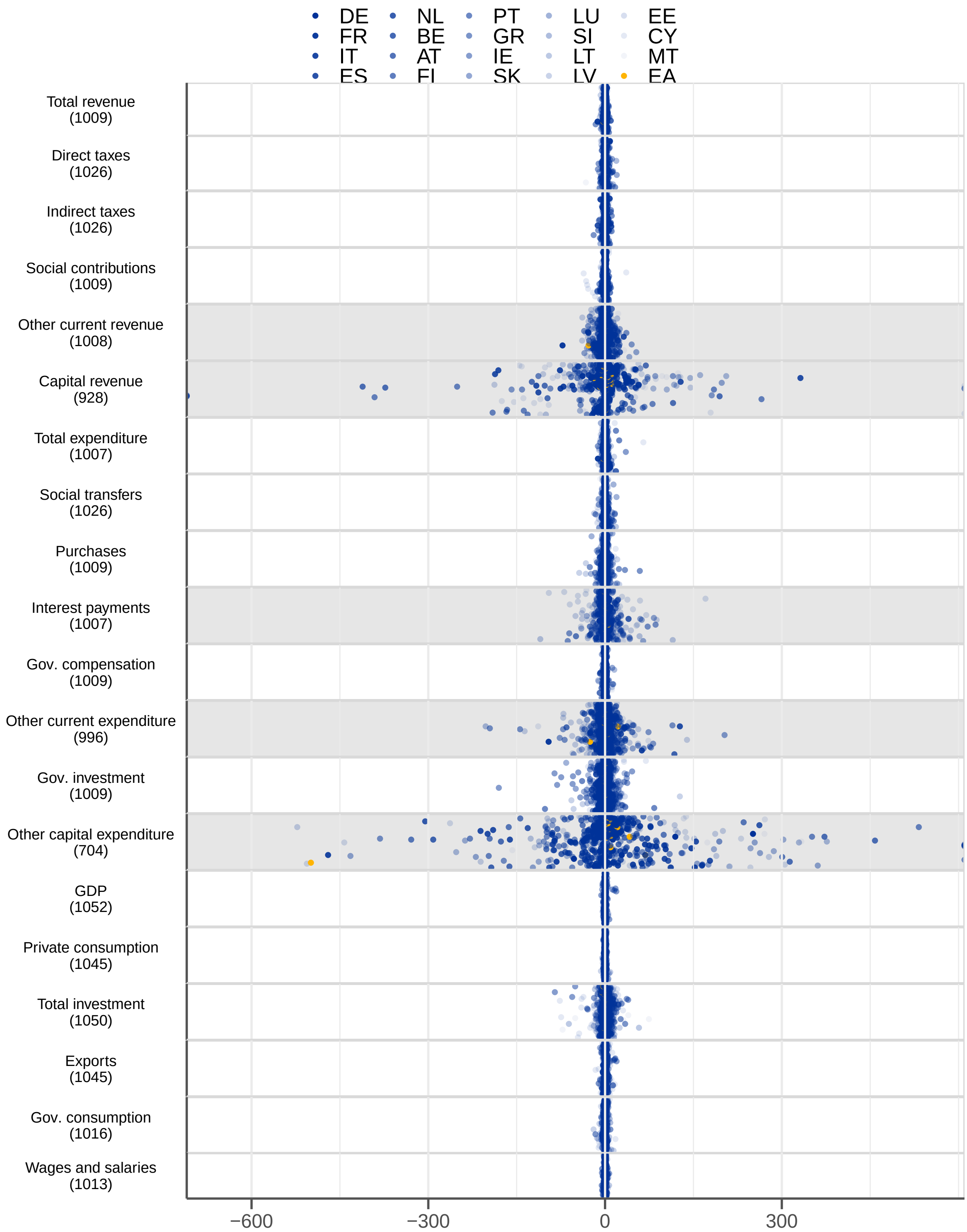


Figure 2: Final revisions across fiscal and macro variables

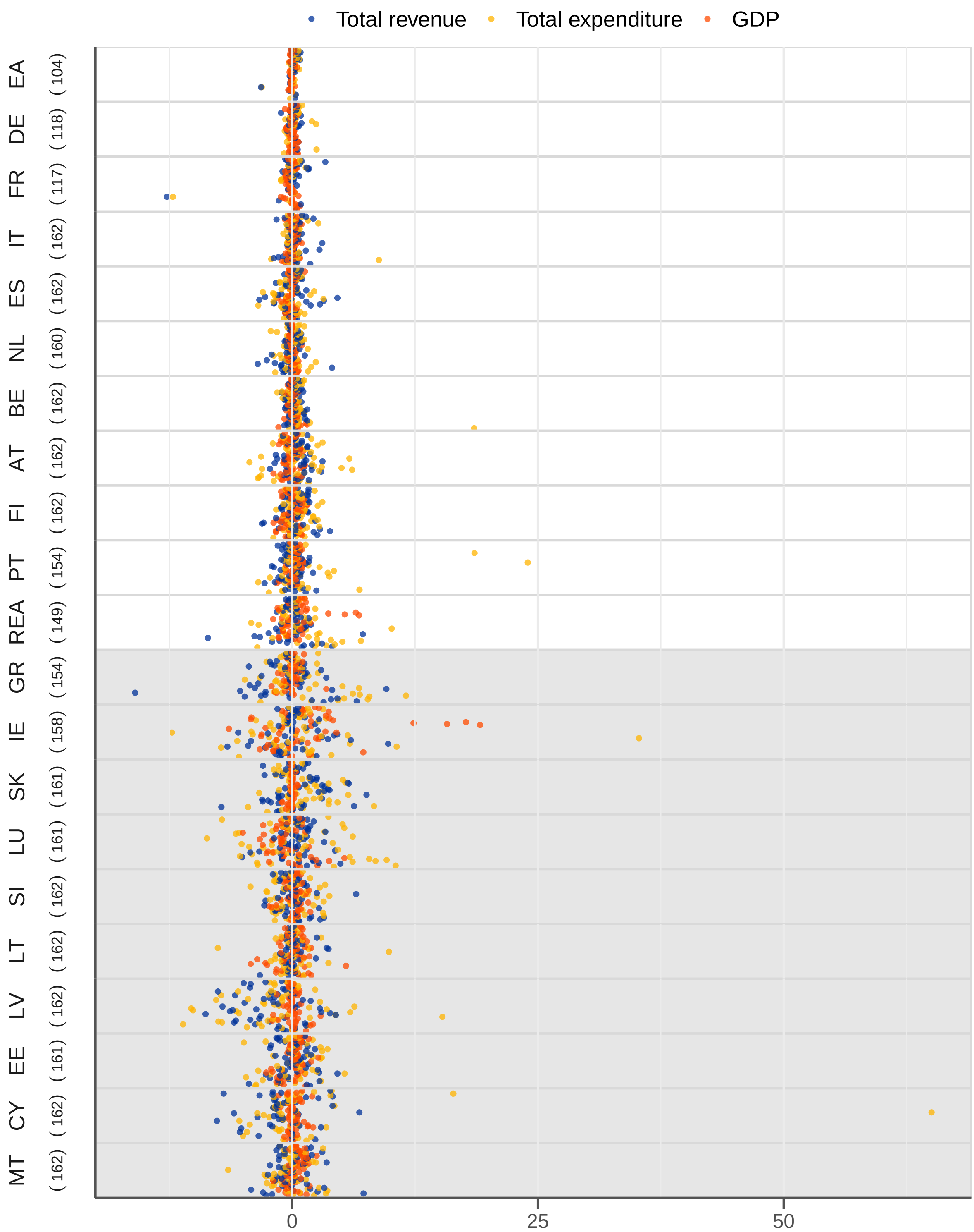


Figure 3: Final revisions across countries

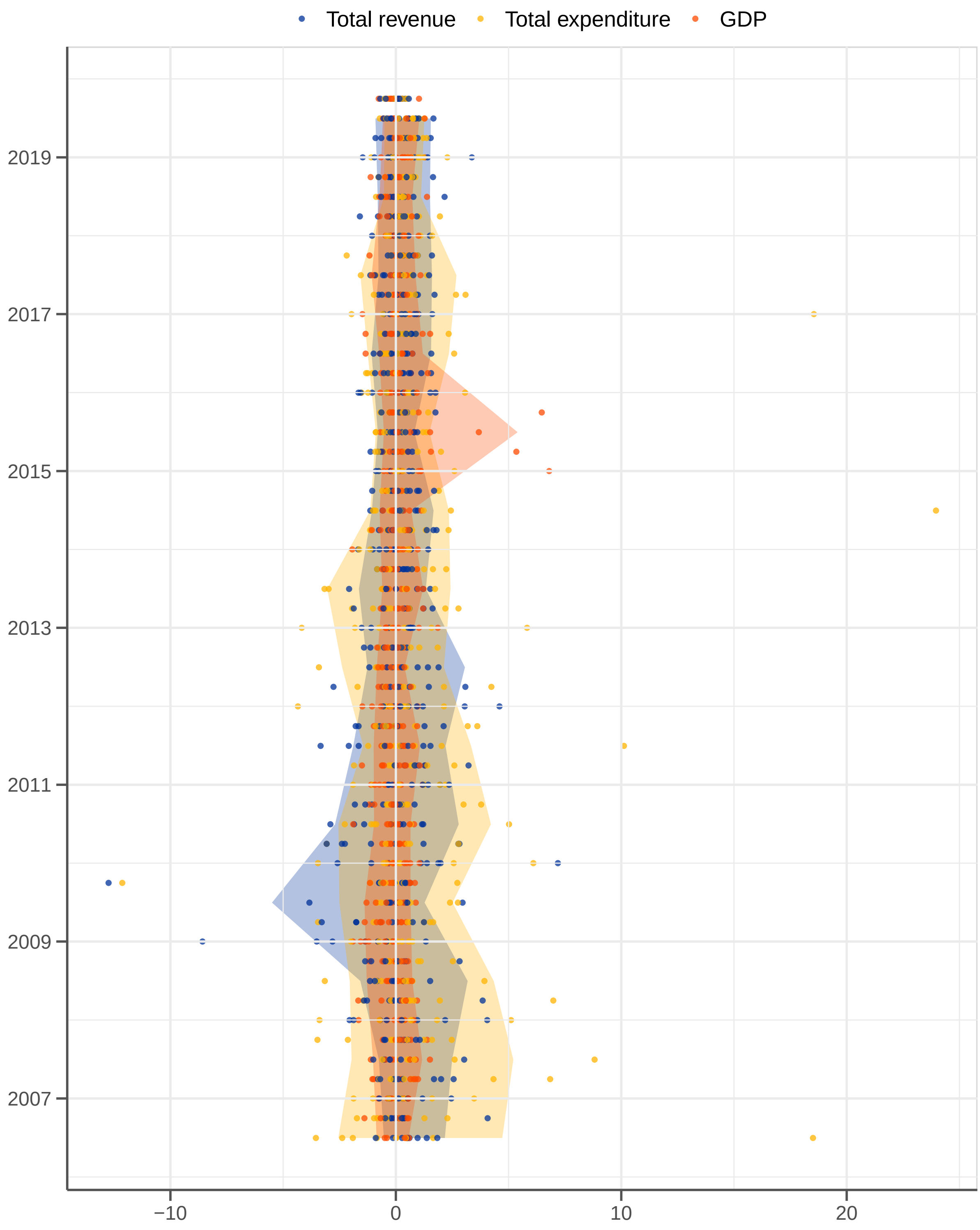


Figure 4: Final revisions across time

3. Unconditional properties of final revisions

To characterise the revisions we look first at the set of summary statistics. To this end, we calculate for all fiscal and macro variables the following metrics:

- Mean revision: $MR = \frac{1}{MT} \sum_{m=1}^{M} \sum_{t=1}^{T} r^f_{t,m}$, where m is a country index, t is a time index, M is the number of countries and T is the number of periods
- Maximum and minimum revision: $MAX = \max r^f_{t,m}$ and $MIN = \min r^f_{t,m}$
- Mean absolute revision: $MAR = \frac{1}{MT} \sum_{m=1}^{M} \sum_{t=1}^{T} |r^f_{t,m}|$
- Root mean square revision: $RMSR = \frac{1}{MT} \left[\sum_{m=1}^{M} \sum_{t=1}^{T} \left(r^f_{t,m} \right)^2 \right]^{\frac{1}{2}}$
- Noise-to-signal ratio (i.e. the standard deviation of final revisions divided by the standard deviations of final values): $N2S = \frac{1}{MT} \left[\sum_{m=1}^{M} \sum_{t=1}^{T} \left(r^f_{t,m} - MR \right)^2 \right]^{\frac{1}{2}} / \frac{1}{MT} \left[\sum_{m=1}^{M} \sum_{t=1}^{T} \left(x^f_{t,m} - \bar{x}^f_t \right)^2 \right]^{\frac{1}{2}}$

The MR statistic will help us assess whether revisions are biased. Other metrics are useful for assessing the dispersion of the revisions.

3.1. Entire sample 2006Q3-2019Q4

The first column of Figure 5 reports the mean revision (MR), which is informative about the bias. The results point to a positive MR for all fiscal variables except for government investment. The interpretation of these results is that statistical agencies tend to initially underestimate fiscal figures. Regarding the size, MR for most of the variable falls into the interval of 0.1-0.3 percentage points. Given that the average growth rate for most of the variables in the sample is slightly above 4% (see Figure B.22) the revision bias is non-negligible, albeit not large. While GDP and private consumption appear to be unbiased other macro variables have a positive MR, like the fiscal variables.

The next two columns present the MIN-MAX range of revisions. The intervals are relatively wide, and in some cases extremely wide (see, for instance, government investment with the range from -102 to $+83$ percentage points). Even the fiscal variables with the most contained ranges, like social transfers, are associated with a wider interval than the usually stable macro categories (i.e. output, private consumption or wages and salaries). The MIN-MAX interval is a first indication that the revisions to fiscal variables may be larger than these associated with the macro data.

Next we report the mean absolute revision (MAR), which by contrast to MR, ensures that negative and positive revisions do not cancel each other out. The statistic summarises the magnitude of the revisions by treating all of them, regardless their sign and size, equally. It turns out that the least revised fiscal items are variables on the revenue side as well as big categories on the spending side, namely social transfers and gov. compensation. MAR associated with them tends to remain below 1 percentage point. The values are significantly higher than for MR and should be regarded as relatively sizeable given the average growth of these variables in the sample (around 4%). MAR values for these fiscal variables are approximately double of the corresponding statistics for the stable macroeconomic variables (i.e. output, private consumption and wages and salaries) amounting to around 0.5 percentage points, which are by no means small. MAR statistics for the remaining fiscal variables are even higher with government investment being characterised by the largest figure (almost 5 percentage points, which even exceeds the average growth rate of this variable below 4%, as can be seen in Figure B.22).

The fifth column of Figure 5 reports the root-mean-square revision (RMSR). Compared to MAR, this statistics penalises big revisions by means of squaring. Notwithstanding this, RMSR gives broadly the same picture as MAR. Its contribution is a magnification of the metric for variables that are subject to big revisions, like government investment, which stands out even by a wider margin than in the case of MAR.

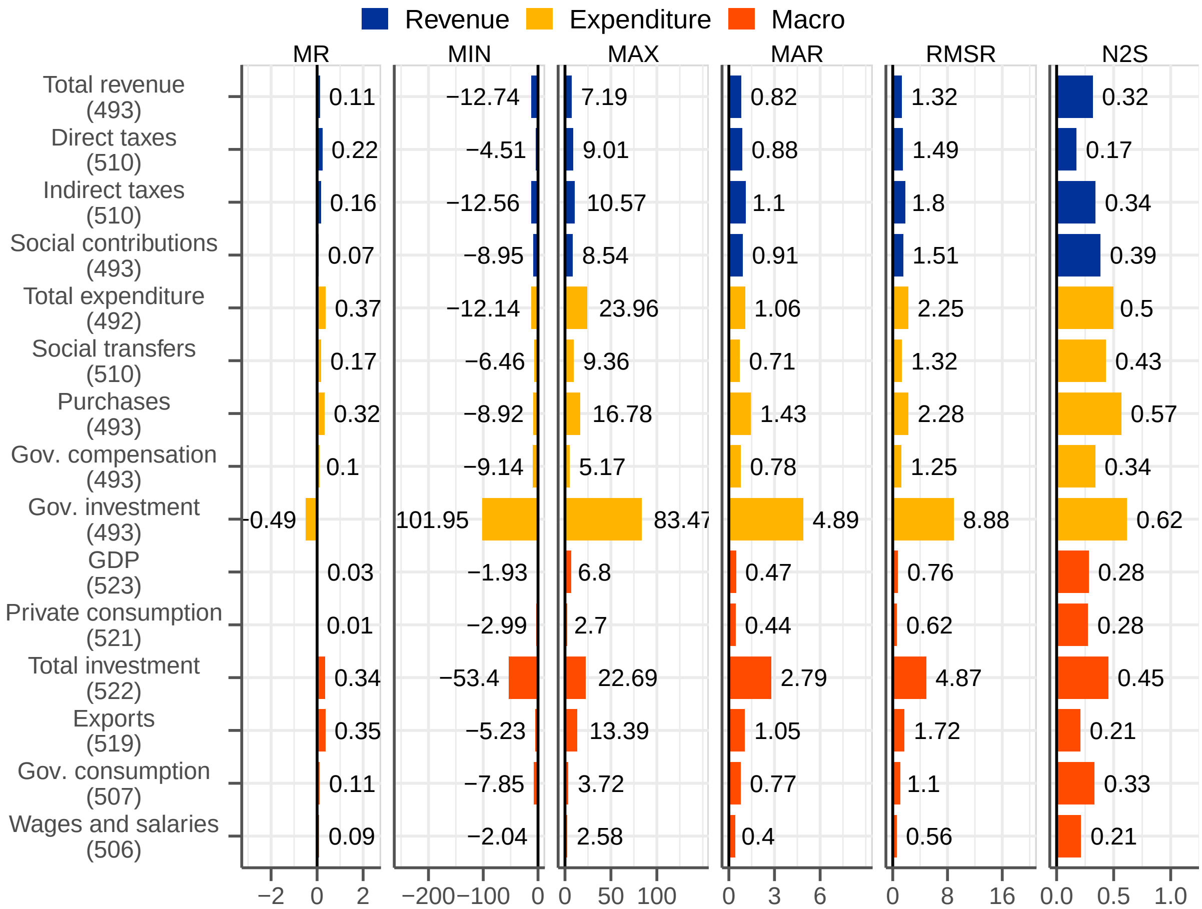


Figure 5: Summary statistics of final revisions in the entire sample

Finally, in the last column we report the noise-to-signal ratio (N2S), which compared to RMSR takes into account the volatility of a variable itself. This measure brings the fiscal variables closer to the macro variables. Since fiscal categories tend to be more volatile compared to the macro variables (see Figure B.22) it is natural that they are more heavily revised. The N2S statistic reflects upon this consideration. Judging by this measure direct taxes turn out to be the variable with the smallest relative revisions. Moreover, the heavily revised government investment do not appear so exceptional any longer compared to other variables.

To sum up the results of Figure 5, it turns out that almost all variables we consider in the analysis are associated with a positive bias, as judged by the MR statistic. The notable exceptions are output and private consumption, which both have roughly a zero mean, and government investment, which has a negative mean. Other measures, namely MIN-MAX range, MAR and RMSR, indicate that the revisions tend to have large dispersion. This particularly applies to fiscal variables, which record twice as large MAR compared to macro variables (at least when it comes to the most stable and largest categories in the two groups). Moreover, government investment, clearly stands out as particularly sensitive to big revisions, similarly to total investment. Once we recognise the fact that certain variables tend to be more volatile than others the variation across variables diminishes considerably, as captured by the N2S ratio statistic.

3.2. Pre and post-2014Q2 subsamples

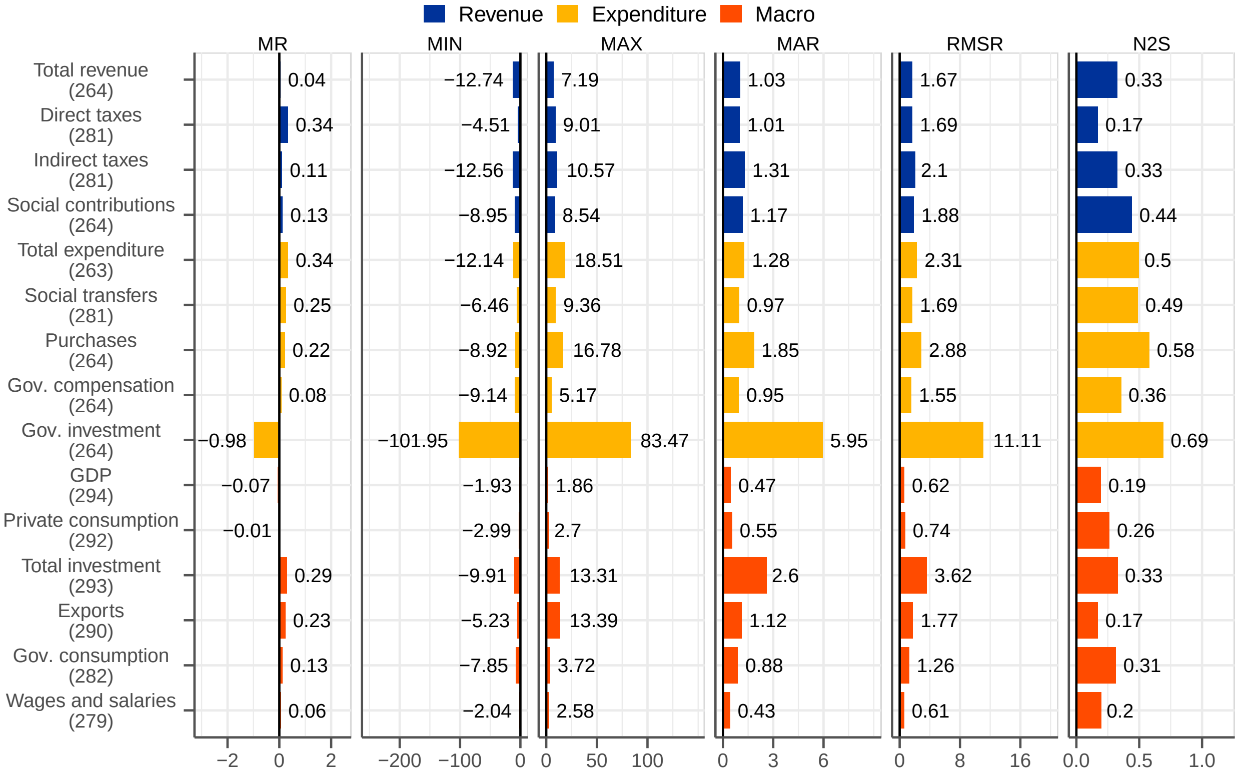
The analysis presented above indicated that fiscal revisions exhibit considerably bigger dispersion than macro revisions (i.e. approximately twice as big when measured by MAR). This is in line with the existing literature, which states that fiscal variables are subject to particularly sizeable revisions (see, for instance, Cimadomo (2016)). This widely held view casts severe doubts on the quality of fiscal data in real time. Having in mind the illustration in Figure 4 indicating that fiscal revisions in the euro area dropped significantly over time we re-evaluate the existing belief. To this end, we split the sample in 2014Q2, which is the quarter for which the initial release was reported according to ESA 2010 for the first time. Also, 2014 is the point at which the reporting of Government Finance Statistics became obligatory, even though countries had been reporting them on voluntary basis before. Having split the sample, coincidentally into two roughly equal parts, we recalculate the summary statistics for the two subsamples.

A close look at Figure 6 reveals that summary statistics in the two periods differ considerably for fiscal variables. While the MR metric points to a positive bias of a comparable magnitude in the both subsamples the differences for statistics representing dispersion are stark. Just to start with, the MIN-MAX interval reported in the second and third column of Figure 6 shrinks significantly for fiscal variables in the post 2014Q2 subsample. In the same vein, the variables in the second subsample are associated with considerably lower (i.e. around half for most of the items) MAR compared to the first subsample. As easy to anticipate, the same applies to the RMSR measure.

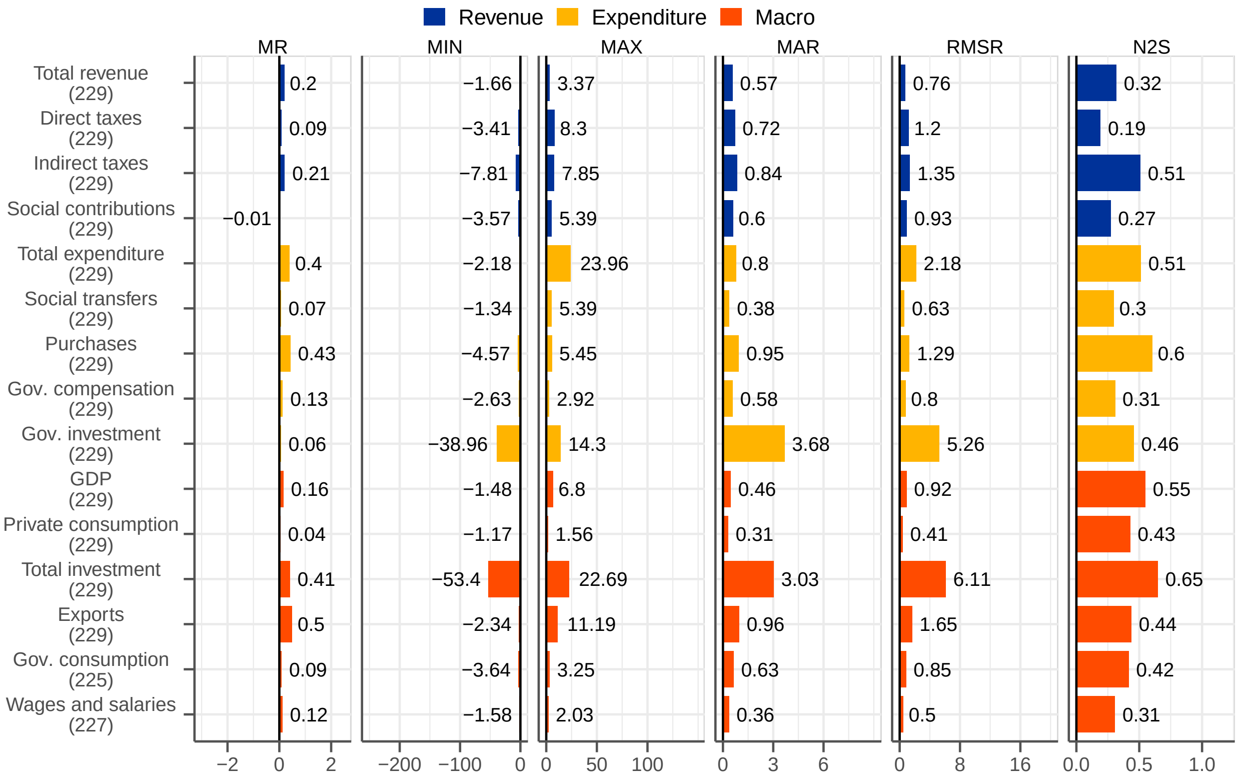
No similar reduction in the statistics measuring the dispersion of the revisions is visible for the macro variables. The MAR statistic, which we regard as the most illustrative, remains broadly the same between the two subsamples. Even though the values differ slightly, no systematic reduction in the metric is visible in the post-2014Q2 subsample.

In general and as expected, the summary measures point out a considerable drop in the magnitude of fiscal revisions in October 2014. The second subsample, which captures post-ESA 2010 introduction observations, is more representative for the description of the current features of the data rather than the entire sample, let alone the first subsample under ESA 95. Looking at Figure 5 and Figure 6 it becomes evident that the statistics for the entire sample are heavily affected by the extraordinarily high values present in the first subsample.[16] If the objective of the analysis is to characterise the current properties of the revisions more focus should be given to the post-2014Q2 horizon.

[16]Some extraordinary values of the revisions in the first subsample may relate to the Great Financial Crisis. At the time governments undertook multiple support measures, most notably to assist the financial sector. The statistical recording of the associated transactions was more uncertain than usually.



(a) pre-2014Q2



(b) post-2014Q2

Figure 6: Summary statistics of final revisions in the two subsamples

As fiscal revisions drop significantly in size and macro revisions remain broadly unchanged the difference between the two types of variables narrows down by a considerable margin. Concretely, post-2014Q2 MAR for fiscal variables is in the same ballpark as for macro categories. The MAR measure does not exceed significantly 0.5 percentage points in the case of both types of variables.

All in all, our analysis contradicts the claim that fiscal variables are particularly prone to revisions. Since 2014 the degree to which fiscal variables are revised is not considerably different compared to macro variables. This is not to say that the revisions are well-behaved as the opposite comes out of our analysis. In the second subsample, which is more representative for describing current data properties, the revisions to both fiscal and macro variables are positively biased and still dispersed. The two properties stand in contrast with the requirements for well-behaved revisions.

4. Predictability final revisions

After verifying the bias and the dispersion of the revisions we check in this section whether revisions are predictable. Our approach in this regard follows the methodology applied in Aruoba (2008). Similarly, we estimate variable-specific models to verify whether the conditional mean of final revisions with respect to the information available at the time of the initial release equals zero. The condition, formally expressed as $E\left(r^f_{t,m} \middle| I_{t+2}\right) = 0$, implies the lack of predictability.[17] Given that our analysis cover multiple countries, differently from Aruoba (2008), we opt for panel regressions. This allows us to overcome the short length of the sample and still to obtain statistically meaningful results.

To this end, we estimate the models of the following form:

$$\text{Complete model: } r^f_{t,m} = \sum_{m=1}^{9} \beta_m C_m + \sum_{j=1}^{4} \gamma_j Q^j_t + \omega \mathbb{1}_{[t \geq 2014Q2]} + \delta x^1_{t,m} + \sum_{i=1}^{S} \rho_i \left(x^{i+1}_{t-i,m} - x^1_{t-i,m} \right) + \epsilon_{t,m}$$

with the dependent variable $r^f_{t,m}$ being the final revision as defined in Subsection 2.1. The explanatory variables are: country-specific dummy variables C_m, quarterly dummy variables Q^j_t, a dummy variable for ESA 2010 (i.e. from 2014Q2 onwards, which are the quarters for which the initial releases followed ESA 2010), the initial release $x^1_{t,m}$ and the past final revisions $\left(x^{i+1}_{t-i} - x^1_{t-i}\right)$. We include country-specific dummy variables (i.e. country fixed effects) to account for the fact that euro area countries carry different characteristics that do not change over time. In the same vein, we use quarterly dummy variables on account of potential seasonality in the revisions. The ESA 2010 dummy should account for a difference existing between the two subsamples described in Section 3 without a necessity to split the sample. We also include the initial release as revisions can be preceded by unusual values published initially. Moreover, we introduce the past revisions to verify whether there is a persistency in revisions. We limit these revisions only to those available at the time of the initial release.[18] By ensuring that all explanatory variables in the model are known at the time of the initial release we make the prediction a valid forecasting exercise.[19]

To select the exact specification of the complete model we rely on the Akaike Information Criterion (AIC). In this context, we estimate all combinations of regressors specified in the equation for the complete model

[17] The information set I_{t+2} consists of all information available at the time of the initial release. Since fiscal data for quarter t are published more than 90 days (around 110 days) after the end of quarter t we use $t+2$ time index for the timing of the release consistently across the paper.

[18] At the time of the initial release of data for quarter t only the first revision of data for quarter $t-1$, the second revision of data for quarter $t-2$ and so on are available.

[19] Strictly speaking, an entirely complete forecasting exercise in real time requires that not only the predictors are these available at the time the forecast is performed but also the forecasting model is estimated in real time. Aruoba (2008) supplements his main analysis with a strictly real-time exercise only to confirm validity of the predictability property in macroeconomic revisions.

(511 combinations).[20] Finally, we pick specifications with the lowest AIC score. Like in Aruoba (2008) our objective is not to find the best model explaining the revisions. The aim of the exercise is to verify whether any information available at the time of the initial release has predictive power. If confirmed we will be able to claim that revisions are predictable.

Having selected the models, to assess predictability we conduct two tests. First, we test for a joint significance of all coefficients in the complete model. The null hypothesis is that all coefficients equal zero, which in turn implies zero conditional mean of final revisions and the lack of predictability. By the same token, a rejection of the hypothesis would point to predictability. Second, we assess the predictive power of the complete model by comparing it to the naive model, as specified below.

$$\text{Naive model: } r^f_{t,m} = \epsilon_{t,m}$$

The naive model gives the revision forecast of $\hat{r}^f_{t,m} = 0$, which is consistent with no predictability of revisions (i.e. zero conditional mean). We check whether and to which extent the complete model outperforms the naive model by looking at the ratio of the root-mean-square errors (RMSE) associated with the two models. If revisions are not predictable adding additional predictors to the naive model will bring no benefit in terms of RMSE reduction, thereby leaving the ratio at unity.

Furthermore, to see the contribution of single regressors to potential predictive power we construct a set of intermediate models spanning the range between the complete model and the naive model. Concretely, we downsize the complete model by gradually removing predictors until the point when we reach the naive model. If an explanatory variable does not enter the complete model based on the selection criterion the elimination step does not change the regression specification. To this end, we take out from the complete model past revisions (which brings us to Interm. model 1), the value of the initial release (which brings us to Interm. model 2), a dummy for the post-2014Q2 period (which brings us to Interm. model 3) and quarterly dummies (which brings us to Interm. model 4). With the elimination of country-specific dummies we reach the naive model. The below equations characterise the specification of all intermediate models.

$$\text{Interm. model 1: } r^f_{t,m} = \sum_{m=1}^{9} \beta_m C_m + \sum_{j=1}^{4} \gamma_j Q^j_t + \omega \mathbb{1}_{[t \geq 2014Q2]} + \delta x^1_{t,m} + \epsilon_{t,m}$$

$$\text{Interm. model 2: } r^f_{t,m} = \sum_{m=1}^{9} \beta_m C_m + \sum_{j=1}^{4} \gamma_j Q^j_t + \omega \mathbb{1}_{[t \geq 2014Q2]} + \epsilon_{t,m}$$

$$\text{Interm. model 3: } r^f_{t,m} = \sum_{m=1}^{9} \beta_m C_m + \sum_{j=1}^{4} \gamma_j Q^j_t + \epsilon_{t,m}$$

$$\text{Interm. model 4: } r^f_{t,m} = \sum_{m=1}^{9} \beta_m C_m + \epsilon_{t,m}$$

Table 2 contains the results of the predictability investigation. In the second column the table contains the list of explanatory variables used in the complete model for each variable. The selection criterion particularly values the initial announcement and past revisions, which enter the complete model for nearly all variables. Also, we report the number of observations underlying each panel regression in the third column.

[20] Since we consider the inclusion of 9 regressors (i.e. country dummy, quarter dummy, ESA 2010 dummy, initial announcement and 5 past revisions the exact number of combinations equals to $2^9 - 1$.)

Table 2: Predictability of the revisions based on AIC

	Expl. variable	N	F-value	Compl/Naive	Intrm1/Naive	Intrm2/Naive	Intrm3/Naive	Intrm4/Naive
Revenue								
Total revenue	$\mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m}$	384	0.01	0.99	0.99	0.99	1.00	1.00
Direct taxes	$\sum_{j=1}^{4} Q^j_t + x^1_{t,m} + R_{t-2,m}$	402	0	0.97	0.98	0.99	0.99	1.00
Indirect taxes	$\mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m} + R_{t-2,m} + R_{t-4,m}$	402	0	0.98	0.99	1.00	1.00	1.00
Social contributions	$\sum_{m=1}^{10} C_m + x^1_{t,m} + R_{t-1,m}$	384	0	0.95	0.96	0.98	0.98	0.98
Expenditure								
Total expenditure	$\sum_{j=1}^{4} Q^j_t + x^1_{t,m} + R_{t-1,m} + R_{t-5,m}$	384	0	0.96	0.97	0.98	0.98	1.00
Social transfers	$\sum_{m=1}^{10} C_m + \mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m} + R_{t-2,m}$	402	0	0.91	0.92	0.96	0.96	0.96
Purchases	$\sum_{m=1}^{10} C_m + \mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m} + R_{t-2,m} + R_{t-4,m}$	384	0	0.84	0.85	0.97	0.97	0.97
Gov. compensation	$\sum_{j=1}^{4} Q^j_t + x^1_{t,m} + R_{t-4,m} + R_{t-5,m}$	384	0	0.95	0.96	0.99	0.99	1.00
Gov. investment	$\sum_{m=1}^{10} C_m + \mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m} + R_{t-1,m} + R_{t-5,m}$	384	0	0.94	0.95	0.96	0.96	0.96
Macro								
GDP	$\sum_{m=1}^{10} C_m + \mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m} + \sum_{i=1}^{4} R_{t-i,m}$	444	0	0.95	0.96	0.96	0.97	0.97
Private consumption	$\mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m}$	442	0.01	0.99	0.99	1.00	1.00	1.00
Total investment	$\mathbb{1}_{[t\geq 2014Q2]} + x^1_{t,m} + \sum_{i=2}^{5} R_{t-i,m}$	443	0	0.94	0.97	1.00	1.00	1.00
Exports	$\sum_{m=1}^{10} C_m + R_{t-2,m} + R_{t-4,m}$	437	0	0.87	0.89	0.89	0.89	0.89
Gov. consumption	$x^1_{t,m} + R_{t-4,m}$	428	0.03	0.99	1.00	1.00	1.00	1.00
Wages and salaries	$\sum_{m=1}^{10} C_m + \mathbb{1}_{[t\geq 2014Q2]} + R_{t-1,m} + R_{t-2,m}$	420	0	0.91	0.92	0.92	0.92	0.92

Note:
$R_{t-i,m}$ in the specification of explanatory variables are past revisions defined by $R_{t-i,m} = \left(x^{i+1}_{t-i,m} - x^1_{t-i,m}\right)$, as introduced in the equation of the complete model.

The p-values of the joint significance test for nearly all variables are less than 1%, indicating that we can reject the null hypothesis even at the 99% significance level. The only variables, for which we are not able to reject the hypothesis at this significance level are total revenue, private consumption and government consumption. The test indicates these variables as the ones with little predictability. In general, the values of the p-statistic are so small that for the significance level of 95% the null hypothersis is rejected for all variables.

The following columns report RMSEs ratios, where, as a reference in the denominator, we always take the naive model. The nominators instead are RMSE statistics corresponding to a particular model that is richer in predictors than the naive model. A reduction in RMSE for the complete model can be observed for all variables, although the magnitude for the three variables identified by the joint significance test is very small. For the majority of variables, however, the relative RMSE ratio equals to 0.95 or less. This points to material predictive power of information available at the time of the initial release, thereby contradicting the no-predictability hypothesis. Also, looking at the figures, both for the joint significance test and for the projection error reduction, fiscal variables do not appear to differ from macro variables in terms of predictability. Both are to a smaller or bigger degree predictable and badly-behaved in this sense.

The inclusion of the intermediate models in the analysis enables us to determine the contribution of particular regressors to RMSE reductions. The decomposition demonstrates that the predictive information is spread across different predictors. Among dummy variables, country dummies bring the largest benefit in terms of predictability, which is particularly the case for macro variables. The regressor that comes with a sizeable prediction improvement among all variables is the initial announcement. Finally, past revisions further reduce RMSE, albeit by less than the initial announcement.

To sum up, the results reveal that fiscal revisions in general are to some degree predictable. This is just another characteristic besides the positive bias and the large dispersion that speaks in favour of treating fiscal revisions as badly-behaved. Considering the predictability dimension fiscal revisions are quite similar to macro variables and they do not appear to be particularly ‘misbehaved’.

As we rely only on AIC a question may arise whether the findings are robust to other information criteria. Given the general conclusion on the presence of predictability, the question, however, is not very relevant for our application. In our exercise it is sufficient to find one model for which we reject the joint significance hypothesis or which is superior in terms of predictive power to the naive model. Other selection criteria that are more restrictive than AIC, for instance Schwartz Information Criterion (SIC), could prevent us from finding such a model and point towards no predictability in the revisions. In fact, this is what happens when the predictability exercise is recalculated with SIC (see Table C.1 in the online appendix). Given the AIC-based results pointing to predictability, any findings based on a more restrictive criterion would not change our conclusions. On the other hand, findings based on a looser criterion than AIC, which would allow even more information to enter the complete model, could only validate, or even strengthen, our conclusions.

5. Properties of intermediate revisions

Intermediate revisions are changes that take place between subsequent releases, as explained in Subsection 2.2. By construction, intermediate revisions make up for final revisions (as illustrated in Figure 1). Analysing intermediate revisions is indispensable for understanding the dynamics between initial and final releases. As such, intermediate revisions can foster understanding of final revisions.

Intuitively, each release should bring the data closer to its final value as gradually with time more information becomes available to data compilers (see the right-hand-side chart in Figure 1 where most of the intermediate revisions go in the direction of the final revisions). In practice, however, it occurs that some releases go into the opposite direction and increase the distance to the final value compared to a previous release. Figure 7 provides an example of a data point where the initial release was closer to the final value than subsequent releases (see the case of Austria). If such cases are frequent our findings based on final revisions may considerably change (as demonstrated with a single calculation on Figure 7), which we verify in this section.[21]

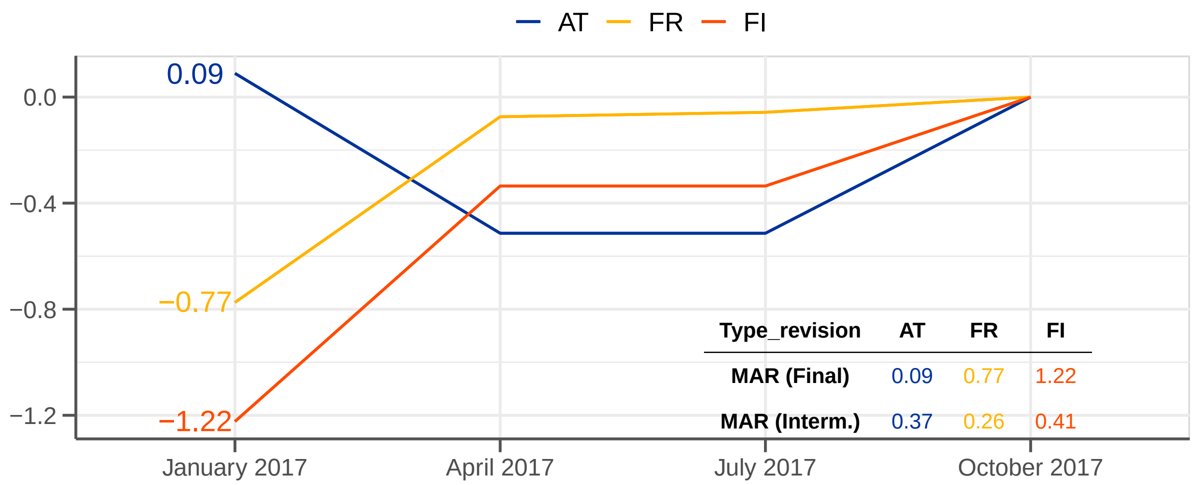


Figure 7: Revisions to the growth rate of 2016Q3 social contributions

Another aspect that can be revealed by analysis of intermediate revisions is the timing of the revisions. In this context, the analysis should inform us whether the revisions mostly take place shortly after an initial

[21] If all intermediate revisions went towards a final value (i.e. are of the same sign as a final revision) intermediate revisions would not bring any additional information to the summary statistics calculated based on final revisions. MAR, for instance, would be just lower by a certain factor because final revisions could be divided into smaller pieces constituting intermediate revisions.

release or maybe closer to the publication of a final value. In the same vein, it will be possible to identify releases within a year (i.e. Jan, Apr, Jul or Oct) when the data are subject to particular revisions, if this is the case.

5.1. Unconditional properties

Figure 8 contains summary statistics of intermediate revisions. Given the great relevance of the 2014Q2 split and its profound effects on the reduction in fiscal revisions, as discussed in Section 3, we present directly the results in the two subsamples. Similarly to Figure 6 for final revisions, we report a set of summary statistics.

The picture constructed on the basis of intermediate revisions is very similar to the one based on final revisions. On the bias, intermediate revisions do not bring any new information to the MR statistic compared to final revisions. The value of the metric is just lower by a constant factor compared to the one based on final revisions. This is not surprising because the change from the initial release to the final release is captured in multiple intermediate revisions rather than in one final revision. Since final revisions consist of 2, 3, 4 or 5 intermediate revisions depending on a quarter there are around 3.5 intermediate revisions per one final revision on average. This is exactly the factor by which the MR statistics based on intermediate revisions is lower compared to the one based on final revisions.[22]

Regarding the dispersion of intermediate revisions, even though they bring new information they paint a very similar picture compared to final revisions. The value of the MAR statistics, which we consider to be the most illustrative as a measure of dispersion, is lower compared to the final revisions. The ratio between the two is not roughly 3.5 but significantly less (i.e. slightly above 2 on average for most of the variables). This indicates that releases that bring data away from final values are relatively common in the dataset.

Notwithstanding these undesirable releases, intermediate revisions point to the same conclusions on the dispersion of the revisions like the final ones. In the pre-2014Q2 subsample fiscal revisions are approximately twice as dispersed as macro revisions, as judged by the MAR measure for the biggest and most stable categories. In the post-2014Q2 subsample the MAR measure for both types of variables fiscal and macro are not far away from each other. Volatile categories, in particular government and total investment, are associated with exceptionally high values of the statistics measuring dispersion, especially in the second subsample.

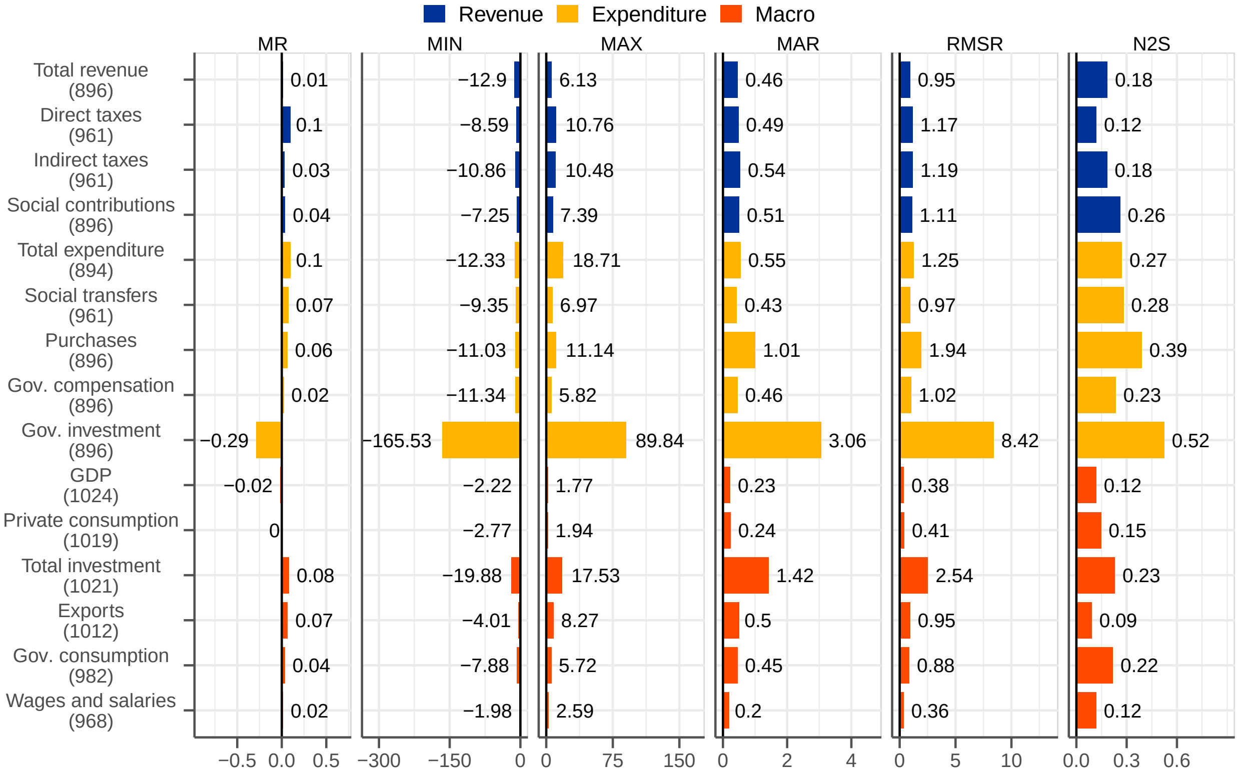
5.2. Dynamics of data releases

Another aspect on which intermediate revisions can shed light is the evolution of releases from the initial one to the final one. This will inform us about the path that intermediate data releases undertake when they converge to the final value. Such analysis should also confirm one of the findings from the previous subsection, namely the existence of incidents when intermediate releases take data away from final values compared to figures already published. Given that the number of intermediate revisions differs depending on a quarter (i.e. Q1 observations have 5 intermediate revisions while Q4 observations only 2 intermediate revisions) we look at Q1-Q4 observations separately (see Figure 9).

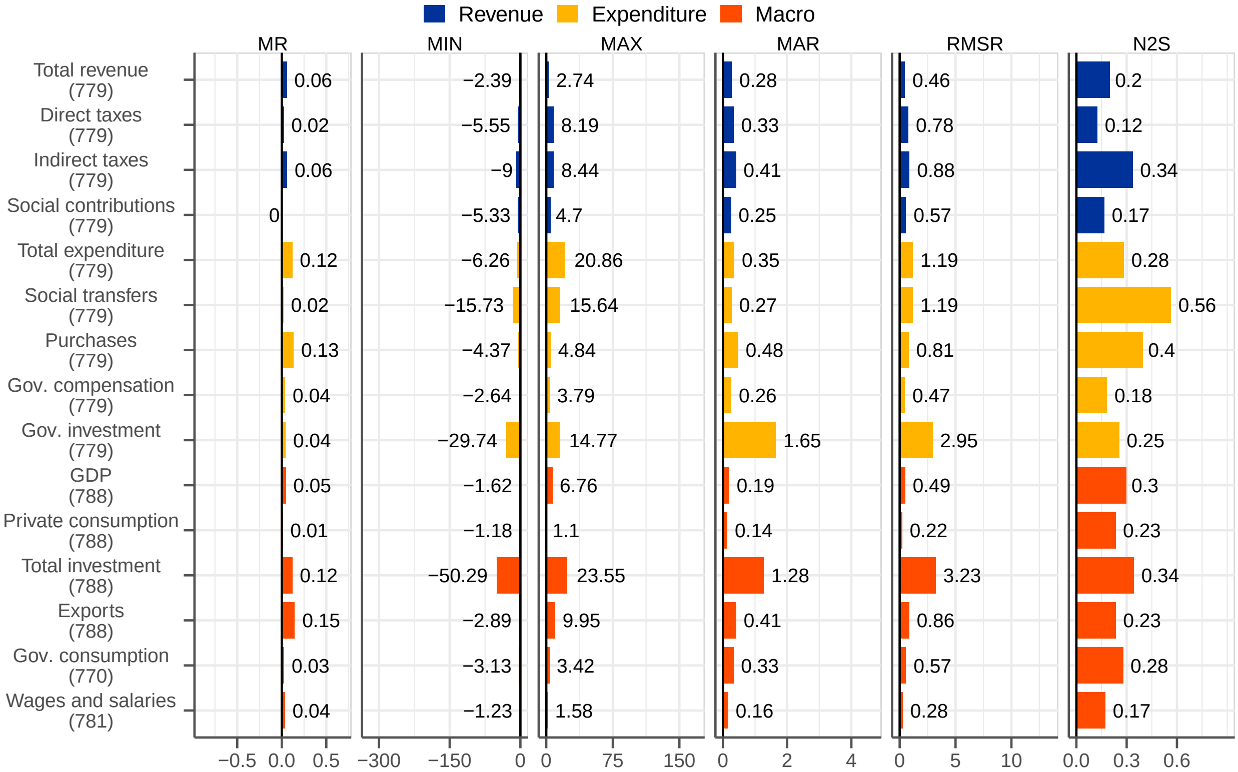
Figure 9 illustrates how initial releases converge towards final values. Strictly speaking, the lines in the charts demonstrate how final revisions, associated with initial releases, move during the revision cycle towards zero, which is the moment of final release. Each line represents average revisions for one variable. Since the conclusions we draw below remain valid for both pre and post-2014Q2 subsamples (see C.24 and C.25 for the two subsamples in the online appendix). Figure 9 is based on the dataset without the split.

Looking at the shapes of the lines in Figure 9 it becomes clear that the evolution of revisions, which bring data to final values, is different for fiscal and macro variables. For the former the most sizable data revisions take place in April and in October of the following year (see that the lines leading to Apr T+1 and Oct T+1

[22] The factor can deviate slightly due to missing observations.



(a) pre-2014Q2



(b) post-2014Q2

Figure 8: Summary statistics of intermediate revisions in the two subsamples

are the steepest of all fragments). These are the releases coinciding with EDP notifications. In April T+1 data for Q4 of year T and for the year as a whole become published for the first time. October T+1 is the second EDP notification for year T when all its quarters can be subject to changes. The release of October T+1 also defines final values in our analysis.[23] By contrast, the revisions for macro variables occur much more gradually (see that the lines are less of a step-wise profile) compared to fiscal variables. This shows that macro variables are revised irrespective of the quarter. January and July releases are also associated with sizable revisions, which is not the case for fiscal variables.

Even by looking at the aggregated data single instances of lines trending upwards are visible (see Figure 9). This only re-affirms that cases where single releases takes us away from final values compared to a preceding release exist in the dataset. Naturally, in such cases the subsequent revisions need to be particularly large as they need to make up for any move in the 'wrong' direction.

6. Conclusions

Our investigation concludes that fiscal revisions are badly-behaved. They fulfil none of the requirements for well-behaved revisions. More specifically, (1) fiscal revisions exhibit a positive bias, (2) they are characterised by a considerable dispersion and (3) they are in general predictable with the information available at the time of the initial release.

While our analysis concludes that fiscal revisions are badly-behaved it is difficult to find support in the data that they are worse than macro revisions presently. Macro revisions are also badly-behaved, which has been already documented in the literature (see, e.g., Faust et al. (2005)). The extent of this 'misbehaviour' is just similar for the two types of variables. Both macro and fiscal revisions exhibit similar bias and they are subject to a comparable dispersion, most notably since 2014 when fiscal revisions became more contained. Moreover, no major difference emerges in the analysis between the two types of revisions when it comes to predictability.

Supplementing the analysis with the intermediate revisions leaves the conclusions unchanged. Notwithstanding this, intermediate revisions do bring additional information to the study. Most notably, they make clear that fiscal variables converge to final values differently from macro variables. While for the former the revisions tend to take place in April and October a more evenly distributed revision pattern is observed for the latter.

[23] As emphasised in Maurer and Keweloh (2017) also EDP Dialogue visits have measurable impact on deficit revisions. To the extent that they have an impact on EDP Notifications they exacerbate revisions in April and October.

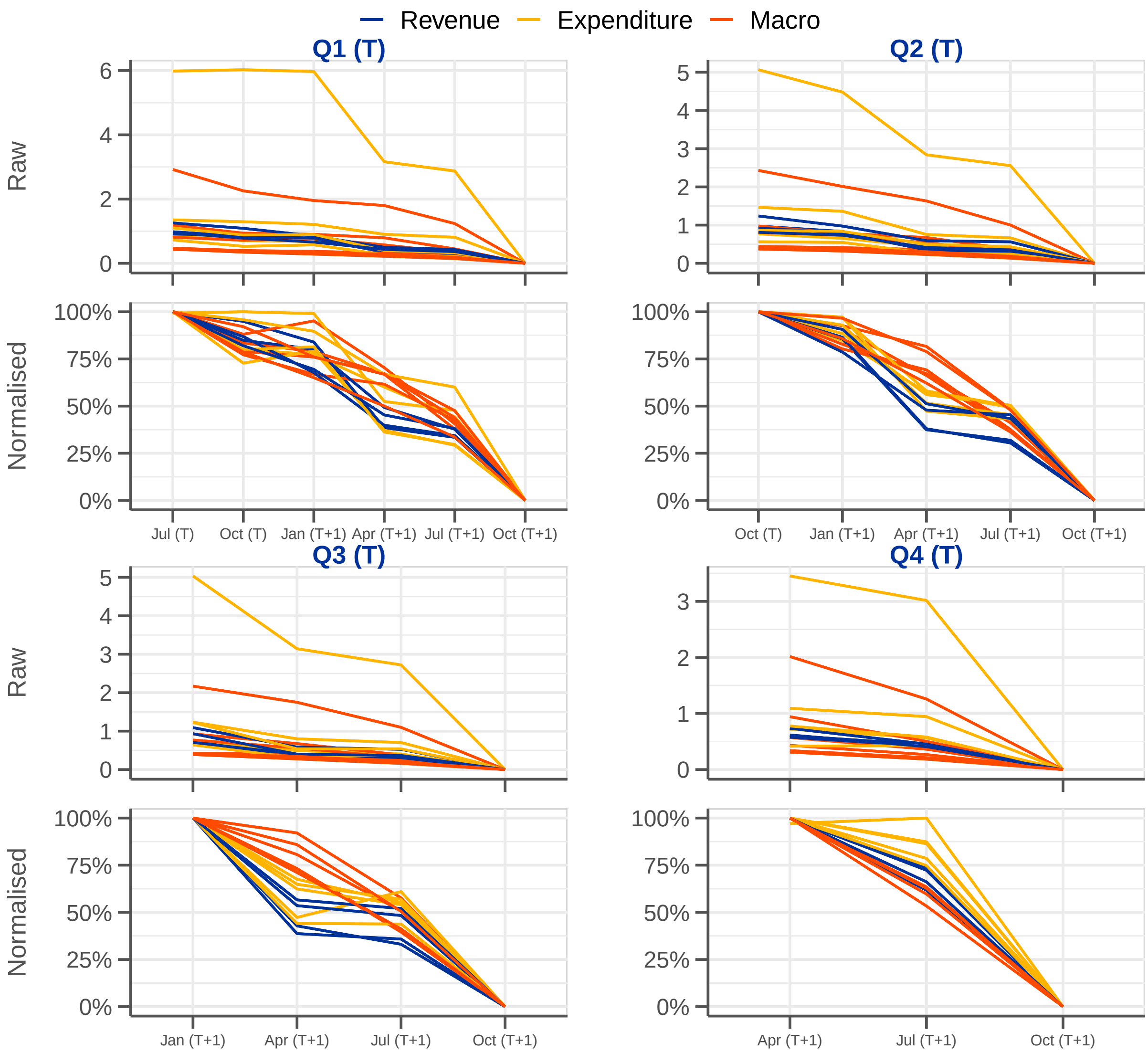


Figure 9: Revision paths across variables

References

Aruoba, S.B., 2008. Data revisions are not well behaved. Journal of Money, Credit and Banking 40, 319–340.

Asimakopoulos, S., Paredes, J., Warmedinger, T., 2020. Real-time fiscal forecasting using mixed-frequency data. The Scandinavian Journal of Economics 122, 369–390.

Branchi, M., Dieden, H.C., Haine, W., Horváth, C., Kanutin, A., Kezbere, L., 2007. Analysis of revisions to general economic statistics. Occasional Paper Series 74. European Central Bank.

Carson, C.S., Khawaja, S., Morrison, T.K., 2004. Revisions policy for official statistics: a matter of governance. Working Paper 04/87. IMF.

Cimadomo, J., 2016. Real-time data and fiscal policy analysis: A survey of the literature. Journal of Economic Surveys 30, 302–326.

Croushore, D., 2011. Frontiers of real-time data analysis. Journal of Economic Literature 49, 72–100.

Croushore, D., Stark, T., 2001. A real-time data set for macroeconomists. Journal of Econometrics 105, 111–130. Forecasting and empirical methods in finance and macroeconomics.

De Castro, F., Pérez, J.J., Rodríguez-Vives, M., 2013. Fiscal data revisions in europe. Journal of Money, Credit and Banking 45, 1187–1209.

Diebold, F.X., Rudebusch, G.D., 1991. Forecasting output with the composite leading index: A real-time analysis. Journal of the American Statistical Association 86, 603–610.

Eurostat, 2019. Practical guidelines for revising ESA 2010 data. Manuals and Guidelines. Eurostat.

Faust, J., Rogers, J.H., Wright, J.H., 2005. News and noise in g-7 gdp announcements. Journal of Money, Credit, and Banking 37, 403 – 419.

Giannone, D., Henry, J., Lalik, M., Modugno, M., 2010. An area-wide real-time database for the euro area. Review of Economics and Statistics 94.

Mankiw, N.G., Shapiro, M.D., 1986. News or Noise? An Analysis of GNP Revisions. Working Paper 1939. National Bureau of Economic Research.

Maurer, H., Keweloh, S., 2017. Quality enhancements in government finance statistics since the introduction of the euro: Econometric evidence .

Orphanides, A., 2001. Monetary policy rules based on real-time data. American Economic Review 91, 964–985.

Pedregal, D.J., Pérez, J.J., 2010. Should quarterly government finance statistics be used for fiscal surveillance in europe? International Journal of Forecasting 26, 794 – 807.

Shrestha, M.L., Marini, M., 2013. Quarterly GDP Revisions in G-20 Countries: Evidence from the 2008 Financial Crisis. Working Paper 13/60. IMF.

Stierholz, K., . Alfred: Capturing data as it happens. Presentation by Federal Reserve Bank of St. Louis (https://alfred.stlouisfed.org/docs/alfred_capturing_data.pdf) .