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REVISIONS IN OFFICIAL DATA AND FORECASTING

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Revisions in official data and forecasting*

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Abstract

This paper deals with the topic of revision of data with the aim of investigating whether consecutive releases of macroeconomic series published by statistical agencies contain useful information for economic analysis and forecasting. The rationality of the revisions process is tested considering the complete history of data and an empirical application to show the usefulness of revisions for improving the precision of forecasting model is proposed. The results for Italian GDP show that embedding the revision process in a dynamic factor model helps to reduce the forecast error.

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1 Introduction

Most macroeconomic data are uncertain - they are estimates rather than perfect measures. Measurement errors may arise because data are based on incomplete samples or because many variables are not easily observable. One symptom of data uncertainty is the propensity of statistical agencies to revise their estimates in the light of new information (larger samples) or methodological advances. As a result, past revisions give a measure of the potential for measurement errors surrounding the latest published estimates.

The inaccuracy of preliminary data obviously complicates decision making by policymakers and other agents whose optimal choice is conditioned to the knowledge of the state of the economy. Revisions to the recent profile of macroeconomic data may affect also the forecasts generated by economic models. Taking published data at face value, ignoring the potential for future revisions, may result in avoidable forecast errors. If data revisions are small and random, then the revisions probably do not matter much for forecasting. But the evidence suggests that data revisions are generally large and systematic.

Following Stark and Croushore (2001) it is possible to consider three key ways in which data revisions can affect model performance: (1) revisions affect the data input into the model; (2) revisions change the estimated coefficients; and (3) revisions lead to a change in the lag structure of the model, or other model specification changes.

Clearly, the magnitude of these effects depends on the data in question and the size of the revisions to the data. For some series revisions may be close to white noise, in which case we would not expect forecasts to change very much by using different releases of data. But for other series, the revision could be very large and idiosyncratic, causing huge changes in the forecasts. Hence, testing for and assessing the rationality of early economic data releases is a topic of considerable importance from both a theoretical and an empirical perspective.

Most of the relevant literature on data revision can be grouped around two different themes. The first group of studies focus on detailing the nature of data revisions, testing for and assessing the rationality of early data release. In brief, two key questions have been addressed: the presence of a bias term in early releases and the predictability of later release using information available at the time of the first release. Indeed, if subsequent data revisions are not predictable using information available at the time of the first release, then early releases are rational forecasts of final data and the revision error series only takes into account news. Hence it is common in the literature to distinguish between the "news hypothesis" versus the "noise hypothesis".

There is no agreement concerning which hypothesis of the two prevails, as the empirical evidence differs across macroeconomic series and time spans, as well as across different methodologies.

For example, Mankiw and Shapiro (1986) find that revisions in GNP are substantially news, but revision in the money stock are better characterized as noise. In a recent paper, Faust, Rogers and Wright (2005) find that for US data, later release are only very marginally predictable, and so there is no strong evidence against the news hypothesis. On the other hand, for UK, Japan and Italy there is rather striking evidence in support of the noise hypothesis. Using a different dataset, Fixler and Grimm (2006) analyze the reliability of their National Income product account and they conclude that revisions are not predictable. Aruoba (2006) finds that for most US macroeconomic series, revision errors have a positive bias, and are highly predictable using information available at the time of their first release.

The second group of studies focus on deriving the optimal forecasts or smoothed estimates of "true" values for a postulated data revision process. This is generally done in the State Space framework, first suggested by Howrey(1978), and more recently applied in different variants to deal with specific cases. For example, Busetti (2001) suggests two simple methods of reducing the impact of the noise in the provisional data: modifying the initial condition of the forecasts by weighting the preliminary observations with the model predictions and using intercept corrections, i.e. adjustments to the constant term of certain equations of the model. Harrison, Kapetanios and Yates (2004) suggest that when measurement uncertainties are greatest, models that downweight recent "experience" may have a superior forecasting performance than models in which all observations are equally weighted. Another alternative is proposed by Kaptanios and Yates (2004) which set out a model that exploits behavioral assumption about the statistical agency producing real-time data. In other words, the model assumption is a conjecture about the scheme used by the statistical agency to weight new information together with old information. Recently, Cunningham et al. (2009) suggest a state-space approach to extract the signal from uncertain data. As long as revisions tend to improve data estimates, moving them towards the truth, the problem boils down to predict the cumulative impact of revisions on the latest estimates of current and past activity. Starting from the works of Aruoba (2006) and Siklos(2006), who note that data revisions typically show more complex behavior than standard models, Jacobs and van Norden (2006) describe a more general State-Space Model that allows for more flexibility in the dynamics of revisions. In this model the authors allow for serial correlation across releases and argue that spillover in measurement errors within any release may also be important.

Referring to the first group of studies, this work inspects the entire revision history rather than just looking at the properties of first versus final releases of data so that it can assess whether earlier releases are in any sense "less rational" than later releases. Put another way, makes it possible to measure how long it takes before the observed data became rational. In addition, this study includes revision histories in the information set used to examine the rationality of a particular release of data. This allows to assess whether the remaining revision is predictable from its own past, suggesting in turns whether revision histories can be used to construct "better" preliminary release of data. Moreover, an application to Italian data is shown in which the evidence suggests that the revision process of the Italian GDP cannot be considered as a rational forecast of final data.

Following the approach of the second group of studies, a short-term forecast model that takes into account data revisions is proposed with the aim to investigate whether the inclusion of data revision improves the performance of an econometric model, producing more accurate estimates and forecasts.

The paper is organized as follow. Section 2 analyses the main features of the Italian revision process and test for rationality. Section 3 presents an empirical application showing that revisions do affect forecast accuracy and thus not rational revisions might be used to improve forecast ability. Concluding remarks end.

2 Rationality of revisions

This section presents an application to assess the rationality of revisions in Italian data testing the hypothesis of noise versus news.

Exploiting the recent data in real time provided by ISTAT, an application to test rationality of Italian National Accounts data is proposed by considering the all history of data.

ISTAT officially revises twice GDP figures for a given quarter. The first estimates of GDP growth rate is released about 45 days after the end of the referring quarter and this is the so-called *flash* estimate. Although it is very useful to have an early estimate of GDP, it has the disadvantage to be based on incomplete information. Using more comprehensive information, the revision of this figure is published about 25 days after the flash and this is the so-called first estimates.

This paper only focuses on growth rates of variables rather than levels, in order to avoid problems such as cointegration and benchmark revisions[1].

Moreover, as final revision is taken the value published 3 years after the end of the respective quarter[2].

The first part of this Section (paragraph 2.1) presents a preliminary analysis to evaluate rationality of Italian National Accounts data by computing summary statistics that can be calculated when performing a revision analysis (McKenzie and Gamba, 2008). The remaining part (paragraph 2.2) introduces standard rationality tests proposed in the literature and provides an application using Swanson-van Dijk test of rationality (Swanson and van Dijk, 2006).

2.1 Preliminary analysis

Thanks to the recent real time dataset provided by ISTAT[3], a preliminary analysis to evaluate predictability of revisions is proposed.

However, rather than examining only preliminary and fully revised data, as is usually the practice, the entire revision history for the variable in question will be considered. This allows to asses, for example whether earlier releases of data are "less" rational than later releases and when the revision process becomes rational.

Table 1 and Table 2 show some summary statistics on both intermediate revision process and final, grouping the measures into five classes: size of revisions, direction of revisions, variability of revisions, impact of revisions on the sign of growth rate and efficiency of revisions.

First, we notice that the range of final revisions is quite large. For example, the

[1]Most of the revisions are due to arrival of new information. However, occasionally (about every 5 years) statistical agencies make changes to their methodologies (change of base year, seasonal weights, etc.). Such revisions are called *benchmark revisions*. For some variables, such as real output, benchmark revisions are problematic because they raise the problem of incoherence with old information set.

[2]In the literature, the final revision is usually defined as the difference between the latest available observation for the variable and its initial announcement. This may not necessarily be the best choice due the benchmark revision. It is true that benchmark revisions often use new information and enhance the existing estimates. However, it is not reasonable to expect benchmark revision in the 1990s to have some *new* information about 1970s. Moreover, benchmark revisions may distort how the economy looks in the past. This would suggest, therefore, to include as many revisions as possible in order to include all relevant revisions, but to avoid including too many benchmark revisions.

[3]The Triangle of revision data is available at:
http://www.istat.it/salastampa/comunicati/non_calendario/20101013_00/
from 1999Q1 through 2010Q2. To obtain a larger dataset we integrate such data with information from the EBCN's Real Time Database. In this way preliminary data are available from 1993Q2.

revision between the preliminary estimate and the final value fluctuates between -0.23 and 0.24 and it remains quite high even in later revisions. This result holds even considering other measures, such as the range that 90 percent of revisions lie within ($Range_{90}$) which is useful to give a normal range not affected by unusually large revisions or outliers.

Moreover, interesting consideration comes from the analysis of the noise-to-signal ratio (N/S). This statistic is defined as the standard deviation of final revisions divided by the standard deviation of the final value and it can give an idea about the size of the original variables. The values range from 0.17 to 0.46 with an average of 0.31. This can be considered as a sizable value compared with the results of Aruoba (2008) who finds an average of the noise-to-signal ratios of 0.39 for revisions on 19 US macroeconomic variables.
This result may suggest that rationality is not supported by the data.

For more details on all statistics listed in the Tables 1 and 2, refer to Appendix.

Following Aruoba (2006), from a statistical point of view, one of the properties that the final revisions have to satisfy to be "well behaved" is that their mean is zero. This would imply that the initial announcement of the statistical agency is an unbiased estimate of the final value. Moreover, if the revision process was rational, we would expect that the news contained in updated data is helpful in predicting final data, which implies that prior revisions should be more biased than subsequent revisions.

The Figure 1 shows the mean of the final revisions (i.e. the difference between each subsequent release and the final estimate) occurred during the period of three years from the date of initial release. The red circles in the graph show a significant bias of the current revision. In computing , the test of significance for these means, Newey-West (Newey and West, 1987) heteroskedasticity and autocorrelation consistent standard errors are used due to apparent autocorrelated structure of revisions.

The results indicate that, from the 15th release, the revision process is characterized by “permanent inefficiency”[4]. In addition to being statistically significant, these means are positive: the latest estimates published by the statistical agencies systematically overestimate the final value.

[4]Swanson and van Dijk (2006) distinguish between “temporary inefficiency” and “permanent inefficiency”. On the one hand, inefficiency may arise simply because preliminary data releases are constructed using incomplete information sets. In this scenario, it follows that after some reasonable amount of time, all subsequent data releases are efficient. They call this situation “temporary inefficiency”. On the other hand, inefficiency may also arise because of systematic factors. This opens up the possibility for inefficiencies to be carried far into the future. They refer to this type of situation as “permanent inefficiency”.

Moreover, following Jacobs and van Norden (2006), when preliminary data are optimal forecasts of revised data (*news* hypothesis) the variance of later revisions should be smaller than the variance of the previous ones because the subsequent revision contains more "news" than the former. This in not the case for the Italian GDP revision process since the variance of subsequent revisions is not always decreasing from one revision to the follow (see Figure 2).

Finally, to illustrate the complex character of the revision process, Figure 3 shows the (absolute) correlations between each revision and both initial estimate (noise hypothesis) and final estimate (news hypothesis). The presence of many non-zero correlation coefficients can suggest that the news and the noise hypotheses are rejected at times. Interestingly, different revisions appear to display different properties. For the first revision, neither correlation coefficient is close to zero, suggesting that both the pure news and the pure noise models would be rejected. For the later revisions (from the second to the seventh revision) the correlation with the final value (blue line) is approximately zero, suggesting that the noise model would be a good feet. Moreover, the dynamics continue to vary also for many quarters after the initial release of the data.

Hence, these results call for a more formal analysis to investigate the predictability of revisions.

2.2 Tests of rationality

This Section introduces main tests of rationality proposed in literature and provide an application using Swanson-van Dijk test showing that the Italian revision process cannot be considered as rational.

Standard rationality test go back to Mankiw et al.(1984) and are based on the following regression model:

$$X_t^f = \alpha + \beta X_t^{t+1} + \gamma W_t^{\prime t+1} + \epsilon_t^{t+1} \tag{1}$$

where W_t^{t+1} is an $m \times 1$ vector of variables representing the conditioning information set available at time period (t+1) and ϵ_t^{t+1} is an error term uncorrelated with X_t^{t+1} and W_t^{t+1}. The null hypothesis is $H_0 : \alpha = 0$, $\beta = 1$ e $\gamma = 0$, and corresponds to the idea of testing for the rationality of X_t^{t+1} for X_t^f, by finding out whether the conditioning information in W_t^{t+1}, available to the data issuing agency at the time of first release, has efficiently been used. Follwing Keane and Runkle (1990), the test of rationality of X_t^{t+1} in the context of model 1 can be broken down into two sub-hypotheses, namely (i) unbiasedness and (ii) efficiency. The hypothesis of unbiasedness can be tested by imposing the restriction that $\gamma = 0$, and testing for $\alpha = 0, \beta = 1$, while efficiency requires that $\alpha = 0, \beta = 1$, and $\gamma = 0$.

The issue of news versus noise is also important for forecast evaluation. In this direction, Clark and McCracken (2008) consider a test for comparing non-nested as well as nested forecasting model, when forecasts are produced using real-time data.They show that, under the news hypothesis, data revision do not affect the limiting distributions of tests for predictive evaluation. On the other hand, the use of real-time data plays a crucial role whenever revision are noisy, and their effect differ in non-nested or nested models.

Most of these papers have examined the issue of rationality using tests based on simple linear regression and an ex-ante prediction is not explicitly considered. In a recent paper, Corradi, Fernandez and Swanson (2009) add to the literature by outlining two out-of-sample rationality tests which are consistent against generic alternatives, namely they are able to detect any form of non-linearity.

Swanson e van Dijk (2006) are the first to consider the entire revision history for each variable, and hence discuss the "timing" of data rationality by generalizing model 1 as follows:

$$X_t^f - X_t^{t+k} = \alpha + \beta X_t^{t+k} + \gamma W_t'^{t+k} + \epsilon_t^{t+k} \tag{2}$$

where $k = 1, 2, ...$ defines the release (or vintage) of data. The objective is to assess whether there is information in the revision error between periods (t+k) and (t+1) that could have been predicted when the initial estimate, X_t^{t+1}, was formed.

With the aim to analyze the entire revision process of the Italian GDP, the remaining part of this Section introduces an application of the test proposed by Swanson and van Dijk (2006).

As mentioned above, this is to test the null hypothesis that $\alpha = \beta = \gamma = 0$ in the regression:

$$X_t^f - X_t^{t+k} = \alpha + \beta X_t^{t+k} + \gamma W_t'^{t+k} + \epsilon_t^{t+k} \tag{3}$$

where $k = 1, 2, ...$ defines the release of data (that is, for $k = 1$ we are looking at preliminary data, for $k = 2$ data has been revised once, etc.), X_t^{t+k} denote the value of the variable of interest which pertains to calendar date t as it is available at time $(t+k)$, X_t^f are the final data, W_t^{t+k} is a $m \times 1$ vector of variables representing the conditioning information set available at the time period *(t+k)* and ϵ_t^{t+k} is an error term assumed to be uncorrelated with X_t^{t+k} and W_t^{t+k}. Note that by considering different values of k it is possible to examine the rationality of different release of data. Moreover, for $k > 1$,

W_t^{t+k} can include certain characteristics of the revisions history, such as the revision between the first and the k^{th} release, $X_t^{t+k} - X_t^{t+1}$. Thus, it is possible to examine whether inefficiency arises via information available in the revision history for a given release of data as well as through other sources.
The main results are shown in Table 3. For the full sample, the F-statistic for testing the hypothesis that $\alpha = \beta = \gamma = 0$ suggests rejection of forecast rationality for every subsequent revision. These results show evidence of strong predictability of Italian GDP revisions.

To sum up, the hypothesis of noise is a reasonable assumption to describe the revision process of the Italian GDP. This implies that the initial announcement is an observation of the final series, measured with errors. Revisions are uncorrelated with the final value but correlated with data available when the initial announcement is released.

3 Revisions and forecasts ability

This Section presents an empirical application showing that revisions do affect forecast accuracy. The basic idea is that the revision process may incorporate considerable information to represent the real state of the economy on which forecasts are based.

For this purpose, a dynamic factor model such as in Mariano and Murasawa (2003) is considered, which has been used by many authors to forecast quarterly GDP exploiting timely and disaggregated economic indicators.

However, the focus of this paper is to investigate whether the inclusion of revised data improve the performance of a selected model, producing more accurate estimates and forecasts whereas the discussion of alternative models for short term forecast is out of the scope of the paper [5].

The novelty of the paper is to include in the information set different vintages of GDP and indicators, with the aim of incorporating the news information of different releases.

Moreover, the dynamic factor model allows for mixed frequency data to mimic the practice of statistical agencies to use monthly indicators, such as Industrial production, to estimate quarterly GDP when the information set is partial, especially for the publication of the flash announcement.

As the dynamic factor model is concerned, refer to Frale et al. (2010) for any

[5] Many works have recently dealt with the issue of comparing alternative models for short term forecast. See, for example, Frale et al. (2010), Chamacho and Perez-Quiros (2010), Arouba et al. (2010).

technical detail and for the State Space formulation. Anyway the main features of the model are reported in the sequel for clarity.

The factor model assumes that the co-movements among the GDP series and some economic indicators, eventually available at higher frequency, $\mathbf{y}_t$, are modeled as the sum of three components. The first two components are the common factors, $f_{1,t}$ e $f_{2,t}$, and reflect the notion that the series dynamics are driven in part by common shocks. The third component, $\boldsymbol{\gamma}_t$, captures the idiosyncratic behavior of each series.

Letting $\boldsymbol{\theta_1}$ and $\boldsymbol{\theta_2}$ denote the two $N \times 1$ vectors of loadings, and assuming that both common and idiosyncratic components are difference stationary and subject to autoregressive dynamics, we can write:

$$\begin{array}{lcll}
\mathbf{y}_t & = & \boldsymbol{\theta}_{10} f_{1,t} + \boldsymbol{\theta}_{11} f_{1,t-1} + \boldsymbol{\theta}_{20} f_{2,t} + \boldsymbol{\gamma}_t + \boldsymbol{X}_t \beta, & t = 1, 2, .., n \\
\phi(L)\Delta\ f_{1,t} & = & \eta_{1,t} & \eta_{1,t} \sim NID(0, \sigma^2_{\eta_1}) \\
\tilde{\phi}(L)\Delta f_{2,t} & = & \eta_{2,t} & \eta_{2,t} \sim NID(0, \sigma^2_{\eta_2}) \\
\boldsymbol{D}(L)\Delta\gamma_t & = & \boldsymbol{\delta} + \boldsymbol{\xi}_t & \boldsymbol{\xi}_t \sim NID(\mathbf{0}, \boldsymbol{\Sigma}_\xi)
\end{array} \tag{4}$$

where $\phi(L)$ and $\tilde{\phi}(L)$ are autoregressive polynomials of order p and $\tilde{p}$ with stationary roots.
The disturbance $\eta_{1,t}$, $\eta_{2,t}$ and $\boldsymbol{\xi}_t$ are mutually uncorrelated at all leads and lags.

The model is formulated in terms of the logarithmic changes in the variable, and the non linear nature of the temporal aggregation constraint is addressed considering a geometric mean relation between monthly and quarterly observation, as in Mariano and Murasawa (2003).

The empirical application refers to Italy and it exploits the triangle of revision for GDP since 1993 published by ISTAT at the time of writing up to the second quarter of 2010, adjusted by seasonality and by working days. As for the monthly indicators, lets simplify the model and consider only one indicator, namely the series of Industrial Production, which is the most used coincident indicator for GDP. As mentioned before, instead of considering many economic indicators, the aim of this paper is to focus on few series but including different vintages.

As a preliminary analysis, Figure 4 shows the trend of the last vintage and the first two series of revisions (i.e the first two "diagonal series" of the available real time dataset) for GDP, while the IP trend is shown in Figure 5. In both graphs the axes are rescaled to make the charts more readable.

It is worth noting that revision series follow the same trend of both GDP and IP series: in the periods in which GDP (and thus IP) has a large variation, revisions also are more uncertain, showing a large width.

This consideration suggests that the revision series (of both GDP and IP) may incorporate relevant information useful to capture the real state of the economy.

Thus lets consider as input data for the model (hereafter Mod_rev)the last vintage and the first two "diagonal series"' of revisions for GDP. Moreover, for IP, not only the last vintage and the first "diagonal series", but also their respective series at time $t-1$ are considered[6].

Assuming that both coincident indexes are standard AR(1), the estimated coefficients in model (1), along with their standard errors, are presented in Table 4.

It is relevant to notice that first of all data revisions series show statistically significant loadings on the common factor and secondly that there is a clear separation between vintages: last releases of GDP and IP load on the second coincident index, whereas past revisions in the first one. This result confirms two facts. First not only the last vintage but also previous releases of indicators give a significant contribution on the estimation of GDP. Second the news information in provisional releases is different from that in the final vintage and therefore it tends to load in a separate common factor.

Even more, it could be shown that the forecasts produced by a model that consider the process of revisions could be more accurate than the analogous based only on final data.

For this purpose a rolling experiment as an out-of-sample exercise is used which compare the forecast ability of the proposed model (Mod_rev hereafter) with two benchmark models: the same dynamic factor models but without the series of revisions still with two common factors (Mod2f) and a single factor model with only final vintage (Mod1) which is taken as basic reference.

In the context of rolling experiment a well known issue is how to split the series between the pre-forecast and the test period. Considering that the sample starts in 1993 and that we are interest in short term forecasts, we consider a good compromise to run the rolling experiment over 60 consecutive observations in the sample 2004M12-2009M11. Hence, starting from December 2004, the three models are estimated at monthly level and quarterly forecasts of the GDP are computed up to 3 step-ahead summing up the monthly figures. Then, the forecast origin is moved one step forward and the process is repeated until the end of sample is reached. The model is re-estimated each time the forecast origin is updated, and so parameter estimation will

[6]The original dataset contains missing values which are due to the presence of benchmark revisions. However the structure of the model and the Kalman filter allows to estimate missing data efficiently by using the conditional expectation equation

contribute as an additional source of forecast variability.

Table 5 reports the mean square forecast error (MSFE) for each of three model under analysis. For clarity, it is also reported the relative mean square forecast error (MSFE_rel) as ratio to models respect the one including revisons.

It is easy to note that, in all cases, the relative MSFE is in favor of the proposed model, confirming the initial assumption that the revision process includes not negligible information for forecasting analysis. This is in line with the evidence shown in Section 2, or that the revision process of the Italian GDP is not rational. As consequence the *noise* component in the data can be used to better understand the "true" state of the economy and thus to make better forecasts. Although the analysis is limited to only one variable and one country, it is relevant to not note that there are cases in which the use of revisions of data may help to improve the forecast performance and thus it is worth to include vintages of indicators in the information set, or at least check for their negligibility.

4 Conclusion

Macroeconomic data are often subject to large revisions after the initial release and the data revision process may continue essentially indefinitely. The inaccuracy of initial data obviously complicates decision making by policymakers and other agents whose optimal choices depend on knowledge.

This paper analyses the revision process in Italian GDP data and shows that irrationality and "'noise hypothesis"' are a better assumptions than perfect unpredictability ("'news hypothesis"') and rationality.

The all history of vintages is considered so as it is possible to see how long it takes before the revision process become rational. The test by Swanson and van Dijk is applied to emamine whether inefficiency arises via information available in the revision history as well as through other sources.

In addition the paper exploits the informations in the revision process itself, which can be eventually used in order to improve the real representation of the economic activity.

In this direction, the paper proposes a model which allows exploiting the information content of each vintage of data.

The reference is Mariano and Murasawa (2003) which has been extended to allow for more than one common factor as in Frale et al (2010). The novelty of the paper is the inclusion in the information set of different vintages of both GDP and the series of

Industrial production, which come up to be statistically significant.

A rolling forecast experiment is conducted showing that the inclusion of revision data do improve the performance of the model, producing more accurate forecasts than the analogous based only on final vintages.

In the light of these results, however, it is important to point out some clarifications. Clearly, these results inevitably depend on the choice of framework as well as the list of variables included in the model. In this direction, one possible extension is the inclusion of a larger list of indicators in order to better capture the business cycle.

Another possible development has to do with anticipating changes in business cycle regimes (also with a nonlinear methodology). Dynamic factor models are probably the most appropriate framework in which to combine the two key features of the business cycle: the idea of co-movements among macroeconomic aggregates and the dichotomy between expansions and recessions. In this context preliminary releases of GDP and indicators might contain signals of turning points that can be detected in advance respect to the publication of the final vintages and thus represent an important instrument for prompt business cycle analysis.

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Table 1: The intermediate revision process of the Italian GDP growth rates: main summary statistics. For more daetails about the listed indicators see Appendix 4

Description	Iintermediate revisions																						
	Rev 1	**Rev 2**	**Rev 3**	**Rev 4**	**Rev 5**	**Rev 6**	**Rev 7**	**Rev 8**	**Rev 9**	**Rev 10**	**Rev 11**	**Rev 12**	**Rev 13**	**Rev 14**	**Rev 15**	**Rev 16**	**Rev 17**	**Rev 18**	**Rev 19**	**Rev 20**	**Rev 21**	**Rev 22**	**Rev 23**
Number of observations	38	37	38	37	38	37	38	37	38	37	38	37	38	36	37	35	36	34	35	33	34	32	33
	Size of revisions																						
MAR	0.05	0.05	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.03
$RMSR$	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$MeAR$	0.03	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.00	0.00
$RMAR$	0.11	0.05	0.06	0.03	0.05	0.04	0.06	0.05	0.06	0.04	0.04	0.04	0.05	0.03	0.07	0.04	0.05	0.02	0.09	0.02	0.05	0.02	0.06
$\bar{P}$	0.47	0.53	0.50	0.57	0.51	0.56	0.51	0.53	0.51	0.54	0.53	0.56	0.46	0.50	0.41	0.49	0.44	0.51	0.39	0.50	0.39	0.49	0.41
$Size > 30\%$	13.16	24.32	18.42	16.22	15.79	18.92	21.05	18.92	10.53	16.22	10.53	18.92	10.53	13.89	13.51	14.29	5.56	5.88	17.14	9.09	11.76	12.50	12.12
	Direction of revisions																						
MR	0.00	-0.01	-0.01	-0.02	0.00	0.01	0.00	0.01	-0.01	0.00	0.00	-0.01	0.00	-0.01	0.01	0.03	-0.01	-0.01	0.01	0.00	0.01	0.00	0.01
SD^{HAC}	0.016	0.016	0.006	0.011	0.006	0.009	0.005	0.013	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.01
t_{MR}	0.15	-0.33	-1.13	-1.84	-0.02	0.87	0.47	0.72	-0.80	0.49	0.18	-1.31	-0.28	-1.62	0.99	2.30	-2.48	-1.88	0.88	-0.63	0.82	0.32	0.93
$t_{MR}, \quad \alpha = 10\%$	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.70	1.69
$t_{MR}, \quad \alpha = 5\%$	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.04	2.03	2.04	2.04
$t_{MR}, \quad \alpha = 1\%$	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.73	2.72	2.73	2.73	2.74	2.73	2.74	2.74
$(p - value)$	0.441	0.373	0.133	0.037	0.506	0.196	0.319	0.238	0.210	0.213	0.213	0.313	0.429	0.098	0.389	0.057	0.163	0.013	0.009	0.034	0.193	0.264	0.210
MeR	0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
$SKEW$	-0.06	0.02	0.04	-0.22	-0.12	0.06	-0.03	0.12	0.03	-0.02	-0.01	-0.15	-0.11	-0.12	0.03	0.19	-0.12	-0.22	0.10	-0.11	0.18	0.05	0.21
$\%Pos$	60.53	45.95	39.47	35.14	57.89	56.76	52.63	51.35	44.74	56.76	55.26	43.24	55.26	41.67	64.86	71.43	30.56	35.29	51.43	24.24	44.12	25.00	18.18
$\%Neg$	39.47	54.05	60.53	64.86	42.11	43.24	47.37	48.65	55.26	43.24	44.74	56.76	44.74	58.33	35.14	28.57	69.44	55.88	40.00	39.39	17.65	15.63	24.24
$\%Null$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.82	8.57	36.36	38.24	59.38	57.58
	Variability of revisions																						
SDR	0.07	0.08	0.04	0.05	0.04	0.05	0.04	0.06	0.04	0.06	0.03	0.06	0.03	0.03	0.05	0.04	0.03	0.03	0.05	0.03	0.04	0.04	0.06
Min	-0.19	-0.23	-0.13	-0.20	-0.19	-0.13	-0.08	-0.15	-0.11	-0.14	-0.10	-0.27	-0.07	-0.07	-0.11	-0.05	-0.15	-0.14	-0.18	-0.07	-0.11	-0.09	-0.09
Max	0.17	0.26	0.14	0.10	0.06	0.21	0.13	0.19	0.13	0.19	0.07	0.13	0.09	0.05	0.14	0.16	0.05	0.07	0.15	0.09	0.13	0.16	0.21
$Range$	-0.03	-0.06	-0.02	-0.02	-0.01	-0.03	-0.01	-0.03	-0.01	-0.03	-0.01	-0.03	-0.01	0.00	-0.02	-0.01	-0.01	-0.01	-0.03	-0.01	-0.01	-0.02	-0.02
$Range_{90}$	0.22	0.20	0.11	0.17	0.09	0.13	0.13	0.21	0.10	0.17	0.09	0.13	0.10	0.08	0.16	0.13	0.09	0.09	0.16	0.09	0.09	0.09	0.23
$Range_{50}$	0.05	0.06	0.04	0.04	0.03	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.03	0.04	0.03	0.04	0.02	0.02	0.04	0.01	0.01	0.00	0.00
Continued																							

Continued

	Intermediate Revisons																						
Descriptions	**Rev 1**	**Rev 2**	**Rev 3**	**Rev 4**	**Rev 5**	**Rev 6**	**Rev 7**	**Rev 8**	**Rev 9**	**Rev 10**	**Rev 11**	**Rev 12**	**Rev 13**	**Rev 14**	**Rev 15**	**Rev 16**	**Rev 17**	**Rev 18**	**Rev 19**	**Rev 20**	**Rev 21**	**Rev 22**	**Rev 23**
N/S	0.10	0.11	0.06	0.07	0.06	0.07	0.06	0.09	0.05	0.08	0.04	0.10	0.05	0.06	0.09	0.10	0.06	0.09	0.10	0.08	0.07	0.11	0.13
	Impact of revisions on sign of growth rate																						
Correlation sign	97.37	91.89	100.00	97.30	97.37	97.30	100.00	94.59	97.37	94.59	100.00	100.00	100.00	100.00	97.30	100.00	100.00	100.00	97.14	100.00	100.00	96.88	100.00
Acceleration	68.42	51.35	39.47	56.76	55.26	40.54	34.21	64.86	52.63	51.35	39.47	56.76	47.37	52.78	48.65	71.43	36.11	29.41	51.43	30.30	44.12	21.88	15.15
Deceleration	31.58	48.65	60.53	43.24	44.74	59.46	65.79	35.14	47.37	48.65	60.53	43.24	52.63	47.22	51.35	28.57	63.89	61.76	40.00	33.33	17.65	18.75	27.27
	Efficiency of revisions																						
$\rho R_t P_t$	0.55	0.30	0.14	0.08	-0.11	-0.11	-0.26	0.27	0.28	-0.31	0.08	0.24	0.08	0.10	-0.13	0.41	-0.13	-0.48	-0.10	-0.17	0.01	0.00	0.11
$\rho R_t L_t$	0.62	0.40	0.20	0.15	-0.05	-0.04	-0.20	0.35	0.33	-0.24	0.12	0.34	0.13	0.16	-0.03	0.49	-0.05	-0.41	0.04	-0.09	0.11	0.11	0.28
$\rho R_t R_{t-1}$		0.63	0.92	0.93	0.95	0.92	0.96	0.94	0.98	0.96	0.98	0.94	0.99	0.99	0.97	0.97	0.97	0.97	0.90	0.98	0.99	0.96	0.96
MSR	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.00	0.02	0.01	0.02	0.01	0.03	0.03	0.03	0.02	0.03	0.03
UM	0.00	0.00	0.02	0.12	0.00	0.02	0.00	0.02	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.01
UR	0.20	0.16	0.09	0.01	0.02	0.00	0.56	0.25	0.22	0.23	0.32	0.88	0.26	0.96	0.68	0.87	0.87	0.96	0.78	0.97	0.88	0.95	0.71
UD	0.80	0.83	0.89	0.87	0.98	0.97	0.44	0.73	0.75	0.77	0.68	0.12	0.74	0.03	0.32	0.09	0.12	0.03	0.21	0.03	0.12	0.05	0.28

Table 2: The final revision process of the Italian GDP growth rates: main summary statistics. for more details about the listed indicators, see Appendix 4

Description	Final revisions Rev 1	Rev 2	Rev 3	Rev 4	Rev 5	Rev 6	Rev 7	Rev 8	Rev 9	Rev 10	Rev 11	Rev 12	Rev 13	Rev 14	Rev 15	Rev 16	Rev 17	Rev 18	Rev 19	Rev 20	Rev 21	Rev 22	Rev 23
Number of observations	27	54	27	54	28	54	30	54	30	54	31	54	32	54	32	54	32	54	32	54	32	54	33
Size of revisions																							
MAR	0.12	0.12	0.10	0.10	0.10	0.11	0.11	0.11	0.09	0.08	0.07	0.07	0.08	0.08	0.08	0.09	0.08	0.08	0.07	0.06	0.05	0.04	0.03
$RMSR$	0.09	0.31	0.09	0.31	0.08	0.26	0.10	0.20	0.08	0.22	0.07	0.20	0.08	0.20	0.09	0.18	0.08	0.18	0.08	0.15	0.07	0.11	0.05
$MeAR$	0.11	0.12	0.08	0.12	0.09	0.13	0.10	0.10	0.07	0.09	0.06	0.09	0.04	0.08	0.04	0.07	0.04	0.06	0.04	0.02	0.02	0.00	0.00
$RMAR$	0.26	0.37	0.20	0.34	0.19	0.29	0.21	0.28	0.18	0.28	0.14	0.25	0.16	0.27	0.20	0.26	0.17	0.23	0.18	0.16	0.13	0.09	0.06
$\bar{P}$	0.47	0.53	0.50	0.57	0.51	0.56	0.51	0.53	0.51	0.54	0.53	0.56	0.46	0.50	0.41	0.49	0.44	0.51	0.39	0.50	0.39	0.49	0.41
$Size > 30\%$	48.28	46.43	41.38	41.07	33.33	41.07	37.50	41.07	34.38	32.14	24.24	30.36	17.65	30.36	21.21	23.64	15.63	25.93	21.88	22.22	15.63	14.81	9.09
Direction of revisions																							
MR	-0.01	0.01	-0.01	0.02	0.00	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.04	0.03	-0.01	0.01	0.03	0.02	0.02	0.01	0.01
SD^{HAC}	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01
t_{MR}	-0.33	1.02	-0.62	0.67	0.17	-0.13	1.37	0.43	1.51	1.49	0.86	1.51	1.27	1.57	1.73	3.02	-0.54	1.75	1.74	2.22	0.91	2.13	0.93
$t_{MR}.\quad \alpha = 10\%$	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.70	1.69
$t_{MR}.\quad \alpha = 5\%$	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.04	2.03	2.04	2.04
$t_{MR}.\quad \alpha = 1\%$	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.72	2.73	2.72	2.73	2.73	2.74	2.73	2.74	2.74
$(p-value)$	0.37	0.16	0.27	0.25	0.43	0.45	0.09	0.34	0.07	0.07	0.20	0.07	0.11	0.06	0.04	0.00	0.30	0.04	0.04	0.02	0.19	0.02	0.19
MeR	-0.01	-0.03	0.00	-0.03	-0.02	0.00	0.03	0.02	0.03	0.02	0.02	-0.02	0.00	0.01	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	
$SKEW$	0.10	0.13	0.17	0.11	0.24	0.30	0.18	-0.03	0.05	-0.08	-0.02	-0.05	0.36	0.20	0.22	0.12	-0.10	0.05	0.15	0.19	0.23	0.21	0.21
$\%Pos$	20.69	18.97	13.79	20.69	18.97	18.97	22.41	22.41	22.41	25.86	20.69	20.69	15.52	18.97	22.41	29.31	20.69	20.69	22.41	18.97	17.24	10.34	6.90
$\%Neg$	25.86	46.55	31.03	46.55	27.59	48.28	25.86	43.10	24.14	39.66	25.86	44.83	31.03	41.38	24.14	36.21	27.59	41.38	20.69	25.86	12.07	10.34	13.79
$\%Null$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.34	5.17	29.31	18.97	55.17	32.76
Variability of revisions																							
SDR	0.14	0.17	0.13	0.14	0.12	0.15	0.14	0.13	0.11	0.15	0.10	0.14	0.10	0.15	0.11	0.13	0.11	0.14	0.10	0.12	0.09	0.07	0.06
Min	-0.23	-0.23	-0.22	-0.20	-0.19	-0.19	-0.18	-0.17	-0.17	-0.17	-0.12	-0.14	-0.19	-0.20	-0.21	-0.23	-0.30	-0.28	-0.27	-0.22	-0.19	-0.09	-0.09
Max	0.24	0.58	0.27	0.39	0.33	0.47	0.42	0.43	0.31	0.27	0.28	0.26	0.28	0.27	0.24	0.24	0.21	0.25	0.24	0.25	0.26	0.22	0.21
$Range$	0.47	0.80	0.49	0.60	0.52	0.66	0.60	0.60	0.48	0.44	0.40	0.40	0.48	0.48	0.46	0.47	0.51	0.52	0.51	0.47	0.45	0.31	0.30
$Range_{90}$	0.38	0.46	0.40	0.42	0.36	0.41	0.38	0.36	0.32	0.34	0.29	0.30	0.29	0.35	0.34	0.34	0.36	0.34	0.31	0.27	0.29	0.24	0.23
$Range_{50}$	0.22	0.19	0.16	0.20	0.17	0.22	0.17	0.16	0.12	0.12	0.12	0.11	0.10	0.10	0.10	0.10	0.09	0.09	0.07	0.02	0.02	0.01	0.00
Continued																							

Continued

Description	Rev 1	Rev 2	Rev 3	Rev 4	Rev 5	Rev 6	Rev 7	Rev 8	Rev 9	Rev 10	Rev 11	Rev 12	Rev 13	Rev 14	Rev 15	Rev 16	Rev 17	Rev 18	Rev 19	Rev 20	Rev 21	Rev 22	Rev 23
	Final revisions																						
N/S	0.39	0.46	0.35	0.39	0.34	0.42	0.38	0.37	0.31	0.29	0.27	0.26	0.28	0.30	0.31	0.31	0.31	0.31	0.29	0.24	0.24	0.18	0.17
	Impact of revisions on sign of growth rate																						
Correlation sign	41.38	86.21	41.38	84.48	41.38	86.21	48.28	86.21	48.28	81.03	48.28	81.03	50.00	82.76	50.00	82.76	51.72	87.93	51.72	89.66	53.45	89.66	56.9
Acceleration	68.42	51.35	39.47	56.76	55.26	40.54	34.21	64.86	52.63	51.35	39.47	56.76	47.37	52.78	48.65	71.43	36.11	29.41	51.43	30.30	44.12	21.88	15.15
Deceleration	31.58	48.65	60.53	43.24	44.74	59.46	65.79	35.14	47.37	48.65	60.53	43.24	52.63	47.22	51.35	28.57	63.89	61.76	40.00	33.33	17.65	18.75	27.27
	Efficienty of revisions																						
$\rho R_t P_t$	-0.16	-0.55	-0.32	-0.52	-0.38	-0.47	-0.29	-0.24	-0.10	-0.31	-0.04	-0.37	-0.03	-0.46	-0.06	-0.29	-0.17	-0.42	-0.03	-0.39	0.11	-0.26	0.11
$\rho R_t L_t$	0.26	0.09	0.03	0.07	-0.06	0.02	0.07	0.18	0.24	0.14	0.22	0.02	0.25	-0.05	0.25	0.07	0.13	-0.07	0.25	-0.11	0.35	-0.04	0.28

Table 3: Swanson-van Dijk test for rationality (standard errors in brackets)

	Revisions with respect to the final value										
Coefficients	Rev1	Rev2	Rev3	Rev4	Rev5	Rev6	Rev7	Rev8	Rev9	Rev10	Rev11
Intercept	0.146	0.142	0.099	0.061	0.065	0.088	0.097	0.086	0.089	0.077	0.055
	(0.002)	(0.003)	(0.019)	(0.087)	(0.409)	(0.008)	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)
X_t^{t+k}	-0.341	-0.354	-0.278	-0.142	-0.130	-0.171	-0.211	-0.118	-0.150	-0.125	-0.075
	(0.000)	(0.000)	(0.000)	(0.126)	(0.178)	(0.002)	(0.000)	(0.014)	(0.002)	(0.003)	(0.026)
$X_t^{t+k} - X_t t + 1$		0.015	0.043	-0.096	-0.195	-0.130	-0.162	-0.168	-0.164	-0.110	-0.036
		(0.964)	(0.551)	(0.299)	(0.016)	(0.121))	(0.019)	(0.008)	(0.009)	(0.060)	(0.429)
F-statistics	22.320	5.861	9.684	3.878	6.579	7.858	6.479	9.244	13.010	8.627	3.285
	(0.000)	(0.000)	(0.000)	(0.027)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.044)

Table 4: *Mod_rev*: parameter estimates and standard errors in brackets

Parameters	GDP	GDP_rev1	GDP_rev2	IP	IP_rev1
θ_{i10}	**0.002**	**1.498**	**1.783**	0.002	**-0.158**
	(0.001)	(0.340)	(0.439)	(0.002)	(0.061
θ_{i11}				0.031	**0.258**
				(0.286)	(0.036)
θ_{i20}	**0.001**	-0.021	-0.045	**0.004**	-0.003
	(0.001)	(0.111)	(0.118)	(0.002)	(0.014)
δ_i	**0.001**	0.034	0.022	-0.001	-0.006
	(0.000)	(0.165)	(0.195)	(0.002)	(0.018)
d_{i1}		-0.803	-0.966	-0.394	-0.568
σ^2_η	0.000	0.995	0.017	0.000	0.014
	$(1+0.264L)\Delta f_{1,t} = \eta_{1,t}, \quad \eta_{1,t} \sim N(0,1)$				
	$(1-0.773L)\Delta f_{2,t} = \eta_{2,t}, \quad \eta_{2,t} \sim N(0,1)$				

Table 5: Statistics on forecast performance for 60 rolling estimates (2004M12-2009M11)

	MSFE			Relative MSFE	
	Mod_rev	Mod2	Mod1	Mod2	Mod1
1-step	0.274	0.293	0.332	1.07	1.21
2-step	0.531	0.753	0.806	1.42	1.52
3-step	0.602	0.998	0.990	1.66	1.64

Figure 1: Bias in the revision process of the Italian GDP growth rates (23 revisions in 3 years). The red circles indicate a significant bias using Newey-West heteroskedasticity and autocorrelation consistent standard errors.

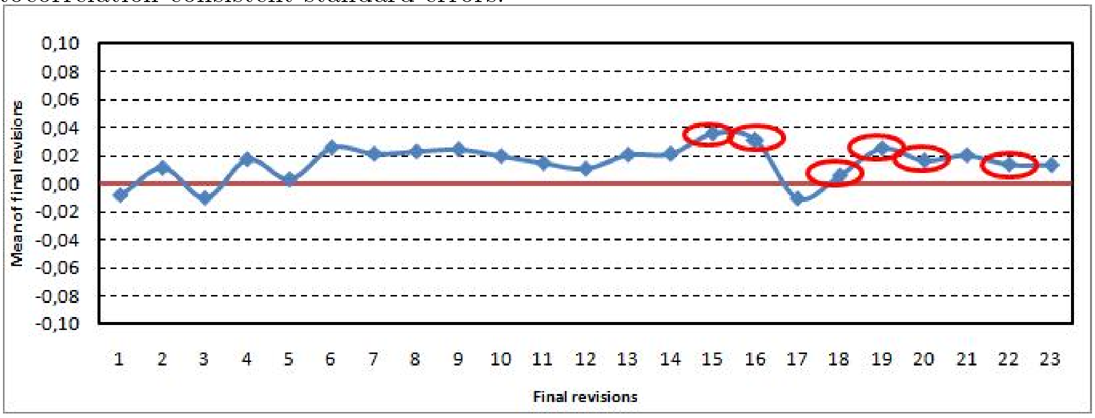


Figure 2: Variability in the revision process of the Italian GDP growth rates (23 revisions in 3 years).

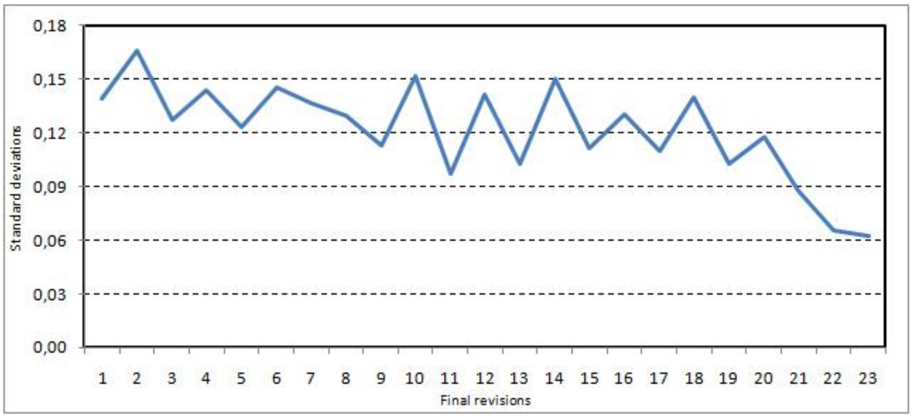


Figure 3: *News* versus *noise* hypothesis in the revision process of the Italian GDP growth rates (23 revisions in 3 years).

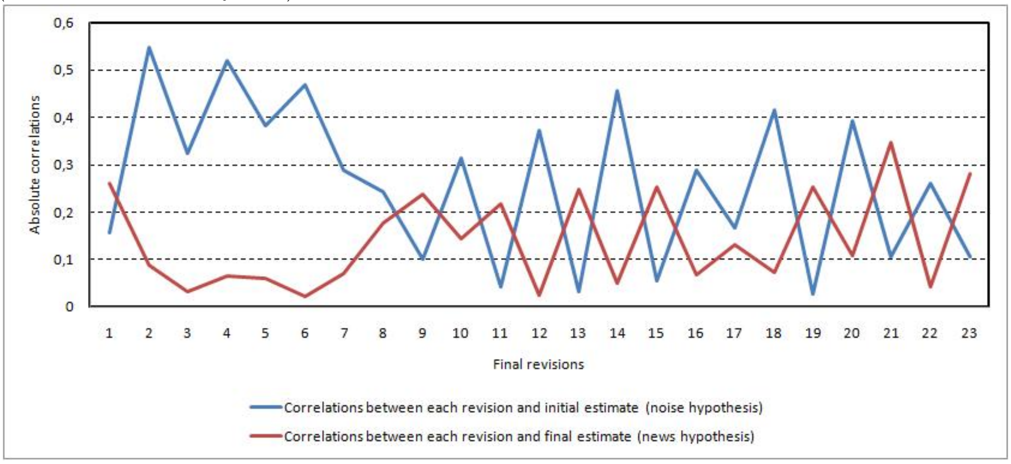


Figure 4: The last vintage and the first two series of revisions (i.e the first two "diagonal series" of the available real time dataset)for GDP.

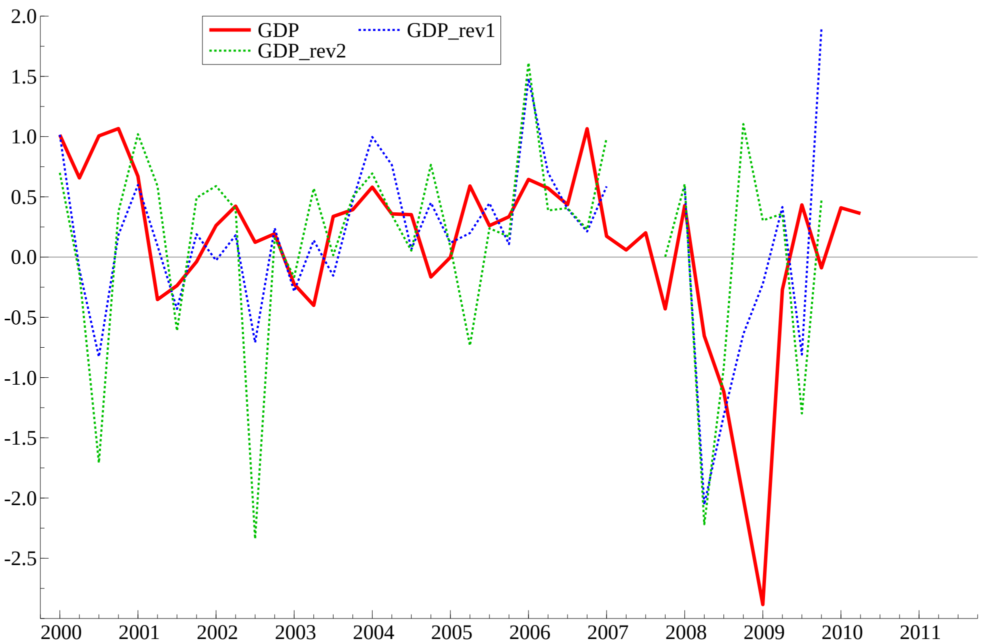
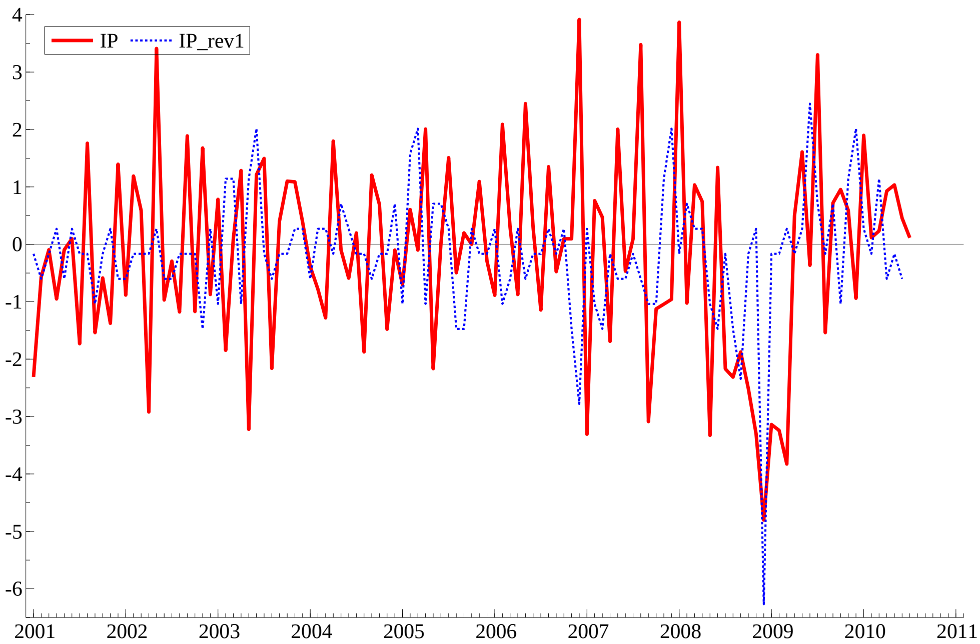


Figure 5: The last vintage and the first series of revisions for Industrial Production



A Interpreting the results of revision analyses: main summary statistics

The results of revision analyses provide important information on the robustness of first published data, and enable producers to better understand the statistical compilation process, possibly facilitating the identification of problems and/or improvements that could be made. Before introducing the main synthetic indicators proposed in this paper, it is useful defining the concept of revision in a formal way. A generic revision R_t^{t+k} is usually defined as:

$$R_t^{t+k} = y_t^{t+1} - y_t^{t+k} \qquad k = 1, 2, ... \tag{5}$$

wherey_t^{t+1} represents the preliminary estimate (the first estimate of y at time t available at the time $t+1$), while y_t^{t+k} indicates the $k-th$ subsequent release, i.e. the estimate of y at the time t published at the time $t+k$, for $k = 1, 2, ...$
For clarity, all of the listed formulas are based on the following notation:

P_t represents the preliminary (earlier) estimate for reference period t

L_t indicates the subsequent (later) release for reference period t

Hence, a generic revision (over a specified interval being analyzed) can be rewritten as:

$$R_t = L_t - P_t$$

In the following summary statistics are grouped the into five categories: size of revisions, direction of revisions, variability of revisions, impact of revisions on sign of growth rate and efficiency of revisions.

A.1 Size of revisions

This type of measures provides informations on the width and the dimension of revisions.

- Mean absolute revision (MAR):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|L_t - P_t| = \frac{1}{n}\sum_{t=1}^{n}|R_t| \tag{6}$$

  it helps judging the size of revisions because it avoids offsetting effects on the indicator from the negative and positive revisions (so it is more stable than the mean revision). It indicates the average size of the revisions, but it cannot provide an indication of directional bias.

- Root mean square revision ($RMSR$):

$$RMSR = \sqrt{\frac{1}{n}\sum_{t=1}^{n} R_t^2} \tag{7}$$

it essentially combines the degree of bias (i.e. mean revision) and the variance of the revision around its mean. As such it is a broader measures than the standard deviation of revision.

- Median absolute revision ($MeAR$):

$$MeAR = Me|R_t| \qquad t = 1, 2, ..., n \tag{8}$$

it is a useful measure of central tendency to compare with the mean absolute revision or to provide supplementary information. The median might be preferred to the mean as expression of the central tendency of the values not affected by extreme observations.

- Relative mean absolute revision (RMAR):

$$RMAR = \frac{\sum_{t=1}^{n} |L_t - P_t|}{\sum_{t=1}^{n} |P_t|} = \frac{\sum_{t=1}^{n} |R_t|}{\sum_{t=1}^{n} |P_t|} \tag{9}$$

this is simply the mean absolute revision scaled in terms of the size of the earlier estimates. It is useful for measuring the robustness of first published estimates and can be interpreted as the expected proportion of the first values that is likely to be revised over the revision interval being considered.

- Average absolute value of first published estimates ($\bar{P}$):

$$\bar{P} = \frac{1}{n}\sum_{t=1}^{n} |P_t| \tag{10}$$

it is used to give context to $RMAR$, and it is only relevant for growth rates analysis.

A.2 Direction of revisions

This measures can be useful for analyzing the direction of revisions, assessing whether the average size of revisions is close to zero or, instead, there is a propensity in a certain direction. Hence, these indicators may suggest the presence of possible bias in the preliminary estimates.

- Arithmetic average or Mean Revision (MR):

$$RM = \frac{1}{n}\sum_{t=1}^{n}(L_t - P_t) = \frac{1}{n}\sum_{t=1}^{n}(R_t) \tag{11}$$

If positive it indicates that, on average, earlier releases have been under-estimated (negative sign means over-estimated). Revisions of opposite sign will have a tendency to cancel out, consequentially the size of the mean revision, beyond determining the average direction of revisions, can be of limited use (also called "average bias").

- Standard deviation of mean revision (SD^{HAC}):

$$SD^{HAC} = \sqrt{\frac{1}{n(n-1)}\left\{\sum_{t=1}^{n}\hat{\epsilon}_t^2 + \frac{4}{3}\sum_{t=1}^{n}\hat{\epsilon}_t\hat{\epsilon}_{t-1} + \frac{2}{3}\sum_{t=3}^{n}\hat{\epsilon}_t\hat{\epsilon}_{t-2}\right\}} \tag{12}$$

where $\hat{\epsilon}_t = R_t - MR$.

It is estimated by the Newey-West (Newey and West, 1987) heteroskedasticity and autocorrelation consistent standard errors to take into account serial correlation of revisions. For clarity of notation, in the formula 12 a second order serial autocorrelation is supposed.

- Adjusted t-statistic for significance of mean revision (t_{MR}):

$$t_{MR} = \frac{MR}{SD^{HAC}} \tag{13}$$

This statistic is able to test the significance of mean revision. The t-critic returns a value t for which $P(|MR| > t) = P(MR < -t \quad or \quad MR > t)$. The $P(|MR| > t) = 0.1, 0.05, 0.01$ define the values of t used for the quantitative interpretation of the statistical significance of the mean revision.

- Median revision (MeR):

$$MeR = Me(R_t) \qquad = 1, 2, ..., n \tag{14}$$

The median revision corresponds to the value in the center of the distribution of revisions. It can be useful for supplementary information to the mean revision as it is not affected by extreme revisions in either a positive or negative direction.

- Skewness ($SKEW$):

$$SKEW = \frac{MR - MeR}{SDR} \tag{15}$$

where SDR represents the standard deviation of revisions. It indicates when the distribution of values around the median value is non-symmetric. The distribution is called negative (positive) when the median is greater (smaller) than the mean, whit the distribution presenting a longer tail towards the left (right). This can be useful to provide context to other tests and statistics that rely on the symmetry and/or normality of distribution of revisions.

- Percentage of positive revisions ($\%Pos\_R_t$):

$$\%Pos\_R_t = \frac{1}{n}\sum_{t=1}^{n} V_t \qquad whereV_t = 1ifR_t > 0 \tag{16}$$

It returns the number of cases revised upward as a proportion of the total number of observations and can therefore useful supplementary information to the mean revisions.

- Percentage of negative revisions ($\%Neg\_R_t$):

$$\%Neg\_R_t = \frac{1}{n}\sum_{t=1}^{n} V_t \qquad whereV_t = 1ifR_t < 0 \tag{17}$$

It returns the number of cases revised downward as a proportion of the total number of observations.

- Percentage of null revisions ($\%Nul\_R_t$):

$$\%Nul\_R_t = \frac{1}{n}\sum_{t=1}^{n} V_t \qquad whereV_t = 1ifR_t = 0 \tag{18}$$

It returns the number of cases with null revision as a proportion of the total number of observations.

A.3 Variability of revisions

This group of measures is useful to capture the variability of revisions.

- Standard deviation of revisions (SDR):

$$SDR = \sqrt{\frac{1}{(n-1)} \sum_{t=1}^{n} (R_t - MR)^2} \tag{19}$$

It is used to measure the spread of revisions around their mean, giving an indication of the volatility of revisions for a given revision interval. It is sensitive to outliers, therefore it is not a good measure of dispersion for revisions with skewed distributions. It is useful for symmetric/normal distributions or comparing volatility for different revision intervals and for international comparison.

- Minimum revision (Min): it returns the lowest value for the revision interval.

- Maximum revision (Max): it returns the highest value for the revision interval.

- Range of revision (Range):

$$Range = Max(R_t) - Min(R_t) \tag{20}$$

It measures the difference between the highest and the lowest revisions for all observation periods. This range indicates the volatility of the first release. The total range covers all the revisions, therefore it may include outliers.

- Range that 90% of revisions lie within ($Range_{90}$):

$$Range_{90} = \xi_{.95} - \xi_{.05} \tag{21}$$

it is the interval of the 5^{th} and the 95^{th} percentile of the distribution of revisions. It gives the normal range expected for the revision without being affected by unusually large revisions or outliers which generally require specific explanation when they occur.

- Noise-to-signal ratio for final revisions(N/S)

$$N/S = \frac{\sigma_{R_t}}{\sigma_{L_t}} \tag{22}$$

  It is defined as the standard deviation of final revisions divided by the standard deviation of the final value of the variable. This statistic, along with the minimum and maximum final revisions, gives an idea about the size of final revisions relative to the size of the original variables.

A.4 The impact of revisions on sign of growth rate

These statistics allow to obtain useful information about the reliability between two subsequent releases. They permit to analyze, for example, how often the later published growth rate is in the opposite direction to the earlier rate. This is an extreme case of unreliability, although it may be that the change of a small positive growth rate to a small negative one (or vice versa) is not so serious.

- Concordance of the sign between the earlier estimate and the later estimate: it is defined as the percentage of observations where the sign of the later estimate and the sign of earlier estimate are the same.
- Acceleration/Deceleration of revisions: It is defined as the percentage of observations for which both the earlier estimate and the later one show an increasing (decreasing) growth rate with respect to the previous period.

A.5 Efficiency of revisions

These measures assess whether the earlier published estimate is a good or "efficient" forecast of the later value.

- Correlation between revision and earlier estimate ($\rho_{R_tP_t}$):

$$\rho_{R_tP_t} = \frac{\sum_{t=1}^{n}(P_t - PM)(R_t - RM)}{(n-1)\hat{\sigma}_P\hat{\sigma}_R} \tag{23}$$

  where PM represents the average of the preliminary estimate and

$$\hat{\sigma}_x = \sqrt{\frac{\sum_{t=1}^{n}(x_t - \bar{x})^2}{n-1}} \tag{24}$$

This measure is useful to test if revisions are "noise". If the revision is correlated with the earlier estimate this implies that not all information available at the time of the earlier estimate has been used efficiently in the estimation process.Thus revisions are noise if the correlation between P_t and R_t is statistically significant.

- Correlation between revision and later estimate ($\rho_{R_tL_t}$):

$$\rho_{R_tL_t} = \frac{\sum_{t=1}^{n}(L_t - LM)(R_t - RM)}{(n-1)\hat{\sigma}_L\hat{\sigma}_R} \tag{25}$$

where LM represents the average of the latest release.

This measure is useful to test the hypothesis of "news". If the revision is correlated with the later estimate this implies that information which becomes available between the compilation of the earlier and the later estimate (i.e. "news") is being effectively incorporated in the estimation process of the later estimate. Provided revisions are not noise (see the above definition), it implies that the earlier estimate can be regarded as an efficient forecast of the later estimate. Thus revisions contain news if the correlation between L_t and R_t is statistically significant.

- Serial correlation of revisions ($\rho_{R_tR_{t-1}}$):

$$\rho_{R_tR_{t-1}} = \frac{\sum_{t=2}^{n}(R_{t-1} - MR)(R_t - MR)}{(n-1)\hat{\sigma}_{R_t}\hat{\sigma}_{R_{t-1}}} \tag{26}$$

The correlation between the revision for subsequent data points needs to be taken into account since there may be some degree of predictability in the revision process.

Note that serial correlation is perhaps more relevant when looking at revisions over short intervals rather than longer intervals because there is a complex interaction of revision between many releases when one looks at longer revision interval.

- Decomposition of the Mean Square Revision: following Theil (1961), the Mean Square Revision (MSR) can be written as:

$$MSR = (MR)^2 + (\sigma_P - \rho\sigma_L)^2 + (1-\rho^2)\sigma_L^2 \tag{27}$$

where MR is the mean revision, σ_L and σ_P are the standard deviation of the latest and preliminary estimates, respectively, while ρ is their correlation.

Dividing the equation 27 by MSR it gives:

$$1 = UM + UR + UD \tag{28}$$

where:

- UM is the proportion of MSR due to mean revision not being equal to zero. It is also known as "mean error":

$$UM = \frac{(RM)^2}{MSR} \tag{29}$$

- UR is the proportion of MSR due to the slope coefficient β being different from zero in a linear regression model of the earlier and later estimates $L_t = \alpha + \beta P_t + u_t$:

$$UR = \frac{(\sigma_P - \rho\sigma_L)^2}{MSR} \tag{30}$$

- UD is the disturbance proportion of MSR, i.e. the proportion of MSR that is not caused by systematic difference between earlier and later estimates:

$$UD = \frac{(1 - \rho^2)\sigma_L^2}{MSR} \tag{31}$$

the lay interpretation of the above measures is that earlier estimates are "well behaved" if the above breakdown gives low values for UM and UR and a high value for UD.