Short-term forecasting of quarterly gross domestic product growth

Joëlle Liebermann*

Abstract

Policy makers need to monitor and assess developments in the economy without complete information. For example, official statistics such as quarterly GDP are released with a lag. However, many other sources of information regarding developments in the economy such as monthly statistical releases and surveys become available in the interim and this information can be used to help predict the likely outturn for GDP. This article reviews a number of statistical tools used to extract the predictive element of these many sources of information for GDP and illustrates their application to the case of Irish economy.

* The author is an economist in the Economic Analysis and Research Department. The views expressed are solely the views of the author and are not necessarily those held by the Central Bank of Ireland or the European System of Central Banks. The author would like to acknowledge the helpful comments of Gerard O'Reilly and Terry Quinn.

1. Introduction

Monitoring and assessing the state of the economy is of paramount importance to policy-makers. However, they face the problem that official economic data are released with a publication lag, i.e., they are only available after the end of the period to which they pertain.

In particular, aggregate series such as quarterly gross domestic product (GDP), which is the most comprehensive measure of the state of the economy, is only released after the close of the reference quarter. In the case of Irish GDP, the Central Statistics Office (CSO) releases its first estimate for a given quarter between ten and eleven weeks after the end of the reference quarter. Nevertheless, in the interim period, many monthly conjunctural indicators become available which provide within-quarter information that can be used to give a more timely assessment of the current state of the economy and hence the likely outturn for GDP. Examples of such indicators include variables measuring the real and nominal side of the economy such as industrial production, retail sales, unemployment and prices data as well as financial variables and qualitative information such as measures of business and consumer sentiment.

Hence, prior to the official GDP release there is a constant flow of data that provides an increasing amount of information with respect to state of the economy in the reference quarter. The aim of short-term forecasting methods is to use such available high frequency information with respect to the reference quarter, and extract the predictive component from this large number of data series in order to obtain an early estimate of GDP growth. This estimate can then be updated as more information becomes available. Two classes of statistical models used for this purpose are bridge equations and factor model approaches and these are discussed in the article.

Incorporating this continual flow of information from a large number of sources into a prediction of quarterly GDP raises a number of difficulties. Standard regression methods are unable to handle a large number of explanatory/predictive variables. This problem is known as the “curse of dimensionality”. Both methods discussed here circumvent the curse of dimensionality in the following ways. With respect to the bridge equation approach, a prediction of GDP based on each individual indicator is first estimated and then one averages over all the individual forecasts. Alternatively, in the factor model approach, one summarises the information contained in the monthly indicator variables regarding the state of the economy at the onset by using statistical techniques to extract the common factors from the set of indicators. These factors capture the co-movement or, common component, in the indicator variables and hence provide an efficient way of summarising this information. These factors are then used to forecast GDP.

The second issue is that the panel of indicator variables is unbalanced at the end of the sample, which is referred in the literature to as a “jagged” edge structure. This is a consequence of the fact that variables are released in a non-synchronous manner and with varying publication lags. For example, suppose at the end of December one wishes to use the panel to produce an estimate of fourth quarter GDP. At that point in time, only surveys and financial variables would be available up until December, whereas employment numbers and retail sales are only available up to November and industrial production is only available for October. Hence, at the end of December, the number of missing observations differs across the series. If one were to use a balanced panel, which means that all series would end in the same month, one would have to end the panel in October, which implies disregarding the available information on the fourth quarter pertaining to November and December. Exploiting this “jagged” edge structure is central to the short-term forecasting process since it enables one to use the most up-to-date information on the current quarter. Finally, each method must deal with a mixed frequency problem which entails linking monthly variables with quarterly GDP. Section 3 will explain how both of these approaches resolve these last two issues.

The tools discussed here are purely statistical models in the sense that they are not built on theoretically founded behavioural equations or accounting identities. Instead, they are based on time series analysis with the aim of exploiting the past predictive content of indicators for GDP in conjunction with their early release to construct an estimate of GDP prior to its official release.

The forecasting literature makes a distinction between an estimate of a variable of interest for a reference quarter made at different points in time. In particular, an estimate of GDP for a reference quarter made prior to that quarter is called a ***forecast*** while an estimate made during the reference period itself is called a ***nowcast***. Finally, an estimate made after the reference period is known as a ***backcast***, i.e., at that point one is predicting what happened in the past. In the rest of this article, we follow Bańbura, Giannone, and Reichlin (2011) and name all these successive estimates for a reference quarter as nowcasts as these authors define nowcasting as "the prediction of the present, the very near future and the very recent past".

In this article, we briefly review the statistical tools used to obtain short-term forecasts of GDP and illustrate their application to the case of the Irish economy. Such methods have initially been applied at the Central Bank of Ireland (CBI) by D'Agostino, McQuinn and O'Brien (2011) and since then these tools, as well as the range of the data used, have been expanded. Section 2 describes the panel of monthly predictors as well as the timing of information releases. Section 3 reviews the statistical tools used to produce an estimate of GDP. The empirical results are presented in Section 4 and Section 5 concludes.

2. The monthly predictors and the timing of information releases

The panel of variables used in this study includes the main quantitative official measures of economic activity such as industrial production, retail sales and the unemployment rate, amongst others. This type of data is commonly referred to as ***hard data*** in the forecasting literature as they are direct measures of economic activity. However, they are only released with a one or two month publication lag.[1] For instance, the official unemployment figures for October will only be known in the course of November, whereas October's industrial production figures will only become available in December.

In addition to the official quantitative indicators, forecasters also use qualitative assessments such as ***surveys*** which are available more promptly than hard data with such data usually released at the end or shortly after the end of the reference period. For example, the Purchasing Managers' Indices (PMI), produced by Markit Group, are a monthly survey of business managers, in their respective sectors, which assesses their perceptions regarding whether business conditions have improved, deteriorated or stayed the same relative to the previous month. These variables only reflect sentiment and/or expectations, and as such are referred to as ***soft data*** in the literature. Such qualitative information has been found to have some predictive content for GDP on its own but contain little information above and beyond the hard data. Hence, their usefulness for a real-time forecaster mainly comes from the fact that they are released prior to the hard data. Also included in the grouping of soft data are prices of traded ***financial*** securities such as interest rates and stock market indices, as the prices of these assets implicitly reveals information about financial market participants assessment of current and future economic conditions. Finally, given the very open nature of the Irish economy, both hard and soft data indicators for the US, UK and the euro area are

1 The exception is the terms of trade index which is released with a three to four month delay.

Table 1: The data set

Domestic side	Publication lag
– 3 month interest rate and stock market index*	0
– measures of businesses sentiment	0 to 1
– unemployment rate and persons on live registration	1
– retail sales, new vehicle registration and new house registration	1
– consumer prices indices and private sector credit	1
– industrial production, orders and turnovers	2
External side	
– EA euro coin indicator	0
– import and export demand**	0
– Euro to US dollar and UK pound exchange rate	0
– measures of businesses sentiment for the US, EA, UK and the world economy***	0 to 1
– US industrial production and retail sale, EA retail sales	1
– EA industrial production and new orders	2
– world industrial production	2
– terms of trade index	3 to 4

* These variables are sampled at the daily frequency, but are included in the models as monthly averages.

** Forecasts from the European Central Bank trade consistency exercise.

*** PMI Markit indicators.

also included. A total of 48 individual variables are used with a list of these monthly predictors, grouped by categories, along with their publication lags, are shown in Table 1 above.

Figure 1 further provides a stylised schematic representation of the timing of the different information releases pertaining to the fourth quarter of 2011. For simplicity, releases for the domestic economy are only shown. The upper part of the figure displays the dates while the lower part shows the flow of information released during the fourth quarter of 2011 and the first quarter of 2012. Furthermore, a colour is associated with each release to indicate which month of the quarter the release refers to. For example, the releases pertaining to October are all the same colour as the colour in which October is displayed in the upper part of the table.

At the end of October, the only information pertaining to the fourth quarter of 2011, are the surveys and financial data. At the end of November, soft data pertaining to the first two months of the quarter has become available alongside some partial hard data for October. Examples of latter include, unemployment (unemp), retail sales, credit and consumer price (cpi) data. Only in December does one start having current fourth quarter information for the hard data released with a two month publication lag such as industrial production (IP), turnovers (T/O) and orders.

At the end of March 2012, the CSO will release the first estimate of GDP for the fourth quarter of 2011. At any given point in time, prior to the official release, one can use the available high frequency information germane to the reference quarter to obtain an early estimate of GDP growth. Furthermore, this estimate taking into account the ongoing flow of information should get closer to the actual CSO outturn as more data pertaining to that quarter is revealed.

Figure 1: Timing of information releases pertaining to the fourth quarter 2011

4th quarter 2011			1st quarter 2012		
October	**November**	**December**	**January**	**February**	**March**
					→ $GDP_{q4-2011}$
surveys & fin.	*surveys & fin.*	*surveys & fin.*			
	unemp., cars houses retail sales credit, cpi	*unemp., cars houses retail sales credit, cpi*	*unemp., cars houses retail sales credit, cpi*		
		ind. prod. T/O, orders	*ind. prod. T/O, orders*	*ind. prod. T/O, orders*	

3. Overview of the statistical models/tools

The statistical tools used for producing short-term forecasts of quarterly GDP growth based on a panel of n – higher frequency (monthly), indicators shares a number of common characteristics. Firstly, since many variables have some predictive content for GDP, both methods make use of a large information set to forecast GDP. Secondly, given that these variables are released in a non-synchronous manner as well as with varying publication lags, the panel is unbalanced at the end of the sample and the data has a "jagged" edge structure. To illustrate this let's go back to the example of the previous section. At the end of December 2011, "soft data" would only be available up to that month, whereas for the "hard data" there would be one or two months missing, i.e. November and December, resulting in an unbalanced panel. Exploiting this "jagged" edge structure is key to the short-term forecasting process since it enables one to use the most up-to-date information on the state of the economy. Finally, each method must deal with bridging monthly variables with quarterly GDP.

As mentioned previously, two classes of statistical models used for short-term forecasting of GDP are the bridge equation and factor model approaches. In a nutshell, both methods can be seen as predictive equations which aim to estimate GDP growth in a given quarter, Y_q, using the value of a predictor, Z_q, in that same quarter:

$$Y_q = \alpha + \beta Z_q + \varepsilon_q \qquad (1)$$

In the bridge equation (BE) framework, Z_q refers to the quarterly aggregate of one of the monthly indicators. However, given publication lags, this variable may not be available for the whole quarter and has to be forecasted over the remainder of the quarter using univariate time series methods.[2] For example, let us assume that in the middle of the second month of the quarter one wanted to obtain an early estimate of GDP based on the unemployment rate. Since the latter is only available for the first month of the quarter at that point in time, one would first need to forecast the indicator for the remaining two months to obtain a quarterly estimate and plug that estimate into equation (1) to derive a nowcast of GDP.

Iterating over this procedure for the n indicators in the panel, one would then obtain n nowcasts of GDP. Note that since the coefficients in equation (1) are estimated with ordinary least squares, one could not include all variables at once in the equation. First, this is feasible only if the number of predictors is smaller than the time dimension over which the equation is estimated. Secondly, even when the former condition holds, but the number of predictors is large, the parameters will be estimated very imprecisely resulting in poor nowcasts. This problem is known as the

2 We follow common practice in the literature and forecast the series using an autoregressive process of order p.

"curse of dimensionality". To circumvent this problem for the bridge equation approach, one summarises the information on GDP available in the panel, by averaging over these n individual predictions to obtain the final GDP nowcasts.[3] Different weighting schemes can be used for this purpose, e.g. assigning an equal weight to each individual indicator or different weights according to some statistical criteria. The latter method is used at the Central Bank, where the weights are inversely proportional to the past forecasting performance of the individual series for GDP.[4] Therefore, higher weight is given to indicators which have been found to have a higher predictive content for GDP.

The dynamic factor model (DFM) used at the Central Bank is based on the work of Giannone, Reichlin and Small (2008). In their model, one first extracts $r \ll n$ factors from the set of the n monthly indicators. These factors are the linear combinations of the monthly variables which explain the largest proportion of the total variation in the data. The factors capture the co-movement or common component in the underlying monthly variables providing an efficient and parsimonious way of summarising the information about the state of the economy for the whole set of indicators. As such, the problem of the "curse of dimensionality" is dealt with at the onset. To obtain monthly factors over the quarterly relevant horizon, these factors also need to be forecasted. The DFM produces efficient forecasts of these factors using their own dynamics as well as all of the available, albeit unbalanced, information by means of a statistical tool known as the Kalman filter and smoother. Lastly, these r quarterly factors are used simultaneously as regressors in equation (1) to obtain a GDP nowcast.[5] A more detailed description of this model is given in Box 1. We estimate the model, and hence produce a GDP nowcast, over a range of specifications. To guard against model instability, the final GDP estimate is then obtained by averaging over the 10 percent best performing specifications.[6] This choice is motivated by Aiolfi and Timmermann (2006) who found strong evidence of persistence among the groups of best forecasting models.

BOX 1: The dynamic factor model

Let X_t^i denote the month t value of an indicator i and $i = 1...n$. The n x 1 vector of stationary monthly predictors X_t is assumed to follow a dynamic factor structure. In such a model, each variable is represented as the sum of two orthogonal unobserved components: a common and an idiosyncratic component. The common component is driven by a small number $r \ll n$ of unobserved common factors that account for most of the co-movement among the variables and hence provide information on the state of the economy. The idiosyncratic component, for its part, is driven by variable-specific shocks.

The model can be written as:

$$X_t = \chi_t + \xi_t = \Lambda F_t + \xi_t \tag{2}$$

where χ_t is a n x 1 vector of common components, F_t is a r x 1 vector of common factors, Λ is the n x r matrix of the factor loadings, and ξ_t is a n x 1 vector of idiosyncratic components. Equation (2) links the unobserved factors to the observed variables, with the additional assumption that the idiosyncratic components are cross-sectionally orthogonal white noises:

$$E(\xi_t \xi_t') = \psi = diag(\psi_1, ..., \psi_n) \tag{3}$$

$$E(\xi_t \xi_{t-s}') = 0, \forall\, s > 0 \tag{4}$$

3 An alternative would be to estimate a bridge equation using shrinkage estimators, which is currently work in progress.

4 This weighting scheme was chosen as it was found to perform better than alternative schemes.

5 In that case Z_q is a vector of dimension r consisting of the r factors.

6 For a given specification one has to choose the number of static and dynamic factors as well as the lag length of the factors dynamics (see box 1).

BOX 1: The dynamic factor model

The factors' dynamics are specified as a vector autoregression (VAR) of order p:

$$F_t = A_1F_{t-1} + \dots A_pF_{t-p} + Bu_t; \quad u_t \sim WN(0,I_q) \tag{5}$$

where $A_1, \dots, A_p$ are r x r matrices of autoregressive coefficients, B is a r x q matrix of rank q, u_t is the q dimensional white noise process of common shocks and it is further assumed that the stochastic process for F_t is stationary. It is also assumed that these shocks, u_t, are orthogonal to the idiosyncratic components, ξ_t:

$$E(\xi_t u'_{t-s}) = 0, \forall\, s \tag{6}$$

Finally, to deal with the missing observation at the end of the sample, i.e. the "jagged" edge structure of the panel, it is assumed that:

$$\psi_t^i = \begin{cases} \psi^i \text{ if } X_t^i \text{ is available} \\ \infty \text{ if } X_t^i \text{ is not available} \end{cases} \tag{7}$$

The estimation method is the two-step estimator of Doz et al. (2011a). In a first step, the factors are extracted using principal components from a balanced panel, i.e truncating the panel at the last month for which all variables are available. Using this factor as initial estimates one estimates all the parameters of the model described by equations (2)-(7). In the second step, the model is cast in the state space form, replacing the parameters by their consistent estimates obtained from the first step, the factors are re-estimated recursively by means of a statistical tool known as the Kalman filter and smoother. Given the assumption on the variance of the idiosyncratic component, the Kalman filter will put a zero weight on missing observations when updating the factors. Furthermore, Doz et al. (2011b) show that by iterating on the two-step estimator one obtains quasi-maximum likelihood estimates.

4. Empirical results

4.1. Data revisions

GDP is revised after its initial release, which raises an issue regarding the choice of which GDP vintage one should use as the appropriate target to evaluate the performance of the models. The latest revised GDP release can be thought of as a closer approximation to the true level of activity in the economy, but it includes benchmarks and others revisions, which a forecaster in real time cannot anticipate.

Chart 1 displays quarter on quarter GDP growth, for both the first released (real-time data) and final revised data for both Ireland and the US.[7] As is evident from the chart, the Irish economy is much more volatile compared to the US economy. Moreover, the average absolute size of revisions to Irish GDP is 1.3 percent compared to 0.3 percent for the US. Very large revisions occurred at the start of current downturn with fourth quarter GDP growth in 2007 and 2008 being revised upwards by 4.2 percent and 3.8 percent respectively[8] while the first and second quarters of 2008 were revised downwards by 2.1 percent and 1.6 percent respectively. Quill (2008) found that the component which contributes the most to GDP revisions is net exports and that a factor contributing to such large revisions is the impact of large multinational companies who frequently change their trading arrangements and structures. This factor could also contribute to the relative large volatility of Irish data.

7 These figures represent non-annualised quarter-over-quarter GDP growth.

8 However, as documented by Quill (2008), in relative terms (i.e. relative to the volatility of growth) the Irish economy would rank in the middle of his panel of OECD countries. Over the sample studied here, we find that relative mean absolute revisions to Irish and US GDP are of the same order of magnitude.

Chart 1: GDP outturns: real-time (first released) and revised (last released)

Sources: CSO and ALFRED database of the St.Louis Federal Reserve Bank.

Given the substantive differences between revised and real-time GDP, nowcasting results are reported for both vintages. Ideally to perform such an exercise, one would also like to have real time and revised data for the panel of monthly indicators.[9] However, since no real-time database is available for Ireland, a final revised dataset is used. It should be borne in mind that such data should be more correlated with revised GDP than its first release counterpart.

4.2. Nowcasting Results

This section presents the out-of-sample performance for nowcasting quarter-over-quarter real GDP growth from the third quarter 2006 to the second quarter 2011. The models are estimated recursively with observations starting in February 2001. For each quarter, six nowcasts are produced using information available at the end of a month, starting from the third month of the previous quarter up to the second month of the subsequent quarter. At each point in time, a nowcast is computed replicating the data availability faced by a forecaster in real time, hence, incorporating the pattern of missing information due to publication lags. However, since revised data for the panel of monthly indicators as available in September 2011 is used instead of the data as available to a real-time forecaster, the exercise is so called ***pseudo real-time***.

Model performance is evaluated using a statistical measure used in the forecasting literature known as the mean square forecast error statistic (MSFE) which is defined as follows:

$$MSFE_j = \frac{1}{Q}\sum_{q=1}^{Q}(GDP_q - \widehat{GDP}_{q,j})^2$$

where q indexes the quarter, GDP_q refers to actual GDP growth reported by the CSO in a given quarter, and $\widehat{GDP}_{q,j}$ is model's j nowcast. Hence, the greater the accuracy of the model the lower will be its mean square forecast error.

The upper part of Table 2 displays the different models performance relative to a standard naïve benchmark. The latter model is commonly used in the forecasting literature and simply forecasts GDP as the average growth witnessed over the last four quarters. Hence, this benchmark doesn't incorporate any information that may become available to the forecaster about the reference quarter. Each entry in the table shows the ratio of the

9 Concerning the soft data, only financials data are not revised, whereas surveys undergo only relatively small revisions, which are mainly due to revisions to seasonal adjustment factors.

Table 2: Relative MSFEs

Relative MSFEs: model versus benchmark

target:	real-time GDP		revised GDP	
	DFM	BE	DFM	BE
3rd month of previous quarter	0.89	0.91	0.82	0.84
1st month of reference quarter	0.89	0.79	0.74	0.76
2nd month of reference quarter	0.66	0.71	0.66	0.68
3rd month of reference quarter	0.62	0.75	0.65	0.66
1st month of next quarter	0.60	0.76	0.57	0.68
2nd month of next quarter	0.60	0.73	0.47	0.68

Relative MSFEs: model versus model at the end of the previous quarter

target:	real-time GDP		revised GDP	
	DFM	BE	DFM	BE
3rd month of previous quarter	1.00	1.00	1.00	1.00
1st month of reference quarter	0.99	0.86	0.91	0.91
2nd month of reference quarter	0.74	0.78	0.81	0.81
3rd month of reference quarter	0.70	0.83	0.77	0.77
1st month of next quarter	0.68	0.84	0.68	0.79
2nd month of next quarter	0.68	0.81	0.56	0.79

Sources: Central Bank of Ireland own calculations, Datastream and Markit Group.

model's MSFE to that of the benchmark at a given date. For both the bridge equation (BE) and dynamic factor model (DFM), all entries are below unity, indicating that the nowcasts are better gauges of the state of the economy on average, than the benchmark. Hence, exploiting the information provided by the high frequency releases helps provide a better estimate of GDP growth ahead of its official release.[10] In addition, the dynamic factor model always performs better than the bridge equation approach and that the models relative performance is greater when using revised GDP as target.

The lower part of Table 2 further displays the average gains in nowcasting accuracy for each model along the real-time data flow. That is, for each model, the corresponding column shows the ratio of MSFEs at a given date relative to its MSFE at the end of the third month of the previous quarter when no information on the reference quarter is yet available. For both nowcasting approaches, the accuracy of the estimates increases significantly as more information becomes available regarding the reference quarter. By the end of the reference quarter, the gain in nowcasting accuracy is of the order of 20 to 30 percent. As more "hard data" on the reference quarter becomes available during the next quarter further increases in accuracy of up to around 40 percent for the dynamic factor model are evident.

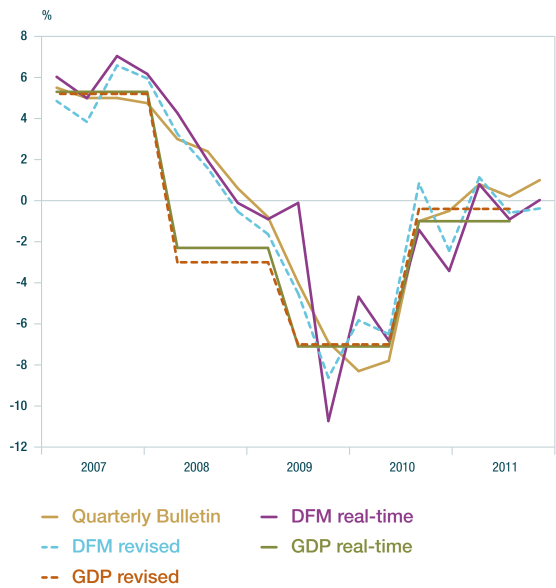
To further illustrate the importance of exploiting monthly releases to obtain an early estimate of current quarter GDP, Chart 2 shows the evolution of nowcasts made for the fourth quarter of 2008, which was the worst quarter of the recession. When the first nowcast was made, at the end of the third quarter of 2008, the model suggested that growth would be close to zero. This is the estimate of GDP growth obtained without using any reference quarter information. As high frequency information on the fourth quarter of 2008 became available, the updated nowcasts were strongly revised downwards, with the DFM consistently pointing to lower growth than from the BE.

10 Note that qualitative similar results are obtained if one uses an autoregressive process for GDP as a benchmark.

Chart 2: Evolution of GDP nowcasts for the fourth quarter of 2008

Sources: Central Bank of Ireland calculations, Datastream and Markit Group.

Chart 3: Average yearly growth



Sources: Central Bank of Ireland calculations, Datastream and Markit Group.

Up to now we have presented the models results for nowcasting, i.e. short-term forecasting. These models can also be used to forecast quarters further ahead with respect to the current quarter and in practice are used to forecast up to the end of the current year to obtain an estimate, i.e. nowcast, of average yearly growth.[11] Indeed, once per quarter, the CBI publishes the bank forecast for yearly growth for the current year in its quarterly bulletin. This is mainly based on the expert judgment of its economists, but is complemented and cross checked using the model based nowcasts. Chart 3 below displays these yearly nowcasts since 2007 as published in the four successive quarterly bulletin (QB) along with the DFM model based nowcasts. These purely model based nowcasts move in general closely to the experts ones, however the latter are smoother as they can make judgemental adjustments.

5. Conclusion

The long publication lags in the quarterly national income accounts data imply that policy makers in real-time do not know exactly the current state of the economy, as measured by quarterly GDP growth. Indeed, the data for a reference quarter are only released at the end of the next quarter. Hence, to monitor and assess the current economic situation, they have to rely on more timely higher frequency information to obtain an early estimate of GDP growth. To complement and cross check existing expert judgment of economists monitoring the many potential predictors for GDP, short-term forecasting models are used. These tools rely on past historical relationships observed in the data and don't posit any underlying behavioural relationships. They have the advantage that they can be automatically updated as new information pertain to a reference quarter is released. This article has reviewed the statistical tools used in central banks for that purpose and illustrated their application to the case of the Irish economy as used at the CBI. The results show that exploiting the information for the reference quarter provided by the high frequency releases helps at obtaining a more precise estimate of GDP growth ahead of its official release.

11 A yearly growth rate for a given year is approximately a weighted average of quarter-over-quarter growth in the previous and current year.

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