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GDP revisions are not cool: the impact of statistical agencies' trade-off

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Abstract

Official estimates of economic growth are regularly revised and therefore forecasts for GDP growth are done on the basis of ever-changing data. The economic literature has intensively studied the properties of those revisions and their implications for forecasting models. However, it is much less known about the reasons for Statistical Agencies (SAs) to revise their estimates. In order to be timely and reliable, SAs have an explicit interest in not revising their initial GDP estimates too much, while they are much more open to revise GDP components over time. More than a curiosity, we exploit this resulting cross-correlation of GDP components revisions to build a model to better forecast GDP.

Keywords: revisions, real-time data, news and noise.

JEL Codes: C01, C82, E01

Non-technical summary

Gross Domestic Product (GDP) is a measure of economic activity published by Statistical Agencies (SAs). It is one of the key data series followed by Central Banks (CBs) to inform monetary policy decisions. Official estimates of economic growth serve as a basis on which CBs forecast future growth. However, those estimates are regularly revised and forecasts for GDP growth are done on the basis of ever-changing data. It is therefore essential to understand how reliable subsequent revisions of GDP data are.

In addition, GDP can be compiled using different approaches. On the output side, GDP measures the sum of the gross value added created through the production of goods and services in the individual sectors of the economy. On the income side, it measures the sum of all incomes generated by the production of goods and services, and on the expenditure side, it measures the sum of domestic and (net) external demand for the produced goods and services (i.e. private and government consumption, investment, net trade, and inventories).

In this paper we combine those two aspects of the GDP compilation, i.e. the bottom-up derivation based on expenditure components is combined with data revision analysis to study patterns and cross-correlations which could be useful for forecasting GDP.

Following the seminal paper of Mankiw, Runkle, and Shapiro (1984), several papers in the literature have shed light on the properties of GDP revisions and how those revisions affect forecasting. Among them, Mankiw and Shapiro (1986), Mork (1987), Croushore and Stark (2003), Faust, Rogers, and Wright (2005), Aruoba (2008), Clements and Galvão (2010) and many others.[1,2]

Another strand in the literature has shown the usefulness of using data vintages for forecasting, see for example Garrat, Lee, Mise, and Shields (2008), Clements and Galvão (2012), Clements and Galvão (2013) and Carriero, Clements, and Galvão (2015). These papers mainly incorporate GDP vintages and its revisions at a vector autoregressive (VAR) approach. In this paper, we built on this strand and investigate the properties of data revisions exploiting the limited change in the GDP initial data announcements.

According to our hypothesis, statisticians consider that the initial GDP growth estimates are accurate enough and have no incentive to revise them. They internalise the trade-off between publication timeliness and reliability as minimizing GDP revisions. SAs rely in one of the compilation methods described above (mostly on the value added one because of its speediness) to form their initial view on the aggregate GDP. Over time statisticians re-allocate shares of GDP among components with new incoming information. This is explicitly stated in Eurostat (2015): "There are two important requirements for quarterly national

[1]For an extensive survey on the impact of data revisions in many different contexts, see Croushore (2011). Researchers have also examined how structural modeling is affected by data revisions, the impact of data revisions on monetary policy analysis and the use of real-time data in current analysis.

[2]Another strand in the literature on revisions focused on fiscal variables, see for example Asimakopoulos, Paredes, and Warmedinger (2020) and Cimadomo (2016) and the references quoted therein.

accounts. Quarterly national accounts must be: available as soon as possible after the end of the reference period; and as accurate as is feasible to require as little subsequent revision as possible." Therefore, we will test statistically the hypothesis whereby SAs try to minimize future GDP revisions as much as possible, which means that revisions to the GDP growth rate published should be statistically 0. Empirically, this would be akin to test if new incoming data, which implies revisions to contributions to growth on some expenditure items in national accounts statistics regularly compensate each other.

We empirically prove indeed this fact and show that new incoming information will change other GDP components, on the expenditure side, whose items are regularly subject to revisions, and cancel each other out at an aggregate level. We further show that some of the expenditure component contribution revisions exhibit high correlation with each other. Using simple econometric analysis we find that the revision of the contribution in the external sector seems to be the most relevant factor explaining the changes in the contributions from inventories, explaining about 50% of the change in inventories across countries and vintages. Incorporating these results to a components vintage VAR (CV-VAR) model, we find that a dis-aggregated forecast of initial GDP announcements using the expenditures components contribution revisions performs better in the short-run than the standard vintage VAR (V-VAR) model using the aggregate revisions.

The consequences of these results are in our opinion twofold. First, it makes sense for economists to base their GDP nowcasts on the use of value added/production indicators such as industrial production, more than other type of indicators, because of their timeliness and the fact that GDP will not be extensively revised by Statistical Agencies after the first release. Second, if expenditure side items are included in a GDP forecast model, their historical revisions should be included to account for the important existing cross-correlation across them and improve the forecast of future initial GDP announcements. Forecasting individual expenditure components in isolation and then aggregating them to produce a GDP forecast is not an optimal strategy.

1 Introduction

Gross Domestic Product (GDP) is a measure of economic activity published by Statistical Agencies (SAs). It is one of the key data series followed by Central Banks (CBs) to inform monetary policy decisions. Official estimates of economic growth serve as a basis on which CBs forecast future growth. They are regularly revised and therefore forecasts for GDP growth are done on the basis of ever-changing data. The revisions would ideally respond to the incorporation of additional and improved data over time. But is it really so?

Users of data understand the uncertainty surrounding the early GDP announcements. In order to make a good use of them, they need to understand how reliable subsequent revisions of GDP data are. Following the seminal paper of Mankiw, Runkle, and Shapiro (1984), several papers in the literature have shed light on the properties of GDP revisions and how those revisions affect forecasting. Among them, Mankiw and Shapiro (1986), Mork (1987), Croushore and Stark (2003), Faust, Rogers, and Wright (2005), Aruoba (2008), Clements and Galvão (2010) and many others.[3,4]

The basic idea of those papers were to check if revisions to GDP were fulfilling desirable statistical properties (rationality tests), i.e. revisions should not be biased and therefore present a zero mean, revisions should be small compared to the volatility of the GDP series itself, and finally they should be unpredictable, which means that they carry information (news). Otherwise, if they are predictable, then they would be considered as noise and therefore no need to be used for a forecasting exercise.

Many of the above cited studies conclude that GDP data revisions are predictable and therefore noise questioning their usefulness in forecasting models. There should be enough information in the first announcement. But, to the best of our knowledge, there is no convincing explanation of the reason for that conclusion. Does it mean that the new incorporation of information to the official statistics do not carry any news? How can this be?

Against this idea, another strand in the literature has nevertheless shown the usefulness of using vintages for forecasting, see for example Garrat, Lee, Mise, and Shields (2008), Clements and Galvão (2012), Clements and Galvão (2013) and Carriero, Clements, and Galvão (2015). These papers mainly incorporate GDP vintages and its revisions at a vector autoregressive (VAR) approach.

In this paper, we built on this second strand and investigate the properties of data revisions exploiting the limited change in the GDP initial data announcements. Undoubtedly, SAs assign utmost importance to data accuracy but they also face several trade-offs which affect data quality. Firstly, there is a well-

[3]For an extensive survey on the impact of data revisions in many different contexts, see Croushore (2011). Researchers have also examined how structural modeling is affected by data revisions, the impact of data revisions on monetary policy analysis and the use of real-time data in current analysis.

[4]Another strand in the literature on revisions focused on fiscal variables, see for example Asimakopoulos, Paredes, and Warmedinger (2020) and Cimadomo (2016) and the references quoted therein.

known trade-off between data timeliness and accuracy. While users of the official statistics expect them to be available as soon as possible in order to measure the current state of the economy, statisticians are constrained by the availability of data sources. The most complete information usually arrives with delay as it comes from structural annual sources. Therefore, the quarterly data need to be partially estimated. Incorporation of information that arrives later leads to data revisions. SAs, however, also face another trade-off related to the various approaches for calculating the GDP. Ideally, the three GDP approaches, i.e. production, expenditure, and income, should be applied for compiling quarterly data starting from the very early stage of the process. In reality, as described in Eurostat (2015), very few data sources are timely enough for this purpose. Moreover, data sources for the three approaches have different quality (usually the production approach is the most reliable). In order to ensure a consistency between the GDP expenditure components and the GDP total figures, SAs need to make maximum use of available sources and to optimise the revisions. In our paper we postulate that SAs have in fact an explicit objective of data credibility, which is achieved by minimizing revisions subject to the data collection constraints.

In other words, borrowing from the quote in Eurostat (2015): "There are two important requirements for quarterly national accounts. Quarterly national accounts must be: available as soon as possible after the end of the reference period; and as accurate as is feasible to require as little subsequent revision as possible." In our case, then the hypothesis is that SAs dislike revisions to their first GDP release, which they want to be seen as reliable. Therefore, we will test statistically this hypothesis on the behaviour of GDP revisions. SAs try to minimize future GDP revisions as much as possible, which means that revisions to the GDP growth rate published should be statistically 0. Empirically, this would be akin to test if new incoming data, which implies revisions to contributions to growth on some expenditure items in national accounts statistics regularly compensate each other.[5]

We find that indeed this is the case for Germany, France, Italy and Spain. The new incoming data collection fosters SAs to revise the contribution of GDP expenditure components, while GDP estimates are broadly kept untouched. This fact is very important to take into account when building a model to forecast GDP when using expenditure components. The real-time cross-correlation in those components revisions should not be neglected. To that end. we follow the framework of Galvao (2017) to construct a Component Vintage VAR (CV-VAR) , where instead of using the revisions to GDP, we employ the contribution revisions of the GDP expenditure components. We show that using the latter can improve over the forecast of the former.

The remainder of the paper is organized as follows. In Section 2, we describe how we constructed a real-time dataset for GDP and its expenditure components for the 4 largest euro area economies. In Section 3 we analyse the unconditional properties of data revisions . Section 4 outlines our theoretical framework and explains the motivation behind focusing on all expenditure components in contrast to relying on GDP revisions only. In Section 5, we test empirically our model to forecast initial announcements of

[5]We should recall that in national accounts GDP on the expenditures side is divided in private and public consumption, investment, net trade and inventories.

GDP. Section 6 concludes the paper.

2 Data

We construct a dataset of revisions to GDP and its expenditure components, such as private and government consumption, investment, net trade and inventories for Germany, France, Italy, and Spain over the period 2002-2022.[6] We work with seasonally adjusted quarterly growth rates for each of those indicators. However, the focus of our analysis is not on the growth rates themselves but on the contributions of the GDP components to the quarter-on-quarter GDP growth rate.

The dataset has been constructed based on national accounts data published by Eurostat. It consists of vintages (or called differently "snapshots") of data that were taken with a monthly frequency between January 2002 and September 2022. Each snapshot records the information as it was available in a given point in time. GDP data are of course published with a quarterly frequency and those monthly snapshots may seem to be superfluous but we decided to follow this approach as it allows us to capture the releases of new data without a need to follow the exact publication calendars for each country. Instead, it is enough to monitor if at the beginning of a given month any new observation appeared. More precisely, we monitor when the information about a real GDP quarter-on-quarter growth rate and all the expenditure components contributions to those GDP growth become available for the first time. We refer to those observations as "first releases (y^t_{t+3})", where t denotes a reference period and $t+3$ denotes the data timeliness. The label $t+3$ (months) indicates that the first information about the expenditure components becomes available at the beginning of the third month following the end of the reference period. It should be noted that we explicitly omit the GDP flash releases, i.e. the very first GDP estimates as they are not accompanied by the information about the expenditure components.

As a result, our series of "first releases (y^t_{t+3})" coincides with the Eurostat's estimate for GDP, which is published with a timeliness of about $t+65$ days. We then construct a series of "second releases (y^t_{t+6})" which contains quarterly growth rates for the reference period t published at $t+6$ months, i.e. together with the first release of data for the reference period $t+3$. In practise the series of the "second releases (y^t_{t+6})" embeds revisions published in the Eurostat's updates at $t+100$ days and other information collected within the quarter. We then call the "third release (y^t_{t+12})" the data that are captured in the snapshots at $t+12$ months, i.e. include the annual revisions. The "final release (y^t_{t+24})" are the data captured in the snapshot $t+24$ months, i.e. 2 years after the reference period when, conventionally, the data are considered to be "final".

The definition of "final" data is not a trivial one and varies across the literature. For example Aruoba

[6] We will nevertheless split the sample into pre-COVID and COVID data. Starting point of the sample is dictated by a limited availability of electronic sources for data vintages prior to 2002.

(2008) finds that for the US national accounts, the period after which the data can be considered "final" is about 3 years. In our paper we focus on a somewhat shorter horizon due to similar reasoning as presented in Giannone, Henry, Lalik, and Modugno (2012). Firstly, the two-year horizon is interesting from a perspective of policy-relevant analysis. For instance the ex-post accuracy of the macroeconomic forecast also refers to this shorter horizon as forecast errors would tend to be reviewed after a relatively short span of time rather than a decade later. Secondly, a two-year period always captures inter alia the update of annual data which are based on more structural sources. This, in turn, leads to a further revision of the the quarterly figures in order to align them with new annual data.

The approach of taking the snapshots at the beginning of every month has also the advantage of capturing information that was used by policy makers during their regular meetings. As a rule, the ECB policy makers meet around every first Thursday of a month. This policy "flavour" of our dataset is also visible along another dimension. Namely, when constructing the dataset we followed the approach of Giannone, Henry, Lalik, and Modugno (2012) whereby we track the data concepts that were actually used for policy making purposes. In particular, we qualify methodological changes as revisions. For instance the introduction of chain-linked volume measures in the course of 2005-06 and the introduction of the ESA2010 methodology in September 2014 are both considered as data revisions.

In our paper we therefore define the revisions as follows:

First revision (r_1^t) = second release (y_{t+6}^t) - first release (y_{t+3}^t)
Second revision (r_2^t) = third release (y_{t+12}^t) - second release (y_{t+6}^t)
Third revision (r_3^t) = final release (y_{t+24}^t) - third release (y_{t+12}^t)
Total revision (Cumulative revision) (r_T^t) = final release (y_{t+24}^t) - first release (y_{t+3}^t)

Finally, it should be noted that the time span of our data covers the COVID-19 period - i.e. 2020Q1 up to September 2022Q3. The outbreak of the pandemic had not only sever economic implications but also significantly affected the collection and processing of statistical data. Especially during the initial period where the restrictions imposed on the movement of people affected the traditional methods of data collection (e.g. face-to-face interviews). To address those difficulties SAs have published several guidance and methodological notes that are available on their website. See for instance Eurostat: https://ec.europa.eu/eurostat/web/covid-19/support-statisticians#Economy. Given the unprecedented patterns of data collections, we therefore split our analysis into two sub-periods and analyse data revision patterns pre-COVID and during the COVID-19 period.

3 Properties of data revisions

In this section we assess the properties of the real-time data and their revisions.[7] Forecasters normally use real-time series, which include the information they have at each point in time, when performing forecasts. Following Aruoba (2008) methodology, we start by assessing the statistical behaviour of revisions based on the following properties:

- **(P1)**: $E(r_T^t) = 0$
- **(P2)**: $var(r_T^t)$ is small
- **(P3)**: Revision-to-announcement ratio $(\overline{r_T^t}/\overline{y_{t+3}^t})$ is relatively small
- **(P4)**: Noise-to-signal ratio $(\sigma_{r_T^t}/\sigma_{y_{t+24}^t})$ is relatively small

where r_T^t represents the total revision. The first desired property is for the mean of the revisions to be zero. This indicates that the initial announcement is an unbiased estimate of the final value. Second, we look at the volatility of the revisions. It is desirable that they are small in comparison to the volatility of the series themselves. As the unconditional moments of revisions might not be completely informative alone, we also report the relative size of those revisions relative to the "first release (y_{t+3}^t)" and noise-to-signal ratios, which are computed as the standard deviation of the total revision divided by the standard deviation of the "final release (y_{t+24}^t)". These statistics shed light on the relative size of revisions' mean/standard deviation compared to the one of the initial/final value of the variables. Finally, we report the correlation with initial announcements which give an indication of the direction of the revisions over time.

In Table 1 we present the summary statistics of the total revisions of the quarter-on-quarter GDP growth and of its national accounts expenditure components contributions for the Big-4 euro area countries, which will help us assessing the aforementioned properties.

The table is organised by panels, one for each country in the analysis. The first column of the table reports the results for the GDP growth rate, while the others present the results for the contributions. For every country, we report the mean and the standard deviation of the final release and of the total revision **(P1-P2)**. In addition, we report the revision-to-announcement ratios and the noise-to-signal ratio **(P3-P4)** and the correlation between the total revisions and the first release.

The first step is to assess the first statistical property, i.e. the desirability of total revisions mean to be zero. This property is satisfied for the GDP growth rate for all countries except of Germany, whose mean total revision is positive (0.051 p.p.) and statistically significant at a 10% level. The reason for that seems to be the positive revision of the private consumption contribution to GDP. Otherwise, we also detect a

[7] This section focuses on pre-COVID data. Results for COVID period are included in the Annex.

significant positive revision for the investment contribution in France, which seems to be compensated by minor contribution revisions in the other expenditure components, making the total GDP revision not statistically significant.

We further explore the properties of the total mean revisions by calculating the revisions-to-announcement ratio. Hence, we can assess the relative size of the total revision compared to the initial announcement. For instance, the revisions-to-announcements ratio for investment contributions in Spain shows that the mean of total revision is almost 10 times the magnitude of the mean of the initial announcement. For the rest of the items, only revisions-to-announcement ratio for investment and inventories contributions for France and net trade in Italy are also above 1. Property **(P3)** would be compromised in these cases.

Next we look at the standard deviation of total revisions. The numbers we find range from 0.063 to 0.476. The item, which is clearly showing the most elevated volatility for all countries is the revision of the contribution of trade and inventories. In order to understand the relative size of the standard deviation of the revisions, we report also noise-to-signal ratios.[8] These ratios are between 0.283 and 1.229. The larger the ratio is, the more sizable are the total revisions as compared to the final variables. For all countries, the largest noise-to-signal ratios are observed for the government consumption. It is mainly due to the fact that the standard deviation of the final series is small. Overall, it is clear that revisions to contributions are larger than revisions to GDP itself, which would already signal some negative correlation among revisions. We will test this formally later. The combination of these findings leads to the conclusion that **(P2-P4)**, i.e. that the volatility of the revisions is small in comparison to the volatility of the series themselves, is not supported by the data.

Finally, we analyse the correlation of total revisions with initial announcements. A positive correlation means that the revision increases the absolute size of the initial announcement. In turn, the negative correlation means that revisions decrease the absolute size of the initial announcement. We find statistically significant negative correlations (not a single positive) for all countries. This is a strong indication that initial announcement is biased in terms of size and then subsequently reduced in following releases for many components.

Insert Table 1 here

In Table 2, we assess similar key properties as in Table 1, but with a focus on the breakdown of revisions as we want to understand if individual revisions might also show some specific patterns.

We find that, in line with the information provided in Table 1, it seems that only Germany is constantly revising GDP growth upwards over the sample at each release that we consider. With respect to mean

[8] This statistic is bounded below by zero, but due to possible negative correlation between the revisions and the final series it is not bounded above by unit

revisions to contributions, a common pattern across countries is that when they are statistically significant at 10% level is mostly only after one year, i.e. after the second revision for us (r_2^t = third release (y_{t+12}^t) - second release (y_{t+6}^t), when data from annual sources are added.

Insert Table 2 here

Finally, in Figure 1 we plot the empirical distributions of the revisions. The first revision r_1^t dispersion is lower than in later revisions. This seems to reflect the process of data collection by SAs as the largest source of new information is incorporated in annual revisions. The plots also show that trade contributions and inventories present a higher dispersion than other items, which is again a signal of the high volatility of those revisions.

Insert Figure 1 here

4 A trade-off for SAs. Timeliness versus reliability.

Statistical agencies (SAs) aim at publishing data series, which reflect as close as possible the economic reality. The publication of the Gross Domestic Product (GDP) reflects a huge effort by SAs to summarise in one single indicator how the economy is evolving over time. Many sources of information are collected and combined in order to arrive at this single indicator. In fact, SAs collects multiple indicators to cover the three different approaches defined in the National Accounts Statistic manuals in order to reach the final GDP figure (see Eurostat (2015)). Those indicators refer to the income, expenditure and production side of the economy. The availability of this information is of course not always the same across different data sources therefore SAs improve the coverage of the indicators over time which leads to data revisions.

Given this collection process, it is clear that statistical agencies face a trade-off. They want to be reliable, but also timely in their publication as users are demanding speedy information. That is the reason why SAs are frequently updating their GDP estimates and making some assumptions for the missing information at the times of publication. In a way, SAs are themselves somehow forecasting in real-time. Nowadays the preliminary GDP flash estimate for many countries is published about 30 days after the end of the reference quarter.[9] This early information on economic growth is complemented by the quarterly GDP estimates released about 45 days and 65 days after the end of the reference quarter t. The $t + 65$ release is the first one containing a full release of components on the expenditure side, which means full release of data series such as private consumption, government consumption, investment, net trade and inventories.

[9]Most of the countries seem to be using production based indicators for this flash release as they consider them as the most accurate indicator for the aggregate GDP.

For our analysis we will use release at $t+65$ days (labelled as $t+3$ months - first release) and the revisions at $t+6$ months, $t+12$ months and $t+24$ months.

Our hypothesis relies on the idea that GDP is the *king*, i.e. even if new information sources are coming in for SAs and this information is reflected in the change of the contributions to GDP growth, the latest should not be revised too much over time, otherwise the initial releases would be seen as unreliable. The only way we think that both objectives could be fulfilled is that there is at least one expenditure component which compensates the news when updating any other component. There would be a "re-distribution" in the contributions to GDP growth on the expenditure side.

The first indication of this phenomenon could be grasped by looking at correlations matrices among revisions. Figure 1 does precisely that. We plot correlations and its significance together with its intensity. We are mostly interested in the cross-correlation among revisions to the contributions for the same vintage, but we also plot the correlation across vintages for completeness.

Looking at Figure 1, there is a strong indication of the phenomenon we have in mind. There exist a statistically significant negative correlation among some components for the same vintage. For all countries and all vintages, the revision of the contribution of inventories has a significant negative correlation with the revision in the trade contribution. This is a strong indication. There are sometimes also other contribution items that have negative correlation with inventories, but those seem to be more country and vintage specific.

Finally, correlations matrices depicted in Figure 1 also illustrate that there are no significant correlations between different vintages of revisions.

4.1 Assessing the information content of revisions

Following Mankiw and Shapiro (1986) and Aruoba (2008), data revisions are sometimes characterized as "news" or "noise". Data revisions are "news" when they add new information, and "noise" when they reduce measurement error. According to Aruoba (2008), under the "news" hypothesis the initial announcement is an efficient forecast that reflects all available information and subsequent estimates reduce the forecast error, incorporating new information. This way the revision is correlated with the final value but uncorrelated with the data available when the estimate is made. However, under the "noise" hypothesis the initial announcement is an observation of the final series, measured with error. This means that the revision is uncorrelated with the final value but correlated with the data available when the estimate is made.

To test the news and noise hypotheses Aruoba (2008) estimates the two equations below:

$$y_{t+24}^{t} = \alpha_1 + \beta_{news} * y_{t+3}^{t} + \epsilon_t^1 \tag{1}$$

$$y_{t+3}^{t} = \alpha_2 + \beta_{noise} * y_{t+24}^{t} + \epsilon_t^2 \tag{2}$$

The first equation tests the "news" hypothesis under the β_{news}=1 and α_1=0 joint F-test. Whereas, the second equation tests the "noise" hypothesis under the β_{noise}=1 and α_2=0 joint F-test. These two hypotheses can be both rejected, where it can be concluded that the data are not informative regarding the news/noise dichotomy.

Table 3 below shows the resulted joint F-statistics for the pre-COVID period in our sample, 2001Q3-2019Q4. For GDP growth there is no clear patterns regarding "news" or "noise" for Germany and Spain, but there are some evidence of "news" for France and Italy. When we move to the expenditure components the results uncover that private consumption contribution revisions appear to be "news" across all the counties in our sample. This is an indication that when the data on private consumption is revised, it brings genuine information about the direction of GDP growth revisions. In addition, the results uncover that the external sector and inventories contribution revisions are not classified as "news" in any of the countries in our sample, and are actually both classified as "noise" for Germany. For France only inventories are also classified as "noise". This fact would reinforce what we detected in the correlation matrix (Figure 1). These elements do not bring any "news" by themselves alone. They only do when considered together with other components as we will again see in the empirical section. For the remaining of the expenditure components we get mixed results when it comes to "news" or "noise" analysis, especially for government consumption. Finally, regarding the investment component, we find that for some countries they are "noise", while for others they are "news" or inconclusive.

Insert Table 3 here

The "news" or "noise" assessment indicates that, with the exception of private consumption, contribution revisions individually do not have any valuable information for the forecast of GDP, but we will show in the next section that this is not the case anymore when one considers GDP expenditure components together and not in isolation.

5 Empirical results

We know from the statistical analysis in Section 2 that the mean of GDP revisions is statistically 0 for almost all vintages and countries. For this reason, contribution revisions at a dis-aggregated level, through the expenditure components, need to cancel out when aggregating them. If there was no econometric pattern across the expenditure components, it would mean that this cancellation would be random. However, our correlation matrix suggests that there is at least one candidate, inventories, that is used to balance the incorporation of new information. In general, it appears that the revisions of the expenditure components exhibit a linear relationship. We have also tested if there is any linear relationship across the three revisions and the results are not statistically significant. Therefore, the statistically significant linear correlation we uncovered is only present within the same revision, i.e. first, second or third revision.

Furthermore, we want to test our hypothesis of SAs disliking revisions to GDP growth for each vintage and if there are any differences among them. It could be that SAs dislike revisions especially close to the first release, but revisions happening in one or two years are less problematic in terms of loss function (credibility) of the SAs.

In order to do that, we test if the revisions of the contribution of inventories to GDP growth can be explained by the revisions to the rest of the contributions. We test that for each vintage and country during the pre-COVID period. For each revision j = 1, 2, 3, T (total) and country i = DE, FR, IT, ES, the following equation is estimated:

$$SCR^t_{j,i} = constant_{j,i} + \delta_1 * PCR^t_{j,i} + \delta_2 * GCR^t_{j,i} + \delta_3 * ITR^t_{j,i} + \delta_4 * BTR^t_{j,i} + u^t_{j,i} \tag{3}$$

where all variables are defined as revisions of contributions to GDP growth: SCR - inventories, PCR - private consumption, GCR - government consumption, ITR - investment and BTR - external sector (net trade). We also estimate the same equation, incorporating one explanatory variable at a time to check the relative importance of each of them.[10]

Results are presented in Tables 4-5. The full model (Model 1), corresponding to equation (3) for each revision is presented in Table 4. In Table 5, we dis-aggregate further equation (3) and show the results of the regression of individual expenditure components on inventories (Models 2-5). We find that all coefficients of revisions to contributions in equation (3) are negative. This is a remarkable indication that inventories could be used as a residual by many SAs to compensate the new incoming information on other items, with the aim of keeping the revision to GDP growth as small as possible. As already suggested by the correlation matrix in Figure 1, the revision of the contribution in the external sector seems to be the most relevant factor explaining the changes in the contributions from inventories. Alone this revision explains around 50 percent of the change in inventories across countries and vintages (Model 2 in Table 5). This is a very strong result. In fact all forecasters should know that revisions to inventories and external sector contributions are going to move in opposite directions, so that the estimate for GDP growth remains broadly unchanged.

[10]We have also pooled together the data to see if this phenomena is not country specific, but widely shared among SAs. Thus, we implement a panel regression with all countries where we also include country-fixed effects. The results are provided in the appendix.

Insert Tables 4-5 here

5.1 Forecasting initial announcements and revisions. The CV-VAR model.

But is this correlation among expenditure contributions of any use when forecasting GDP? In this section, we present a modelling approach to better forecast the first announcements of GDP growth and its future revisions using the expenditure components.

Many papers have focused on the use of vintages for forecasting final releases of economic activity. For example, Kishor and Koenig (2012) is proposing a Kalman Filter approach to a state space model with unobserved components. Galvao (2017) also suggests similar estimation based on a DSGE modelling approach. When the aim is to model a range of different vintages, a vector autoregression (VAR) approach is implemented, but vintages are subject to revisions. To deal with that, Garrat, Lee, Mise, and Shields (2008) apply a VAR model on the (log) levels of output assuming that different vintage estimates are cointegrated of order one such that their revisions (differences) are cointegrated of order zero. Their VAR model includes three elements: the difference across vintage and observation; as well as two subsequent data revisions. The disadvantage of this modelling approach is that the levels of output are affected by base-year changes and other measurement changes.

A way to overcome this issue is to work with "same-vintage-growth-rates", as in Clements and Galvão (2012), Clements and Galvão (2013) and Carriero, Clements, and Galvão (2015). The resulted model will be a vintage-VAR (V-VAR) model that takes into consideration the full information available at a given point in time. This will include the underlying output (initial announcement) and revision processes. Having three rounds of revisions in our set-up, we can model four processes jointly in a V-VAR model. In general, the VAR should be of size $q+1$, where q is the number of revisions after the first release. Defining as quarterly output growth level at time $t-3$ that is released in time t by y_t^{t-3}, and the relevant three revisions of GDP available at time t as r_1^{t-6}, r_2^{t-12}, and r_3^{t-24} respectively, we can get the following V-VAR representation:

$$\begin{bmatrix} y_t^{t-3} \\ r_1^{t-6} \\ r_2^{t-12} \\ r_3^{t-24} \end{bmatrix} = c + \Gamma \begin{bmatrix} y_{t-3}^{t-6} \\ r_1^{t-9} \\ r_2^{t-15} \\ r_3^{t-27} \end{bmatrix} + \epsilon_t \tag{4}$$

where the lag length of the V-VAR has been determined by the Akaike and Bayesian information criteria and it is of order 1. The vector of variables at the left hand side of the equation includes initial release of GDP and its revisions. For example, at any given quarter t we have one new release for $t-3$ quarter (the initial announcement), y_t^{t-3}; the first revision for quarter $t-6$, r_1^{t-6}; the second revision for quarter $t-12$, r_2^{t-12}; and the final revision of $t-24$ quarter, r_3^{t-24}. Similarly at the right hand side we have the lagged initial announcement of GDP, y_{t-3}^{t-6}; its lagged first revision, r_1^{t-9}; its lagged second revision,r_2^{t-15}; and the lagged third revision, r_3^{t-27}. This data handling ensures that we only include data that are available in real-time.

The above V-VAR model is the standard approach to capture the various revisions that exist in vintage releases and avoid misspecification errors (Kishor and Koenig, 2012). However, the above representation ignores the existence of measurement errors that come from the expenditure components' revisions and correlations, even if the output growth is stationary (as in Garrat, Lee, Mise, and Shields (2008)).

In particular, in our model we take into account the fact that output growth is the aggregation of the five expenditures components: private consumption, government consumption, investment, external sector and inventories; and test if we can utilise it to improve the forecasting accuracy of the initial announcement of GDP and its revisions. To achieve this, we extend the V-VAR model presented in equation (4), used in the related literature (e.g. Clements and Galvão (2012), Clements and Galvão (2013) and Carriero, Clements, and Galvão (2015)), to include the revisions of all the expenditure components instead of the revisions to GDP. Specifically, our components V-VAR (CV-VAR) model will be:

$$\begin{bmatrix} y_t^{t-3} \\ r_{1,j}^{t-6} \\ r_{2,j}^{t-12} \\ r_{3,j}^{t-24} \end{bmatrix} = b + \Delta \begin{bmatrix} y_{t-3}^{t-6} \\ r_{1,j}^{t-9} \\ r_{2,j}^{t-15} \\ r_{3,j}^{t-27} \end{bmatrix} + \phi_t \tag{5}$$

with the lag length of the CV-VAR being again of order 1. The difference of this model with the model presented in equation (4) is that now we have replaced the GDP revisions with the revisions of the expenditures components, where j = [1,2,3,4,5] indicates the different expenditures components. Therefore, in the CV-VAR model each revision variable is a 5x1 vector.

At the CV-VAR presented in equation (5), we have at the left hand side the new release for GDP in $t-3$ quarter (the initial announcement), y_t^{t-3}, similar to equation (4); but for the remaining variables we have the first revision of every expenditures component for quarter $t-6$, $r_{1,j}^{t-6}$; the second revision of every expenditures component for quarter $t-12$, $r_{2,j}^{t-12}$; and the final revision of every expenditures component for $t-24$ quarter, $r_{3,j}^{t-24}$. Finally, at the right hand side we have the same variables but lagged by one quarter.

Given that there is no strong cross-correlation of the expenditure components across the three revisions (see Figure 1), we will use each revision of the expenditures components in separate CV-VAR models when we move to our forecasting exercise. This approach will give us three CV-VAR models where all of them will include the initial GDP announcement and a given revision, leading to six variables in total (the initial GDP and the five expenditures components for a given revision) per CV-VAR model. As a result, the three CV-VARs will provide three different initial GDP announcement forecasts per-revision that we will average to get a single forecast for the initial GDP announcement and compare it with the relevant forecast produced by the standard V-VAR model, as shown in equation (4).[11]

Furthermore, having estimated the CV-VAR model across all the expenditure components and revisions, we can not only compare our approach with the standard V-VAR model in terms of the forecast accuracy of the initial GDP announcements, but also the GDP revisions. For the standard V-VAR model we can obtain the GDP revisions directly from the model. However, in our components V-VAR model we take into account the contemporaneous relationship of output growth with the five expenditures components to calculate and forecast each revision of output growth post-estimation as following:

$$r_1^{t-6} = \sum_{j=1}^{5} r_{1,j}^{t-6} \tag{6}$$

$$r_2^{t-12} = \sum_{j=1}^{5} r_{2,j}^{t-12} \tag{7}$$

$$r_3^{t-24} = \sum_{j=1}^{5} r_{3,j}^{t-24} \tag{8}$$

where equations 6-8 show the calculation of GDP's first, second and third revision using the revisions of the five expenditures components respectively.

5.2 Forecasting initial announcements and revisions. Results.

We now utilise the CV-VAR model with the expenditure components revisions, as shown in equation (5), in a forecasting exercise and assess if it produces reasonable forecasts against the standard V-VAR model of equation (4).

In particular, we implement an expanding window estimation strategy where we collect at each point in time the one quarter ahead and four quarters ahead forecast. For example, we first estimate our CV-VAR model up until 2014Q4 and then we perform a forecast for the next quarter. When the next quarter, 2015Q1 is released, we re-estimate our CV-VAR model for each revision using the new quarter of data and then we perform a forecast for the next quarter, 2015Q2. We repeat this approach until the end of 2021 and we obtain 28 forecasts in total for the period 2015-2021 for the one quarter ahead forecasts (h=1).

Regarding the four quarters ahead forecast (h=4), we follow the same approach as above, but now when we have data up until 2014Q4 we perform a four quarters ahead forecast (h=4) for 2015Q4. When the next quarter of data becomes available, 2015Q1, we repeat our forecast for four quarters ahead, 2016Q1,

[11] We did not find any of the specific CV-VAR models to be superior to the other in terms of forecast performance.

having first estimated our model up until 2015Q1. We repeat this forecasting exercise and we obtain 25 different four quarter ahead forecasts for the period 2015-2021.[12]

Having performed both of the two aforementioned forecasting exercises, we compare their forecasting accuracy with the relevant forecasts produced in the same way by the standard V-VAR model, as shown in equation (4). The results in Table 6 show the average RMSFEs when comparing the forecasts between the standard V-VAR model with GDP revisions and our CV-VAR model where we replaced GDP revisions with the revision of the expenditure component contributions to GDP. A value less than one indicates that the CV-VAR approach performs better on average than the alternative. The Diebold-Mariano test is also applied and we show the statistical significance with asterisks.

We find that the CV-VAR approach can improve the forecast of the initial announcements for the majority of the cases compared to the standard V-VAR model that does not utilise the expenditures components. In particular, the one period (h=1) ahead forecasts generate lower average RMSFEs across all the countries, and sub-periods, in our sample apart from Italy, compared to the standard V-VAR model. In some instances these improvements are also statistically significant and there is no case at all where the V-VAR model generates a statistically significant better forecast than our CV-VAR model for the initial GDP announcement. When it comes to the four periods (h=4) ahead forecasts we find that the two models are not very different but still there is no evidence that the standard V-VAR approach can consistently outperform our CV-VAR model in any case. We even find that for Spain during the pre-Covid period our CV-VAR model produces statistically significant better forecasts for GDP's initial announcements over the standard V-VAR approach.

These results show significant evidence that the use of the revisions of the expenditure component contributions instead of the aggregate GDP revisions can improve the forecasts of GDP initial announcements in the short-run.

Insert Table 6 here

To better understand the driving forces of this result, we further compare the forecasting accuracy of the CV-VAR for the GDP revisions with those of the standard V-VAR predictions. As mentioned before, for our CV-VAR model we do not obtain directly the GDP revisions but we construct them post estimation from the revisions of the expenditure component revisions, as shown on equations (6)-(8).

The results in Table 7 present again the average RMSFEs for the GDP revisions forecast between our CV-VAR model and the standard V-VAR model. Similar to Table 6 above, a value less than one indicates that the CV-VAR approach performs better on average than the alternative. The Diebold-Mariano test

[12] We have also performed the same forecasting exercise as above but for two (h=2) and three (h=3) periods ahead separately. The results are very similar to the four periods ahead forecast (h=4). The relevant tables are not provided, but are available upon request.

is also applied and we show the statistical significance with asterisks.

As we can see from the results, the improved forecast for the initial GDP announcement that we obtained in the previous forecasting exercise is not driven by any specific revision, i.e. first, second or third. Our CV-VAR model can produce lower average RMSFEs across the majority of the revisions and countries in our sample for the one period ahead (h=1) forecasts. We can also see that for the four periods ahead forecasts (h=4), even though we can obtain many favourable RSMFEs ratios, mainly during the Covid period, we cannot obtain any statistically significant improvements. This indicates that the CV-VAR model long-run forecasts are volatile when the economy experiences high levels of uncertainty.[13]

Insert Table 7 here

Overall, the aforementioned forecasting exercises show that the replacement of the aggregate GDP revisions with the revisions of the expenditures component contributions can lead to improved forecasts of the GDP initial announcements in the short-run.

6 Conclusion

GDP is the main summary indicator of economic activity and can be compiled using different approaches. On the output side, GDP measures the sum of the gross value added created through the production of goods and services in the individual sectors of the economy. On the income side, it measures the sum of all incomes generated by the production of goods and services, and on the expenditure side, it measures the sum of domestic and (net) external demand for the produced goods and services.

According to Eurostat (Eurostat (2015)), the production approach is the most common approach for compiling quarterly GDP, predominantly because of the availability of data within the statistical systems. Therefore, GDP initial release is mostly calculated on the basis of value added/production side indicators. According to our hypothesis, statisticians consider that the initial GDP growth estimates are accurate enough and have no incentive to revise them. They internalise the trade-off between publication timeliness and reliability as minimizing GDP revisions. We empirically prove indeed this fact and show that new incoming information will change other GDP components, for example, on the expenditure side, whose items are regularly subject to revisions, which cancel each other out at an aggregate level.

We further show that some of the expenditure component contribution revisions exhibit high correlation with each other. Using simple econometric analysis we find that the revision of the contribution in the external sector seems to be the most relevant factor explaining the changes in the contributions from

[13]The results are very similar for the two (h=2) and three (h=3) periods ahead forecasts.

inventories, explaining about 50% of the change in inventories across countries and vintages. Incorporating these results into a components V-VAR (CV-VAR) model, we find that a dis-aggregated forecast of initial GDP announcements using the expenditures components contribution revisions performs better in the short-run than the standard V-VAR model using the aggregate revisions.

The consequences of these results are in our opinion twofold.
First, it makes sense for economists to base their GDP nowcasts on the use of value added/production indicators such as industrial production, more than other type of indicators, because of their timeliness and the fact that GDP will not be extensively revised by Statistical Agencies after the first release.
Second, if expenditure side items are included in a GDP forecast model, their historical revisions should be included to account for the important existing cross-correlation across them and improve the forecast of future initial GDP announcements. Forecasting individual expenditure components in isolation and then aggregating them to produce a GDP forecast is not an optimal strategy.

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Table 1: Summary Statistics of Total Revisions

	GDP growth rate	Private consumption contribution	Government consumption contribution	Investment contribution	Trade contribution	Inventories contribution
Panel A: Germany						
Mean of final series ($\overline{y^t_{t+24}}$)	**0.300**	**0.117**	**0.075**	0.045	0.057	0.006
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.707	0.310	0.115	0.359	0.750	0.641
Mean of total revisions ($\overline{r^t_T}$)	**0.051**	**0.044**	0.010	-0.006	0.003	0.000
Standard deviation of total revisions ($\sigma_{r^t_T}$)	0.221	0.217	0.122	0.181	0.346	0.419
Corr. with initial ($\rho_{r^t_T, y^t_{t+3}}$)	-0.192	**-0.228**	**-0.527**	**-0.233**	**-0.535**	**-0.439**
Noise-to-signal ratio ($\sigma_{r^t_T}/\sigma_{y^t_{t+24}}$)	0.313	0.699	1.059	0.505	0.461	0.653
Revisions-to-announcements ratio ($\overline{r^t_T}/\overline{y^t_{t+3}}$)	0.205	0.606	0.158	-0.110	0.048	-0.035
Panel B: France						
Mean of final series ($\overline{y^t_{t+24}}$)	**0.256**	**0.177**	**0.097**	**0.071**	-0.055	-0.034
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.187	0.133	0.063	0.120	0.227	0.240
Mean of total revisions ($\overline{r^t_T}$)	-0.006	-0.015	-0.001	**0.036**	0.001	-0.027
Standard deviation of total revisions ($\sigma_{r^t_T}$)	0.187	0.133	0.063	0.120	0.227	0.240
Corr. with initial ($\rho_{r^t_T, y^t_{t+3}}$)	**0.194**	**-0.251**	**-0.382**	-0.010	**-0.280**	**-0.413**
Noise-to-signal ratio ($\sigma_{r^t_T}/\sigma_{y^t_{t+24}}$)	0.412	0.628	0.923	0.570	0.596	0.607
Revisions-to-announcements ratio ($\overline{r^t_T}/\overline{y^t_{t+3}}$)	-0.023	-0.079	-0.014	1.010	-0.024	3.733
Panel C: Italy						
Mean of final series ($\overline{y^t_{t+24}}$)	0.003	0.013	0.004	-0.048	0.043	-0.008
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.184	0.173	0.110	0.161	0.377	0.476
Mean of total revisions ($\overline{r^t_T}$)	0.000	-0.029	-0.015	0.008	0.027	0.008
Standard deviation of total revisions ($\sigma_{r^t_T}$)	0.184	0.173	0.110	0.161	0.377	0.476
Corr. with initial ($\rho_{r^t_T, y^t_{t+3}}$)	0.141	0.118	**-0.452**	**-0.277**	**-0.519**	**-0.585**
Noise-to-signal ratio ($\sigma_{r^t_T}/\sigma_{y^t_{t+24}}$)	0.307	0.524	1.088	0.457	0.854	1.021
Revisions-to-announcements ratio ($\overline{r^t_T}/\overline{y^t_{t+3}}$)	-0.140	-0.699	-0.803	-0.149	1.711	-0.487
Panel D: Spain						
Mean of final series ($\overline{y^t_{t+24}}$)	**0.392**	**0.187**	**0.084**	0.025	0.078	0.018
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.566	0.469	0.189	0.471	0.528	0.208
Mean of total revisions ($\overline{r^t_T}$)	-0.006	-0.016	-0.004	0.028	0.001	-0.015
Standard deviation of total revisions ($\sigma_{r^t_T}$)	0.160	0.286	0.232	0.255	0.430	0.253
Corr. with initial ($\rho_{r^t_T, y^t_{t+3}}$)	-0.086	-0.160	**-0.713**	-0.186	**-0.398**	**-0.600**
Noise-to-signal ratio ($\sigma_{r^t_T}/\sigma_{y^t_{t+24}}$)	0.283	0.610	1.229	0.542	0.814	1.217
Revisions-to-announcements ratio ($\overline{r^t_T}/\overline{y^t_{t+3}}$)	-0.014	-0.078	-0.046	-9.799	0.014	-0.463

Note: N = 74, Boldface denotes significance at the 10% level

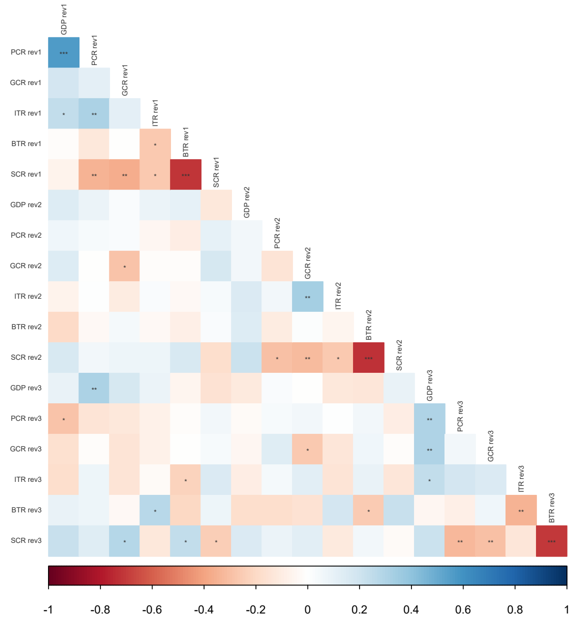
Table 2: Summary statistics for breakdown of revisions

	GDP growth rate	Private consumption contribution	Government consumption contribution	Investment contribution	Trade contribution	Inventories contribution
Panel A: Germany						
Mean of final series ($\overline{y^t_{t+24}}$)	**0.300**	**0.117**	**0.075**	0.045	0.057	0.006
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.707	0.310	0.115	0.359	0.750	0.641
Mean of revisions						
1^{st} revision ($\overline{r^t_1}$)	0.012	-0.008	0.012	-0.006	0.029	-0.013
2^{nd} revision ($\overline{r^t_2}$)	**0.023**	**0.035**	0.003	0.007	-0.005	-0.017
3^{rd} revision ($\overline{r^t_3}$)	0.016	0.017	-0.004	-0.007	-0.021	0.030
Standard deviation of revisions						
1^{st} revision ($\sigma_{r^t_1}$)	0.107	0.145	0.103	0.115	0.267	0.302
2^{nd} revision ($\sigma_{r^t_2}$)	0.112	0.115	0.079	0.071	0.222	0.270
3^{rd} revision ($\sigma_{r^t_3}$)	0.153	0.141	0.097	0.131	0.259	0.305
Noise-to-signal ratio						
1^{st} revision ($\sigma_{r^t_1}/\sigma_{y^t_{t+24}}$)	0.152	0.466	0.894	0.320	0.356	0.471
2^{nd} revision ($\sigma_{r^t_2}/\sigma_{y^t_{t+24}}$)	0.158	0.370	0.684	0.197	0.296	0.421
3^{rd} revision ($\sigma_{r^t_3}/\sigma_{y^t_{t+24}}$)	0.216	0.453	0.840	0.364	0.345	0.476
Revisions-to-announcements ratio						
1^{st} revision ($\overline{r^t_1}/\overline{y^t_{t+3}}$)	0.050	-0.116	0.179	-0.121	0.528	-2.212
2^{nd} revision ($\overline{r^t_2}/\overline{y^t_{t+3}}$)	0.092	0.484	0.042	0.144	-0.098	-2.858
3^{rd} revision ($\overline{r^t_3}/\overline{y^t_{t+3}}$)	0.063	0.237	-0.063	-0.133	-0.383	5.034
A/C(1)						
1^{st} revision ($\rho_{r^t_1,r^{t-1}_1}$)	0.004	**0.204**	-0.126	0.008	-0.014	-0.151
2^{nd} revision ($\rho_{r^t_2,r^{t-1}_2}$)	-0.116	0.054	-0.052	**0.202**	-0.037	-0.105
3^{rd} revision ($\rho_{r^t_3,r^{t-1}_3}$)	-0.159	-0.102	**-0.332**	**-0.383**	-0.156	-0.119
Panel B: France						
Mean of final series ($\overline{y^t_{t+24}}$)	**0.256**	**0.177**	**0.097**	**0.071**	-0.055	-0.034
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.187	0.133	0.063	0.120	0.227	0.240
Mean of revisions						
1^{st} revision ($\overline{r^t_1}$)	-0.016	-0.010	0.002	0.006	0.010	-0.024
2^{nd} revision ($\overline{r^t_2}$)	-0.002	-0.001	-0.001	**0.015**	-0.015	0.001
3^{rd} revision ($\overline{r^t_3}$)	0.012	-0.004	-0.003	0.015	0.006	-0.003
Standard deviation of revisions						
1^{st} revision ($\sigma_{r^t_1}$)	0.110	0.082	0.033	0.066	0.104	0.151
2^{nd} revision ($\sigma_{r^t_2}$)	0.104	0.077	0.035	0.060	0.151	0.155
3^{rd} revision ($\sigma_{r^t_3}$)	0.109	0.088	0.039	0.076	0.186	0.197
Noise-to-signal ratio						
1^{st} revision ($\sigma_{r^t_1}/\sigma_{y^t_{t+24}}$)	0.241	0.385	0.482	0.310	0.272	0.382
2^{nd} revision ($\sigma_{r^t_2}/\sigma_{y^t_{t+24}}$)	0.228	0.365	0.505	0.285	0.396	0.391
3^{rd} revision ($\sigma_{r^t_3}/\sigma_{y^t_{t+24}}$)	0.240	0.414	0.571	0.360	0.488	0.499
Revisions-to-announcements ratio						
1^{st} revision ($\overline{r^t_1}/\overline{y^t_{t+3}}$)	-0.060	-0.054	0.022	0.182	-0.184	3.431
2^{nd} revision ($\overline{r^t_2}/\overline{y^t_{t+3}}$)	-0.008	-0.006	-0.010	0.415	0.273	-0.101
3^{rd} revision ($\overline{r^t_3}/\overline{y^t_{t+3}}$)	0.045	-0.019	-0.026	0.412	-0.113	0.403
A/C(1)						
1^{st} revision ($\rho_{r^t_1,r^{t-1}_1}$)	-0.014	0.113	**-0.200**	0.140	-0.078	-0.032
2^{nd} revision ($\rho_{r^t_2,r^{t-1}_2}$)	0.154	0.076	**0.308**	0.175	-0.040	-0.043
3^{rd} revision ($\rho_{r^t_3,r^{t-1}_3}$)	-0.032	0.011	0.145	0.024	-0.114	-0.098

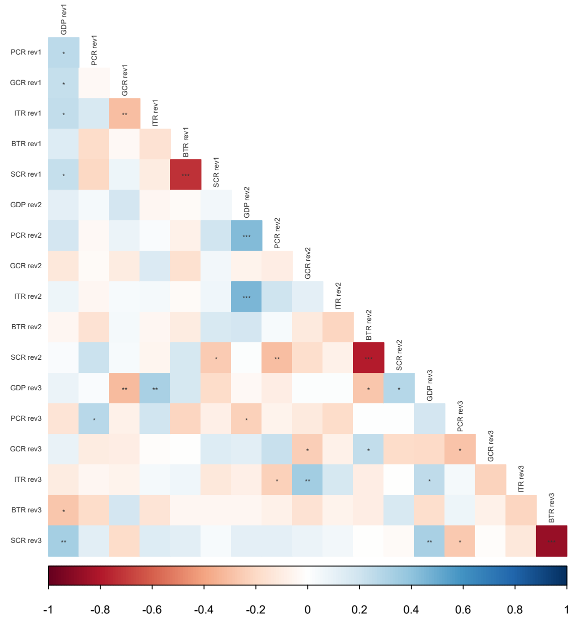
Table 2: Summary statistics for breakdown of revisions

	GDP growth rate	Private consumption contribution	Government consumption contribution	Investment contribution	Trade contribution	Inventories contribution
Panel C: Italy						
Mean of final series ($\overline{y^t_{t+24}}$)	0.003	0.013	0.004	-0.048	0.043	-0.008
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.184	0.173	0.110	0.161	0.377	0.476
Mean of revisions						
1^{st} revision ($\overline{r^t_1}$)	0.002	0.002	0.003	0.014	-0.006	-0.011
2^{nd} revision ($\overline{r^t_2}$)	-0.006	**-0.024**	**-0.015**	-0.004	**0.052**	-0.015
3^{rd} revision ($\overline{r^t_3}$)	0.003	-0.007	-0.003	-0.002	-0.019	0.035
Standard deviation of revisions						
1^{st} revision ($\sigma_{r^t_1}$)	0.072	0.075	0.043	0.101	0.238	0.266
2^{nd} revision ($\sigma_{r^t_2}$)	0.085	0.114	0.070	0.102	0.237	0.294
3^{rd} revision ($\sigma_{r^t_3}$)	0.133	0.132	0.069	0.105	0.289	0.372
Noise-to-signal ratio						
1^{st} revision ($\sigma_{r^t_1}/\sigma_{y^t_{t+24}}$)	0.120	0.228	0.427	0.286	0.538	0.570
2^{nd} revision ($\sigma_{r^t_2}/\sigma_{y^t_{t+24}}$)	0.142	0.345	0.699	0.290	0.537	0.631
3^{rd} revision ($\sigma_{r^t_3}/\sigma_{y^t_{t+24}}$)	0.222	0.400	0.688	0.298	0.654	0.799
Revisions-to-announcements ratio						
1^{st} revision ($\overline{r^t_1}/\overline{y^t_{t+3}}$)	0.672	0.052	0.189	-0.249	-0.380	0.679
2^{nd} revision ($\overline{r^t_2}/\overline{y^t_{t+3}}$)	-1.771	-0.578	-0.820	0.067	3.307	0.928
3^{rd} revision ($\overline{r^t_3}/\overline{y^t_{t+3}}$)	0.960	-0.174	-0.173	0.033	-1.216	-2.095
A/C(1)						
1^{st} revision ($\rho_{r^t_1,r^{t-1}_1}$)	**0.266**	0.061	0.118	-0.043	0.066	-0.008
2^{nd} revision ($\rho_{r^t_2,r^{t-1}_2}$)	0.034	-0.109	0.103	0.090	0.072	**0.220**
3^{rd} revision ($\rho_{r^t_3,r^{t-1}_3}$)	0.010	-0.013	-0.101	-0.151	**-0.255**	**-0.378**
Panel D: Spain						
Mean of final series ($\overline{y^t_{t+24}}$)	**0.392**	**0.187**	**0.084**	0.025	0.078	0.018
Standard deviation of final series ($\sigma_{y^t_{t+24}}$)	0.566	0.469	0.189	0.471	0.528	0.208
Mean of revisions						
1^{st} revision ($\overline{r^t_1}$)	0.009	0.018	0.003	-0.003	-0.007	-0.002
2^{nd} revision ($\overline{r^t_2}$)	-0.007	-0.007	0.000	0.021	-0.033	0.011
3^{rd} revision ($\overline{r^t_3}$)	-0.008	-0.028	-0.007	0.010	0.041	-0.024
Standard deviation of revisions						
1^{st} revision ($\sigma_{r^t_1}$)	0.098	0.125	0.156	0.130	0.216	0.153
2^{nd} revision ($\sigma_{r^t_2}$)	0.082	0.175	0.153	0.140	0.293	0.211
3^{rd} revision ($\sigma_{r^t_3}$)	0.097	0.242	0.116	0.172	0.380	0.293
Noise-to-signal ratio						
1^{st} revision ($\sigma_{r^t_1}/\sigma_{y^t_{t+24}}$)	0.173	0.267	0.827	0.277	0.408	0.736
2^{nd} revision ($\sigma_{r^t_2}/\sigma_{y^t_{t+24}}$)	0.144	0.374	0.809	0.297	0.555	1.015
3^{rd} revision ($\sigma_{r^t_3}/\sigma_{y^t_{t+24}}$)	0.172	0.516	0.613	0.365	0.720	1.412
Revisions-to-announcements ratio						
1^{st} revision ($\overline{r^t_1}/\overline{y^t_{t+3}}$)	0.023	0.091	0.031	0.978	-0.091	-0.068
2^{nd} revision ($\overline{r^t_2}/\overline{y^t_{t+3}}$)	-0.017	-0.033	0.000	-7.370	-0.422	0.340
3^{rd} revision ($\overline{r^t_3}/\overline{y^t_{t+3}}$)	-0.020	-0.136	-0.078	-3.408	0.527	-0.735
A/C(1)						
1^{st} revision ($\rho_{r^t_1,r^{t-1}_1}$)	0.015	-0.029	**-0.207**	0.151	0.022	**0.207**
2^{nd} revision ($\rho_{r^t_2,r^{t-1}_2}$)	0.095	-0.030	**-0.265**	-0.008	-0.010	-0.106
3^{rd} revision ($\rho_{r^t_3,r^{t-1}_3}$)	-0.168	0.071	-0.105	**-0.230**	-0.066	**0.230**

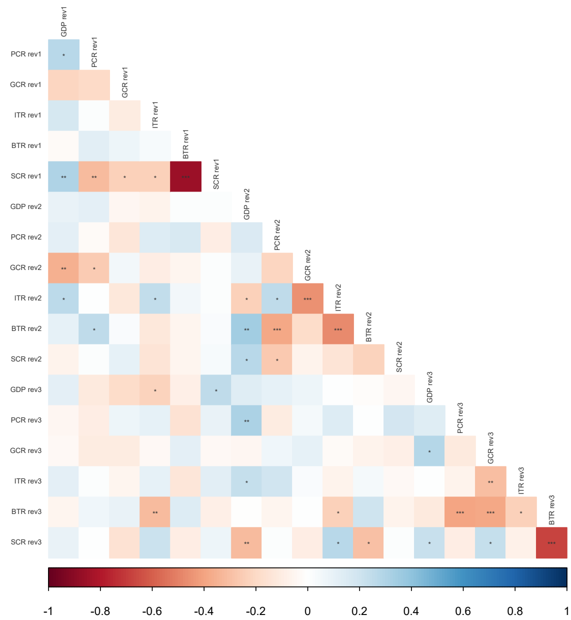
Figure 1: Correlation Matrix



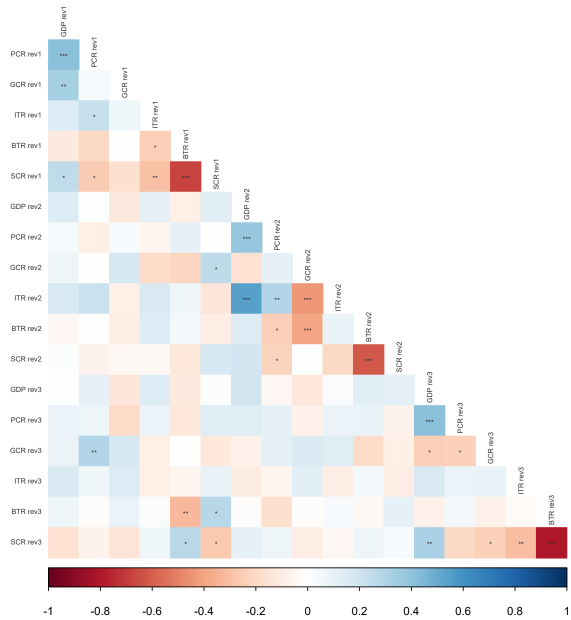
(a) Germany



(b) France



(c) Italy



(d) Spain

Table 3: Joint F-statistics (robust Wald statistic) for news and noise

Germany	**GDP**	**PCR**	**GCR**	**ITR**	**BTR**	**SCR**
News	4.22**	1.91	14.68***	1.08	9.98***	4.72**
Noise	2.29*	16.77***	12.87***	2.39*	0.75	1.07
France	**GDP**	**PCR**	**GCR**	**ITR**	**BTR**	**SCR**
News	1.66	1.69	2.69*	4.08**	2.94**	5.54***
Noise	14.82***	7.37***	21.08***	23.52***	4.25**	2.25
Italy	**GDP**	**PCR**	**GCR**	**ITR**	**BTR**	**SCR**
News	0.37	1.11	9.73***	3.82**	12.30***	18.59***
Noise	4.21**	22.24***	25.10***	0.70	3.53**	4.62**
Spain	**GDP**	**PCR**	**GCR**	**ITR**	**BTR**	**SCR**
News	0.33	1.37	19.82***	1.16	6.51***	9.56***
Noise	0.63	7.25***	4.11**	5.22***	7.77***	19.74***

Notes: The results above show the joint F-statistics (robust Wald statistic) for each regression and each component. 1%, 5% and 10% significance levels are denoted by ***, ** and * respectively. Where we have defined as PCR: Private Consumption Contribution; GCR: Government Consumption Contribution; ITR: Investment Contribution; BTR: Trade Contribution; SCR: Inventories Contribution.

Table 4: Results OLS - by country

	Germany				France			
	r_1^t	r_2^t	r_3^t	r_T^t	r_1^t	r_2^t	r_3^t	r_T^t
Private Consumption	-0.646***	-0.923***	-0.703***	-0.650***	-0.744***	-0.633***	-0.613***	-0.560***
	(0.080)	(0.118)	(0.118)	(0.112)	(0.144)	(0.138)	(0.138)	(0.143)
Government Consumption	-0.853***	-0.956***	-0.600***	-0.455**	-0.243	-0.048	-1.067***	-0.419
	(0.104)	(0.184)	(0.173)	(0.193)	(0.325)	(0.306)	(0.271)	(0.286)
Investment Contribution	-0.873***	-0.751***	-0.810***	-0.928***	-0.319*	-0.347*	-0.393**	-0.276*
	(0.103)	(0.199)	(0.138)	(0.139)	(0.176)	(0.180)	(0.147)	(0.158)
Trade Contribution	-0.969***	-0.931***	-0.975***	-1.004***	-0.863***	-0.842***	-0.862***	-0.844***
	(0.041)	(0.059)	(0.068)	(0.071)	(0.105)	(0.070)	(0.058)	(0.080)
Constant	0.013	0.019	0.014	0.030	-0.021*	-0.008	0.003	-0.025
	(0.011)	(0.014)	(0.017)	(0.024)	(0.011)	(0.011)	(0.011)	(0.018)
Observations	74	74	74	74	74	74	74	74
R^2	0.915	0.838	0.800	0.785	0.655	0.689	0.804	0.640

	Italy				Spain			
	r_1^t	r_2^t	r_3^t	r_T^t	r_1^t	r_2^t	r_3^t	r_T^t
Private Consumption	-0.884***	-0.789***	-0.734***	-0.602***	-0.898***	-0.851***	-0.962***	-0.695***
	(0.114)	(0.085)	(0.085)	(0.117)	(0.098)	(0.064)	(0.064)	(0.072)
Government Consumption	-1.219***	-1.050***	-1.165***	-1.086***	-0.840***	-0.734***	-0.937***	-0.711***
	(0.200)	(0.136)	(0.224)	(0.185)	(0.096)	(0.081)	(0.117)	(0.089)
Investment Contribution	-0.894***	-0.844***	-0.864***	-0.816***	-1.012***	-0.860***	-0.972***	-0.780***
	(0.084)	(0.095)	(0.145)	(0.124)	(0.121)	(0.081)	(0.077)	(0.096)
Trade Contribution	-1.054***	-0.958***	-1.030***	-1.066***	-0.778***	-0.930***	-0.984***	-0.775***
	(0.035)	(0.041)	(0.053)	(0.053)	(0.073)	(0.044)	(0.043)	(0.065)
Constant	0.001	-0.003	0.004	0.010	0.008	-0.006	-0.007	-0.006
	(0.008)	(0.010)	(0.015)	(0.020)	(0.011)	(0.009)	(0.012)	(0.017)
Observations	74	74	74	74	74	74	74	74
R^2	0.934	0.929	0.885	0.881	0.678	0.873	0.891	0.697

Note: Standard errors in parenthesis; ***:$p < 0.01$,**:$p < 0.05$,*:$p < 0.1$

Table 5: Results OLS - Summary

	r_1^t					r_2^t					r_3^t					r_T^t				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
A) Germany																				
PCR	-0.646***		-0.097***			-0.923***		-0.799***			-0.703***		-0.848***			-0.650***		-0.837***		
	(0.080)		(0.128)			(0.118)		(0.156)			(0.119)		(0.155)			(0.113)		(0.144)		
GCR	-0.853***			-1.023***		-0.956			-0.880		-0.560***			-0.847***		-0.455**			-0.595**	
	(0.104)			(0.206)		(0.184)			(0.246)		(0.173)			(0.249)		(0.193)			(0.298)	
ITR	-0.873***				-1.237***	-0.751***				-1.180***	-0.810***				-1.030***	-0.928***				-1.153***
	(0.103)				(0.167)	(0.199)				(0.261)	(0.138)				(0.171)	(0.139)				(0.166)
BTR	-0.969***	-0.821***	-0.896***	-0.820***	-0.961***	-0.931***	-0.920 ***	-0.948 ***	-0.891 ***	-0.942***	-0.975***	-0.824***	-0.860***	-0.799***	-1.000***	-1.000***	-0.799***	-0.890***	-0.795***	-0.970***
	(0.041)	(0.092)	(0.069)	(0.079)	(0.072)	(0.060)	(0.094)	(0.081)	(0.087)	(0.083)	(0.068)	(0.107)	(0.090)	(0.093)	(0.087)	(0.071)	(0.114)	(0.093)	(0.105)	(0.087)
Constant	0.014	0.010	0.004	0.022	0.007	0.019	-0.022	0.006	-0.019	-0.013	0.014	0.013	0.027	0.010	0.002	0.030	0.002	0.039	0.008	-0.004
	(0.011)	(0.024)	(0.018)	(0.021)	(0.018)	(0.014)	(0.021)	(0.019)	(0.019)	(0.018)	(0.017)	(0.026)	(0.022)	(0.024)	(0.021)	(0.024)	(0.037)	(0.031)	(0.036)	(0.029)
Observations	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74
R^2	0.915	0.528	0.737	0.649	0.734	0.828	0.573	0.688	0.638	0.668	0.780	0.488	0.640	0.560	0.660	0.785	0.436	0.618	0.466	0.665
B) France																				
PCR	-0.744***		-0.853***			-0.633***		-0.671***			-0.613***		-0.755***			-0.560***		-0.640***		
	(0.144)		(0.134)			(0.138)		(0.138)			(0.126)		(0.136)			(0.143)		(0.135)		
GCR	-0.243			-0.440		-0.048			0.132		-1.066***			-1.199**		-0.419			-0.231	
	(0.144)			(0.406)		(0.306)			(0.350)		(0.271)			(0.338)		(0.286)			(0.323)	
ITR	-0.319*				-0.662***	-0.347*				-0.458**	-0.393***				-0.596***	-0.276*				-0.444***
	(0.176)				(0.191)	(0.180)				(0.196)	(0.147)				(0.177)	(0.158)				(0.159)
BTR	-0.863***	-0.955***	-0.850***	-0.960***	-0.949***	-0.842***	-0.771***	-0.828***	-0.770***	-0.793***	-0.862***	-0.843***	-0.868***	-0.811***	-0.886***	-0.844***	-0.747***	-0.826***	-0.760***	-0.755***
	(0.105)	(0.130)	(0.106)	(0.130)	(0.121)	(0.070)	(0.080)	(0.071)	(0.081)	(0.078)	(0.058)	(0.076)	(0.064)	(0.071)	(0.072)	(0.080)	(0.089)	(0.079)	(0.091)	(0.085)
Constant	-0.021*	-0.015	-0.024**	-0.014	-0.010	-0.008*	-0.011	-0.013	-0.011	-0.004	-0.003	-0.002	-0.0001	-0.001	0.011	-0.025	-0.026	-0.035**	-0.026	-0.010
	(0.011)	(0.013)	(0.011)	(0.013)	(0.013)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.014)	(0.012)	(0.013)	(0.013)	(0.018)	(0.020)	(0.018)	(0.020)	(0.020)
Observations	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74
R^2	0.655	0.429	0.636	0.438	0.512	0.689	0.562	0.671	0.563	0.593	0.804	0.630	0.742	0.685	0.681	0.640	0.497	0.618	0.501	0.547

Note: Standard errors in parenthesis; *******:$p < 0.01$,******:$p < 0.05$,*****:$p < 0.1$

Table 5: Results OLS - Summary

	r_1^t					r_2^t					r_3^t					r_T^t				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
C) Italy																				
PCR	-0.884***		-0.715***			-0.789***		-0.927***			-0.734***		-0.612***			-0.602***		-0.528***		
	(0.114)		(0.194)			(0.085)		(0.140)			(0.118)		(0.156)			(0.117)		(0.170)		
GCR	-1.219***			-0.812**		-1.050***			-0.981***		-1.165***			-0.857***		-1.086***			-1.007	
	(0.200)			(0.359)		(0.136)			(0.265)		(0.224)			(0.310)		(0.185)			(0.259)	
ITR	-0.894***				-0.901***	-0.844***				-0.950***	-0.864***				-0.803***	-0.816***				-0.929***
	(0.084)				(0.120)	(0.095)				(0.163)	(0.145)				(0.192)	(0.124)				(0.159)
BTR	-1.054***	-0.967***	-0.949***	-0.986***	-1.048***	-0.958***	-1.015***	-1.071***	-0.967***	-0.955***	-1.030***	-1.110***	-1.073***	-1.095***	-1.095***	-1.066***	-1.051***	-1.042***	-1.064***	-1.063***
	(0.036)	(0.066)	(0.061)	(0.065)	(0.051)	(0.041)	(0.084)	(0.067)	(0.079)	(0.070)	(0.053)	(0.077)	(0.071)	(0.074)	(0.070)	(0.053)	(0.082)	(0.078)	(0.075)	(0.068)
Constant	-0.001	-0.017	-0.015	-0.014	-0.005	-0.003	0.038	0.018	0.020	0.031	0.004	0.013	0.010	0.011	0.012	0.010	0.036	0.021	0.022	0.045*
	(0.008)	(0.016)	(0.014)	(0.015)	(0.012)	(0.010)	(0.020)	(0.016)	(0.019)	(0.017)	(0.015)	(0.022)	(0.020)	(0.021)	(0.020)	(0.020)	(0.031)	(0.030)	(0.028)	(0.026)
Observations	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74
R^2	0.934	0.748	0.788	0.765	0.859	0.923	0.669	0.795	0.723	0.776	0.885	0.740	0.786	0.766	0.792	0.881	0.695	0.731	0.748	0.793
D) Spain																				
PCR	-0.898***		-0.607***			-0.851***		-0.509***			-0.962***		-0.733***			-0.695***		-0.418***		
	(0.098)		(0.135)			(0.064)		(0.093)			(0.057)		(0.102)			(0.072)		(0.095)		
GCR	-0.840***			-0.113		-0.734***			-0.049		-0.937***			-0.312		-0.711***			-0.259**	
	(0.096)			(0.114)		(0.081)			(0.127)		(0.117)			(0.270)		(0.089)			(0.120)	
ITR	-1.012				-0.387***	-0.860***				-0.327**	-0.972***				-0.531***	-0.780***				-0.184
	(0.121)				(0.147)	(0.081)				(0.126)	(0.077)				(0.166)	(0.096)				(0.126)
BTR	-0.777***	-0.164**	-0.301***	-0.180**	-0.276***	-0.930***	-0.499***	-0.616***	-0.509***	-0.533***	-0.984***	-0.435***	-0.649***	-0.474***	-0.517***	-0.775***	-0.223***	-0.342***	-0.262***	-0.282***
	(0.073)	(0.081)	(0.078)	(0.083)	(0.089)	(0.044)	(0.061)	(0.056)	(0.066)	(0.060)	(0.043)	(0.075)	(0.065)	(0.082)	(0.075)	(0.065)	(0.064)	(0.063)	(0.065)	(0.075)
Constant	0.008	-0.003	0.007	-0.003	-0.005	-0.006	-0.005	-0.012	-0.005	-0.001	-0.007	-0.006	-0.018	-0.008	0.002	-0.006	-0.015	-0.021	-0.016	-0.010
	(0.011)	(0.017)	(0.016)	(0.017)	(0.017)	(0.009)	(0.018)	(0.015)	(0.018)	(0.017)	(0.012)	(0.029)	(0.022)	(0.028)	(0.027)	(0.017)	(0.027)	(0.024)	(0.027)	(0.027)
Observations	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74	74
R^2	0.678	0.054	0.263	0.066	0.138	0.873	0.483	0.636	0.484	0.528	0.891	0.318	0.607	0.330	0.404	0.697	0.144	0.327	0.197	0.169

Note: Standard errors in parenthesis; *******:$p < 0.01$,******:$p < 0.05$,*****:$p < 0.1$

Table 6: Forecast comparison of GDP initial announcements 1 and 4 periods ahead

	Germany		France		Italy		Spain	
	h=1	h=4	h=1	h=4	h=1	h=4	h=1	h=4
pre-Covid	0.913	1.045	0.859*	1.042	1.134	0.966	0.891*	0.870**
Covid	0.987**	0.971	0.997	1.052	0.990	0.948	0.998	1.027
full sample	0.934*	1.021	0.899	1.045	1.093	0.960	0.923	0.920

Notes: The results above show the ratio of the average RMSFEs when comparing the forecasts between the standard V-VAR model without the components and our real-time CV-VAR model with components. A value less than one indicates that the CV-VAR approach performs better on average than the alternative. The Diebold-Mariano statistic is also applied and we show the statistical significance with asterisks, ***:$p < 0.01$,**:$p < 0.05$,*:$p < 0.1$.

Table 7: Forecast comparison of GDP revisions 1 and 4 periods ahead

Germany

	1st rev.	2nd rev.	3rd rev.	1st rev.	2nd rev.	3rd rev.
		h=1			h=4	
pre-Covid	0.9032	1.0182	0.9823	0.9903	1.0077	0.9984
Covid	0.7344	1.0742**	0.6881***	0.6342	1.1519	0.8278
full sample	0.7624	1.0581	0.8512**	0.6791	1.1043	0.9223

France

	1st rev.	2nd rev.	3rd rev.	1st rev.	2nd rev.	3rd rev.
		h=1			h=4	
pre-Covid	1.0137	1.2763	1.0056	1.0355*	0.9716	1.0036
Covid	0.8162*	0.5745	0.7364	0.4084	0.1642	0.4699
full sample	0.8659	0.6789	0.8539	0.4883	0.18525	0.5894

Italy

	1st rev.	2nd rev.	3rd rev.	1st rev.	2nd rev.	3rd rev.
		h=1			h=4	
pre-Covid	1.0935	1.0965	0.9434	1.0706*	0.9951	1.0020
Covid	0.6938	0.9758	1.1359	0.1476	0.1681	0.6810
full sample	0.7827	1.0573	1.0197	0.1721	0.2911	0.7657

Spain

	1st rev.	2nd rev.	3rd rev.	1st rev.	2nd rev.	3rd rev.
		h=1			h=4	
pre-Covid	1.2598	0.9521	1.1008	1.0655*	0.9433	1.0047
Covid	0.8887	0.5558*	0.4440	0.3300	0.1374	0.0552
full sample	0.8912	0.5749	0.7613	0.3317	0.1430	0.1205

Notes: The results above show the ratio of the average RMSFEs when comparing between the direct forecasts of GDP revisions via the standard V-VAR model without the components and the indirect forecast of GDP revisions via the components revisions using our real-time CV-VAR model. A value less than one indicates that the CV-VAR approach performs better on average than the alternative. The Diebold-Mariano statistic is also applied and we show the statistical significance with asterisks, ***:$p < 0.01$,**:$p < 0.05$,*:$p < 0.1$.

Appendix A

Table A1: Results Pooled OLS - Fixed Effects

	r_1^t	r_2^t	r_3^t	r_T^t
Private Consumption	-0.770***	-0.829***	-0.825***	-0.680***
	(0.051)	(0.045)	(0.045)	(0.050)
Government Consumption	-0.811***	-0.785***	-0.859***	-0.779***
	(0.058)	(0.059)	(0.083)	(0.072)
Investment Contribution	-0.889***	-0.818***	-0.821***	-0.824***
	(0.057)	(0.056)	(0.058)	(0.058)
Trade Contribution	-0.925***	-0.938***	-0.953***	-0.927***
	(0.027)	(0.024)	(0.026)	(0.032)
Constant	0.0001	0.001	0.006	0.008
	(0.005)	(0.005)	(0.007)	(0.010)
Observations	296	296	296	296
R^2	0.8354	0.8523	0.8409	0.7693

Note: Standard errors in parenthesis; ***:$p < 0.01$,**:$p < 0.05$,*:$p < 0.1$

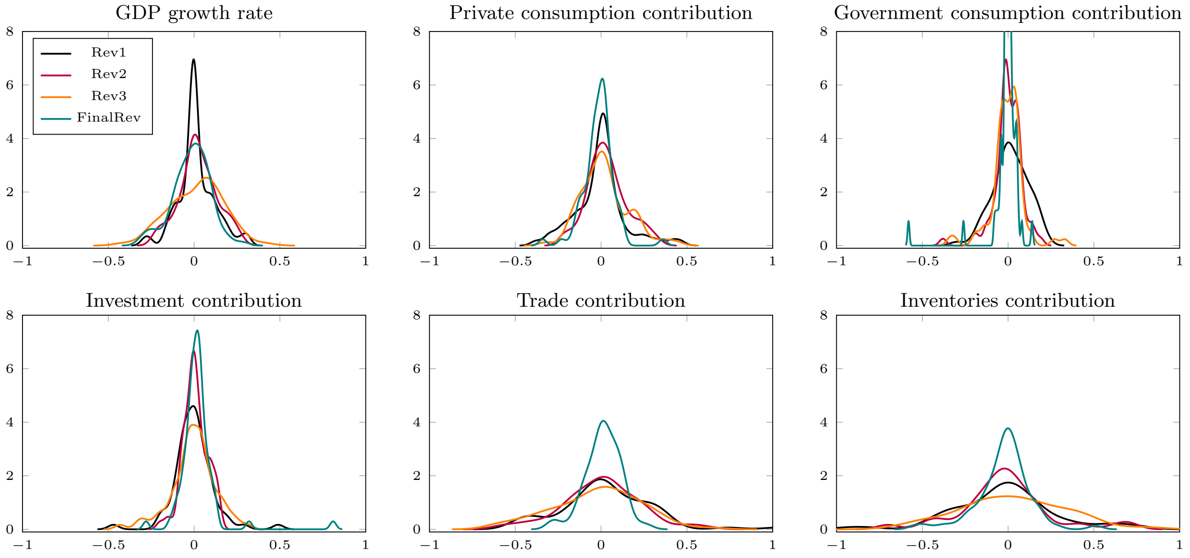
Table A2: COVID Annex: Summary Statistics of 1^{st} Revisions

	GDP growth rate	Private consumption contribution	Government consumption contribution	Investment contribution	Trade contribution	Inventories contribution
Panel A: Germany						
Mean of 1^{st} revision ($\overline{r_1^t}$)	0.062	0.156	0.058	0.035	-0.018	-0.170
Standard deviation of 1^{st} revision ($\overline{r_1^t}$)	0.189	0.236	0.273	0.206	0.179	0.450
Noise-to-signal ratio ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	-0.257	-0.488	0.804	-0.302	0.390	-0.984
A/C(1) ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	**-0.661**	-0.328	-0.552	-0.388	-0.285	**-0.743**
Panel B: France						
Mean of 1^{st} revision ($\overline{r_1^t}$)	0.044	0.078	**-0.150**	0.108	-0.056	0.064
Standard deviation of 1^{st} revision ($\overline{r_1^t}$)	0.250	0.264	0.208	0.388	0.216	0.265
Noise-to-signal ratio ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	0.149	0.686	-0.505	-7.442	0.911	-1.469
A/C(1) ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	-0.222	-0.475	0.171	0.223	-0.680	**-0.576**
Panel C: Italy						
Mean of 1^{st} revision ($\overline{r_1^t}$)	-0.024	0.042	0.025	-0.071	0.069	-0.089
Standard deviation of 1^{st} revision ($\overline{r_1^t}$)	0.135	0.151	0.127	0.215	0.185	0.247
Noise-to-signal ratio ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	-0.101	-0.326	1.504	-0.175	-0.635	-1.639
A/C(1) ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	0.284	-0.280	0.088	0.171	-0.259	-0.398
Panel D: Spain						
Mean of 1^{st} revision ($\overline{r_1^t}$)	-0.095	0.147	-0.108	0.119	**-0.275**	0.022
Standard deviation of 1^{st} revision ($\overline{r_1^t}$)	0.755	0.964	0.221	0.360	0.366	0.352
Noise-to-signal ratio ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	2.196	-0.844	-0.480	-0.505	-1.786	-1.936
A/C(1) ($\sigma_{r_T^t}/\sigma_{y_{t+24}^t}$)	-0.326	-0.069	-0.099	0.502	**-0.844**	0.493

Note: N = 8, Boldface denotes significance at the 10% level

Figure A1: Kernel distribution breakdown

Panel A: Germany



Panel B: France

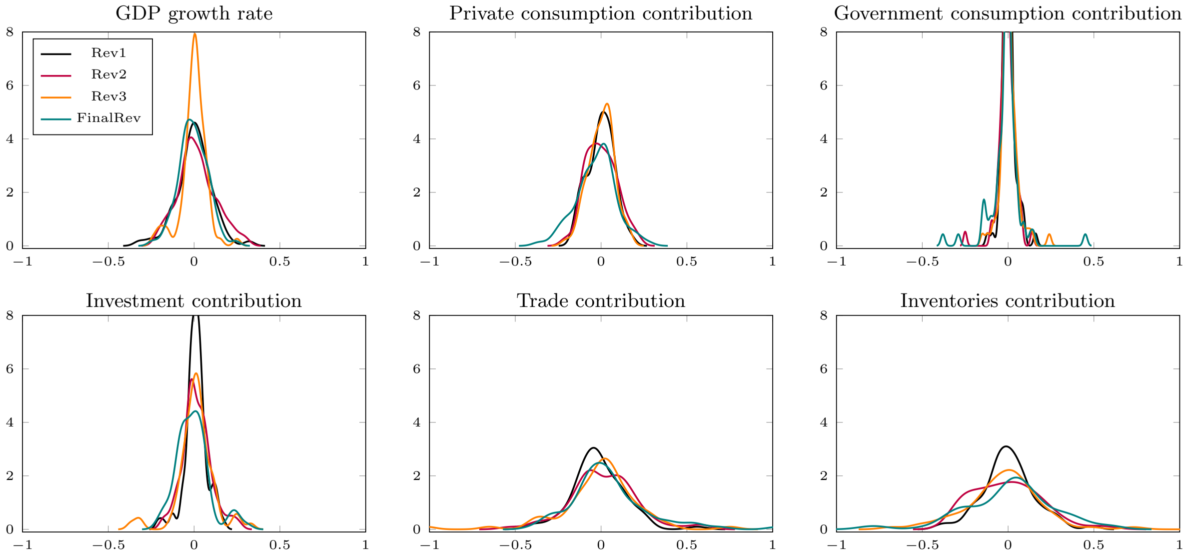


Figure A1: Kernel distribution breakdown

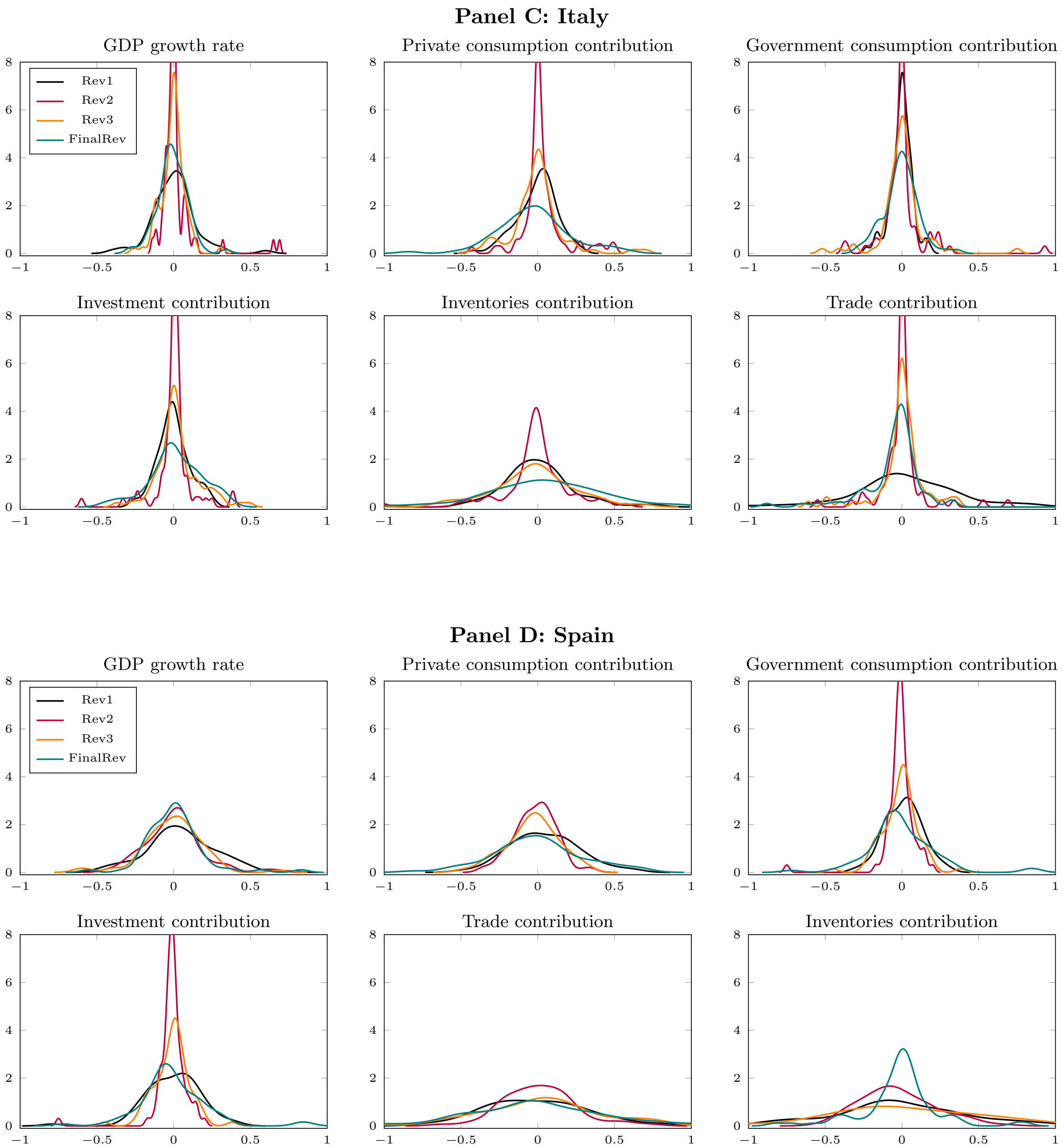
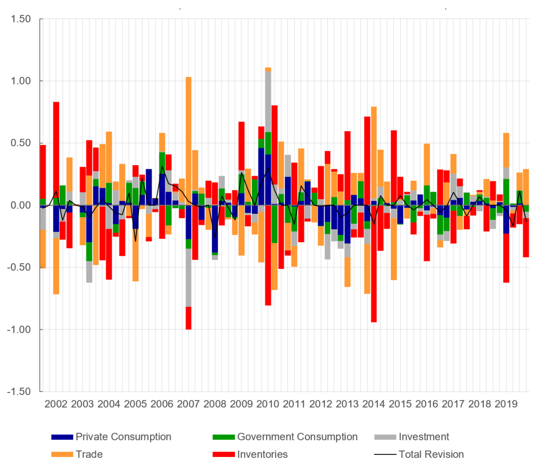
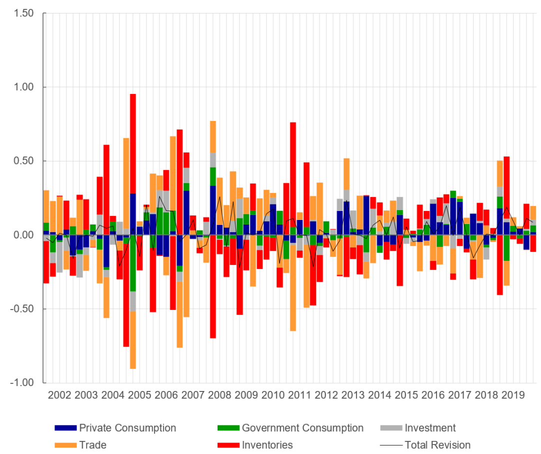
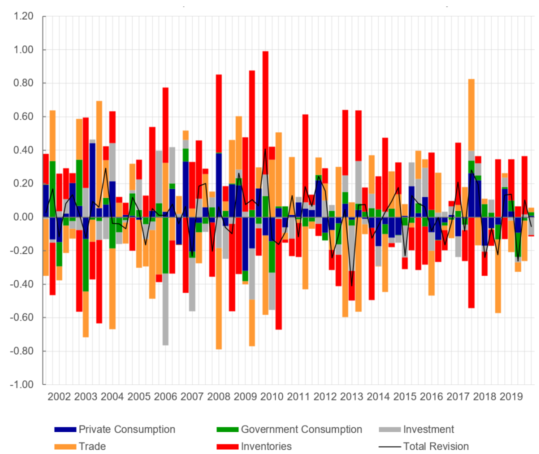


Table A3: Graphs

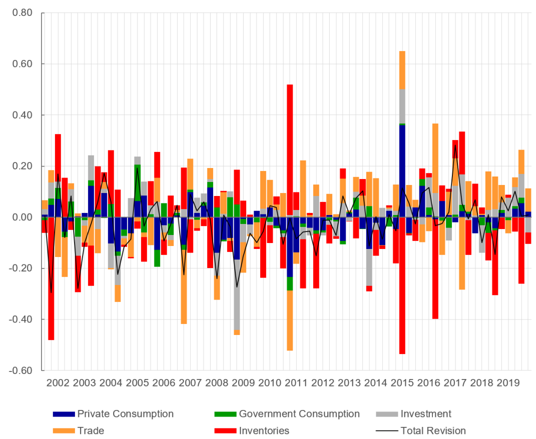
r_1^t	r_2^t	r_3^t

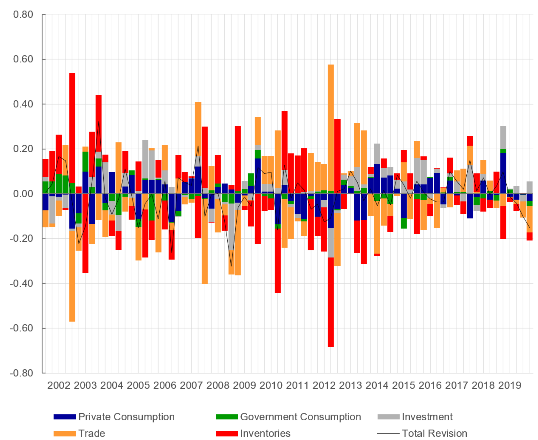


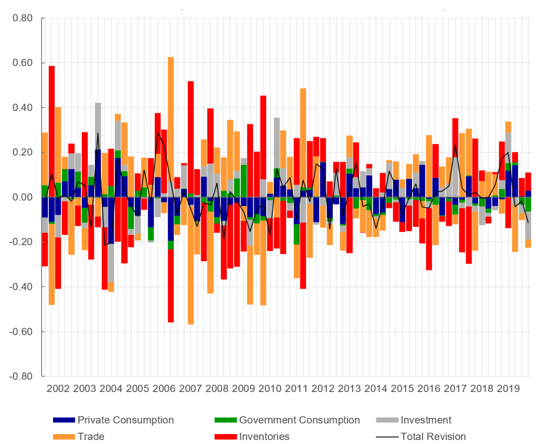




a) Germany

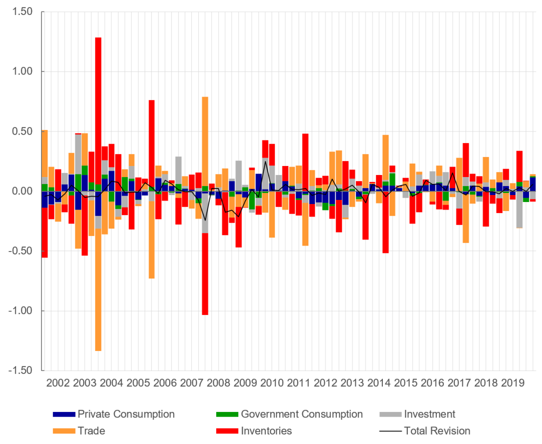
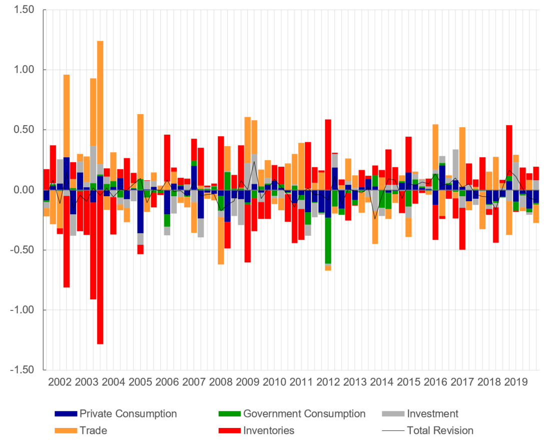
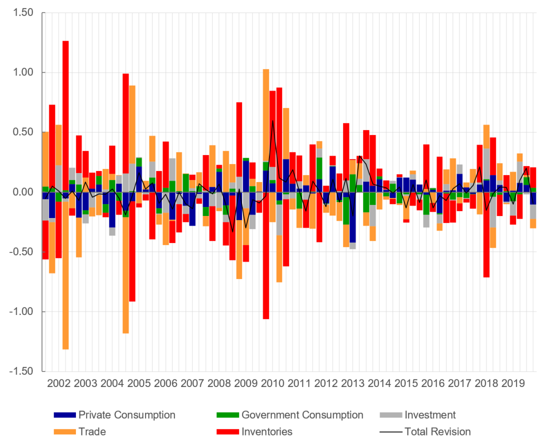




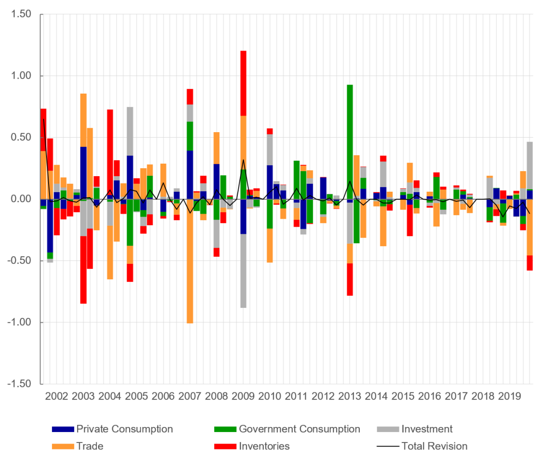
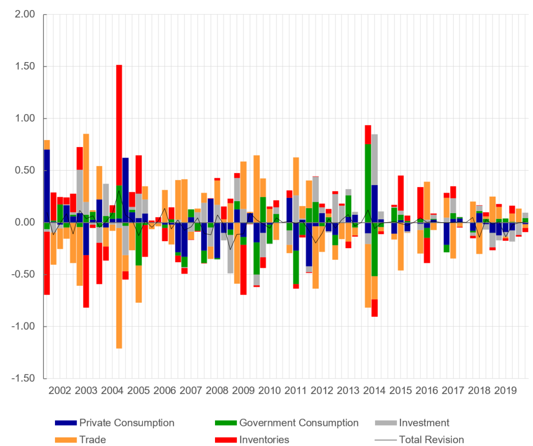
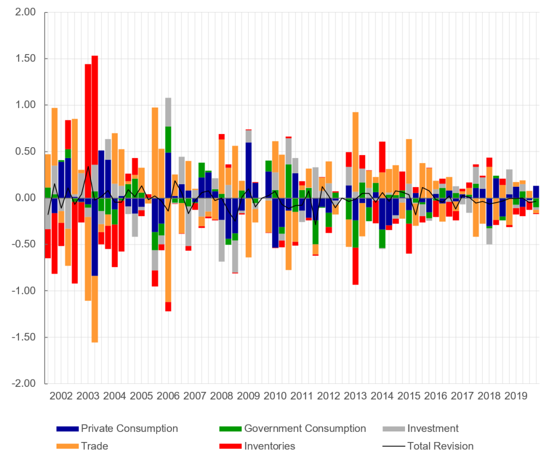


a) France

Table A4: Graphs

r_1^t	r_2^t	r_3^t
		

c) Italy

d) Spain

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