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Abstract

In this paper we present a dynamic factor model that produces nowcasts and backcasts of Irish quarterly GDP using timely data from a panel dataset of 35 indicators. We apply a recently developed methodology, whereby numerous potentially useful indicator series for Irish GDP can be availed of in a parsimonious manner and the unsynchronized nature of the release calendar for a wide range of higher frequency indicators can be handled. The nowcasts in this paper are generated by using dynamic factor analysis to extract common factors from the panel dataset. Bridge equations are then used to relate these factors to quarterly GDP estimates. We conduct an out-of-sample forecasting simulation exercise, where the performance of the factor model is compared with that of a standard benchmark model.

JEL classification: C33, C53, E52.

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[*] The views expressed in this paper are our own, and do not necessarily reflect the views of the European Central Bank or the Central Bank of Ireland

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1 Introduction

In this paper early estimates or nowcasts and backcasts of quarterly Irish GDP are presented. A nowcast (backcast) is a prediction of the present (near past) series with a publication lag. We draw upon the factor analysis based literature in seeking to distill significant information from relatively large amounts of variables. The approach follows that of Giannone, Reichlin and Small (2008) who produce nowcasts of output for the US using a dynamic factor model. The nowcasting methodology has been applied to many countries including Euro Area (Angelini et al, 2010), Norway , (Aastveit and Trovik, 2011), Switzerland (Siliverstovs and Khoodilin, 2010), New Zealand (Matheson, 2011). For a survey of the literature see Banbura, Giannone and Reichlin (2011).

A nowcast estimate of GDP is obtained in two steps. In the first step, monthly indicators are used to estimate factors. These factors are then used as regressors in an associated bridge equation. In the Irish case, we compile a monthly panel dataset of 35 variables. In terms of the timeliness of Irish GDP releases, for the first two months in any given quarter, the most recent available release of GDP is for the second last quarter. By the end of the third month in each quarter, releases of GDP are available for the previous quarter. In this paper we generate estimates for the current quarter, (nowcast), and for the previous quarter, (backcast). In the case of the latter, this is only done when no release is available, i.e. for the first two months of the quarter.

We generate the nowcasts using a pseudo-real time approach. By this, we mean that when a nowcast is derived from the data in every quarter, the data availability, which existed at that quarter, is replicated exactly. In essence, we are seeking to replicate the timeliness, which would have pertained for an analyst at the time the GDP estimate was formulated. By pseudo we mean that it is the final vintage of this data that is used to produce the forecasts and not the the “real-time” data available at the time of the forecast, however, there is evidence that the qualitative results of the model are unaffected by data revisions (see Liebermann, 2011).

This approach does give rise to what has been referred to as the “jagged edge” issue; that is, some data series do not have observations for the most recent month or two, so the panel from which the factor is derived is unbalanced in nature. In addressing this problem, we follow the same two-step approach as Giannone, Reichlin and Small (2008), in which current and recent GDP is estimated conditional on the number of indicators for which current information is already available.

This modeling approach represents a significant addition to the policy-analysis tool kit of the Irish Central Bank. The coherent nature of policy making within the Eurosystem necessitates the provision of timely and accurate estimates of output growth by Member States. Evaluating the present state of the economy and generating "credible" short-term forecasts has often been a complex task of combining information from both qualitative and quantitative based sources usually available at different time delays. Qualitative, survey-type information concerning present conditions within the economy tends to be available on a timely and up to date basis, whereas data more typically used in model based forecasts is often only available at a significant time lag. Additionally, many timely and useful variables are released at monthly intervals, whereas the variable of interest - GDP is normally on a quarterly basis. Therefore, from a policy perspective, the flexibility afforded by the nowcasting model is a particularly attractive feature of this approach.

To place the nowcasting exercise in context, in the next section, we discuss both the type and timeliness of Irish macroeconomic data releases. In section 3, the nowcasting model is presented along with the results of an out-of-sample forecast simulation. A final section offers some concluding comments.

2 Real-time Data Flow and the Indicator Dataset

The Quarterly National Accounts (QNA) releases of the Irish Central Statistics Office (CSO) provide the most comprehensive available information on recent developments in the Irish economy. The QNA provide estimates of GDP and its main output and expenditure components with the income accounts only available on an annual basis. The current release delay is no later than 90 days, meaning that GDP growth for a reference quarter is available towards the end of the subsequent quarter. In view of this significant release delay, conjunctural assessments of the Irish economy would benefit greatly from an early indicator of quarterly GDP of sufficient accuracy and timeliness. Such an early indicator could avail of the many releases of monthly Irish data.

In order to illustrate more fully the benefits of producing backcasts and nowcasts for Irish GDP, it is helpful to examine the timeline of releases of Irish macroeconomic data more carefully. Let's suppose we are currently half way through a particular quarter and label the quarter q_t. The release of the quarterly national accounts for the previous quarter, q_{t-1}, will still not appear for another six weeks or so i.e. close to the end of q_t. However, there is considerable monthly information now available for the previous quarter including monthly releases of retail sales and industrial production for each month of the previous quarter. This paper proposes to make use of the available monthly information to produce a timely backcast of GDP i.e. an estimate of GDP for q_{t-1}. At the current juncture in the middle of q_t, there is already partial information available on the current quarter including the unemployment rate and exchange rate data for the first month of the quarter. The methodology adopted in this paper also makes use of these monthly data to produce a timely nowcast of GDP for q_t. Such a nowcast yields significant benefits in terms of providing important timely information on the state of the economy. The official quarterly national accounts for q_t are released at the end of q_{t+1}. The nowcasts and backcasts for GDP can be computed at any point during q_t but clearly the nowcasts are more reliable as we proceed through the quarter when more and more information on monthly indicators can be incorporated.

The GDP nowcasting model incorporates information from a large set of more timely, higher frequency indicators that try to capture conjunctural developments in the Irish and international economies. There are 35 indicator series in the conditioning set. The full list of indicators along with their respective sources and release delays are presented in Table 1. These series are part of a larger set of series used by the Central Bank of Ireland in projection exercises but the series in the conditioning set satisfied a number of additional criteria including having a sufficiently timely release delay. The series are generally of monthly frequency and are significantly more timely than the GDP releases, with the longest release delay for the monthly series at about 40 days. Each of the series must also be sufficiently long for modeling purposes. The dataset begins in January 1985 and is unbalanced at the end of the sample reflecting the different release delays of the indicators. The structure of the dataset should be largely the same, at least for the set of monthly series, at each monthly update of the quarterly GDP nowcast. The model attempts to nowcast year-on-year GDP growth for a given quarter and the indicator series undergo transformations before entering the model. Typically, the series are converted to year-on-year growth rates helping to avoid the excessive volatility of quarter-on-quarter growth rates.

The dataset contains direct measures of economic activity and price dynamics along with indirect measures such as business and consumer sentiment surveys. The monthly indicators presented in Table 1 can be broadly grouped in terms of type and release delay (in brackets) as follows

- Hard data 1 (release delays of less than 10 days) - includes live register of unemployment benefit claimants, the unemployment rate and car sales
- Hard data 2 (between 20 and 40 days) - includes housing data, retail sales and industrial production
- Price data (within 12 days) - consumer price sub-indices
- Survey data (within 8 days) - Irish consumer sentiment surveys and euro area consumer and business sentiment surveys
- Financial data 1 (at the end of reference month) - euro sterling and euro dollar exchanges rates
- Financial data 2 (within 30 days) - monetary aggregates and private sector credit

The importance of developments in trading partners for the Irish economy is captured by the inclusion of quarterly weighted import demand and competitiveness variables along with higher frequency indicators such as consumer and business sentiment indicators for the euro area and euro exchange rate movements vis-à-vis sterling and the dollar. Sentiment indicators offer very timely information on conditions in the domestic and international economies. Exchange rate data are daily but they enter the model as monthly averages. Almost each sector of the economy is represented but efforts are made to adequately cover particularly those sectors with both higher weighting and more volatile outturns. Industrial output, which accounts for about a quarter of GDP at factor cost, is an important source of volatility, as illustrated in Table 2. The volatility is particularly pronounced in certain manufacturing sub-sectors, such as the manufacture of basic chemicals, and this can present significant challenges in a forecasting context. The overall monthly industrial output index is included as an indicator.

It is worth noting that the explanatory power of industrial production indices may be limited by the fact that the monthly industrial production series are not adjusted for royalties and licence services imports whereas GDP is adjusted as these inputs are not regarded as value added. In this respect, it is worth observing that the increasing use of service inputs over time may not be adequately taken into account (data on services inputs are only available quarterly with the Balance of International Payments, which is released at the same time as the QNA). Monetary aggregates have been shown to be useful in short-term forecasting of activity and are also included.

The contribution of the construction sector to GDP growth has undergone significant changes during this decade and indicators such as housing completions, housing registrations and private sector credit are included to capture activity in the sector. Activity in the market services sector is accounted for, primarily, by the monthly retail sales and car sales indices. The inclusion of a range of public finance series was also considered but unfortunately the data were not available at a high frequency over a sufficiently long period of time.[1] Altogether, seven subindices of the CPI remained in our final set of indicators after the various steps of the selection process. Finally, there are two labour market indicators i.e. the monthly unemployment rate and the numbers on the live register of unemployment benefit claimants.

[1] There is the option of interpolating some of the series and we may revisit this at some future date as some of these series could prove useful.

3 The Model

In this section we outline the dynamic factor model (Giannone, Reichlin and Small (2008)) used to generate the monthly estimates of GDP. The estimation strategy with this approach is twofold, in the first, a set of factors are extracted from a panel of monthly indicators, in the second step, the GDP series is projected onto the factors via a bridge equation.

The Giannone, Reichlin and Small (2008) model can be summarized as follows. A vector of n monthly, stationary (standardized), year-on-year variables $x_t = (x_{1,t}, x_{2,t}, ..., x_{n,t})'$, $t = 1, 2, ..., T$ is assumed to have the following dynamic factor model characterisation:[2]

$$x_t = \chi_t + \xi_t = \Lambda f_t + \xi_t \tag{1}$$

$$f_t = \sum_{i=1}^{p} A_i f_{t-i} + \zeta_t \tag{2}$$

$$\zeta_t = B\eta_t \tag{3}$$

where x_t in eq.(1) is the sum of two orthogonal components, the common component χ_t, and the idiosyncratic component ξ_t. The common component is the product of an $n \times r$ matrix of loadings Λ and a $r \times 1$ vector of latent factors f_t. The idiosyncratic component is a multivariate white noise with diagonal covariance matrix Σ_ξ. Factor dynamics are described in eq.(2), which is a VAR(p). $A_1, A_2, ..., A_p$ are matrices of parameters and $\zeta_t \sim N(0, BB')$, where B is a $(r \times q)$ matrix[3] with $q \leq r$; $\eta_t \sim N(0, I_q)$.

In the Appendix, we outline how consistent estimates of the parameters of the model can be obtained. Using these estimates, the factors can be estimated in the following manner:

$$\hat{F}_t = proj[F_t | x_1, ..., x_T; \hat{\Lambda}, \hat{A}, \hat{B}, \hat{\Sigma}_\xi]$$

that is, by applying the Kalman filter to the state-space representation obtained by replacing estimated parameters in the factor representation:

[2] T is the last date available in the monthly year-on-year dataset.

[3] We assume $B'B = \Sigma$

$$x_t = \hat{\Lambda} f_t + \xi_t \tag{4}$$

$$f_t = \sum_{i=1}^{p} \hat{A}_i f_{t-i} + \zeta_t \tag{5}$$

The Kalman filter can be also used to evaluate the degree of precision of the factor estimates

$$V_k = E[(F_t - \hat{F}_t)(F_t - \hat{F}_t)|x_1, ..., x_T; \hat{\Lambda}, \hat{A}, \hat{B}, \hat{\Sigma}_\xi].$$

while, the estimates of the signal and their degree of precision are given, respectively, by

$$\chi_t = Proj[\chi_t | x_1, ..., x_T; \hat{\Lambda}, \hat{A}, \hat{B}, \hat{\Sigma}_\xi] = \hat{\Lambda}\hat{F}_t$$

$$E(\chi_t - \hat{\chi}_t)^2 = \hat{\Lambda}' V_0 \hat{\Lambda}$$

This framework is adapted to estimate the factors on the basis of an incomplete dataset, i.e. a dataset which contains some missing values corresponding to data which has not yet been released. We impose that the variance of the idiosyncratic part of the series with the missing observation is infinite at time t. This implies that no weight is put on the missing variable in the computation of the factors at time t.

We define the level of the GDP for a quarter q as the average of latent, monthly observations of GDP within that quarter, $GDP_t^q = \frac{1}{3}(GDP_t^m + GDP_{t-1}^m + GDP_{t-2}^m)$; where GDP_t^m denotes the unobservable latent realization of GDP at the monthly frequency. Year-on-year GDP growth is computed as $gdp_t^q = GDP_t^q - GDP_{t-12}^q$ within the same quarter q. Quarterly factors are computed by averaging over the year-on-year monthly factors $f_t^q = \frac{1}{3}(f_t^m + f_{t-1}^m + f_{t-2}^m)$.

The estimates of year-on-year changes of GDP, on quarterly variables, are computed with the following bridge equation:

$$\widehat{gdp_t}^q = \hat{\beta}' \hat{f}_t^q \tag{6}$$

where $\widehat{gdp_t}^q$ denotes the yearly estimated growth rate of GDP and $\hat{\beta}$ is a $r \times 1$ vector of estimated parameters; this is computed for all the available $t's$ belonging to a certain quarter q. Backcasts, nowcasts and forecasts of the GDP series can be computed every month as soon as new information becomes available.

The forecast error is defined as the difference between the (ex post) realized and the estimated value of gdp: $\varepsilon_t^q = gdp_t^q - \widehat{gdp}_t^q$. We assume that $\varepsilon_t^q \sim N(0, \sigma_\varepsilon^2)$ and that ξ_t, ζ_t and ε_t are mutually independent at all leads and lags.

3.1 Model Evaluation

To evaluate the forecast performance of the modelling approach, we perform a pseudo real-time out of sample simulation. In using the pseudo real-time approach, we are seeking to replicate the actual data availability situation, which pertained at the time the nowcast/forecast is generated. Therefore, the parameters of the model are generated recursively based on the data availability at a particular quarter.

The out of sample simulation procedure is as follows; the exercise begins by estimating the model on a sub-sample called the estimation window 1980:Q1 to 1996:Q4. The estimated parameters are then used to backcast and nowcast GDP. The estimation window is updated sequentially with one observation and the parameters are re-estimated based on the new sample available. The estimates of GDP are again generated using the new sample. This procedure is then iterated until the end of the sample.

We evaluate the performance of the model by generating the Mean Squared Forecast Error (MSFE), which is defined as

$$MSFE = \frac{1}{(t_1 - t_0 + 1)} \sum_{t=t_0}^{t_1} (gdp_t^q - \widehat{gdp}_t^q)^2, \tag{7}$$

The MSFE refers to Mean Squared Nowcast Error (MSNE) when the evaluation is computed for the months within the current quarter or refers to Mean Squared Backcast Error (MSBE) when the evaluation is computed in the months falling in the next quarter.

We also compare the accuracy of the models estimates with that of a benchmark model.[4]

[4]The standard benchmark model in this literature is the constant growth model. However, owing to the particularly volatile nature of Irish quarter-on-quarter GDP changes, we elect to use, as the standard GDP transformation, year-on-year changes. Therefore, for such a transformation, the average growth rates is a more appropriate model rather than the constant growth rate. Nonetheless, we also compare our results

In our case we take, as the benchmark model, the average of the last four most recently available year-on-year GDP changes. The results in the model simulation are generated with a specification with one dynamic factor, one static factor and the VAR for the factors of order 4. This specification results in the lowest mean square forecast error in a training sample from 1990 quarter 1 to 1996 quarter 4 as well as in the sample used for the simulation.[5]

3.2 Results

We now compare the forecast performance of the model in terms of both nowcasts and backcasts vis-a-vis that of the benchmark model. Table 3 presents the mean squared errors (MSE) for the different applications. These are presented for the case where the nowcast or the backcast is generated for each of the three different months in each quarter.

It can be seen from the Table that in both the case of the backcasts and the nowcasts, the mean squared backcast error (MSBE) and the mean squared nowcast error (MSNE) of the benchmark model is considerably greater than the model proposed here. In terms of the month in the quarter the now/backcast is generated, it is evident, as one would expect, that as one moves from the first month to the second and onto the third month, there are notable declines in the MSBE and the MSNE.

In Figures 2 and 3, we plot the backcast and the nowcast respectively along with the observed series and the results from the benchmark model. From Figure 2, it may be observed that the backcast generated for the second month tracks the observed series quite well, particularly when compared with the estimate of the benchmark. In the case of the nowcast estimates in Figure 3, the estimate generated for the third month can also be seen to improve on that estimated in the first and second months of the quarter.

As a final exercise, we examine the effect of individual data releases on the forecast accuracy of the approach. In Figure 4, we plot the MSFE for the nowcast associated with the addition of each data release. This is compared with the score for the benchmark. As

with those of the standard benchmark model - the results do not change. They are available, upon request, from the authors.

[5]Given that the number of dynamic factors is equal to the number of static factors, the dataset is characterised by low dynamics which are captured by the lags in the factors VAR.

can be seen from Table 1, the first set of available releases contains exchange rates while the last is for extra euro area demand for Irish exports and competitors' prices on the export side. Apart from surveys, a marginal improvement can be observed relative to the forecasting performance of the previous release. The improvement is particularly notable for the releases of the live register of unemployment claimants, housing data and monetary aggregates.

4 Conclusions

The use of the dynamic factor model framework for producing nowcasts and backcasts represents a significant addition to the forecasting tool kit of the Central Bank of Ireland. In providing timely estimates of quarterly GDP, the approach has some appealing features. A large panel dataset of potential indicators for GDP may be parsimoniously employed through the dynamic factor model methodology and at any time during a quarter the estimation approach can handle and exploit the unsynchronized flow of generally higher frequency data.

In evaluating the dynamic factor model, a pseudo-real time approach is followed in that the data availability situation, which existed for each quarter, is replicated when computing the model estimates. An out-of-sample simulation is performed where the estimates of the model are compared with that of a benchmark approach. We find that the mean squared forecast errors for both the nowcasts and the backcasts are considerably smaller than those of the benchmark model. Unsurprisingly, the later in the quarter the nowcast or the backcast is generated, the more accurate the estimate proves to be relative to the observed series. This suggests that macroeconomic data releases have an important informational content; it is hence worth updating the forecast many times within the same quarter to incorporate the most recent information.

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Appendix A: Parameters Estimation

In this Appendix, we outline how consistent estimates of the parameters of the dynamic factor model are obtained. Suppose that $z_{it} = y_{it} - \hat{\mu}_i$ and that $x_{it} = \frac{1}{\hat{\sigma}_i}(y_{it} - \hat{\mu}_i)$, where $\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} y_t$ and $\hat{\sigma}_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{\mu}_i)^2}$. Consider the following estimator of the common factors:

$$(\tilde{F}_t, \hat{\Lambda}) = \arg\min_{F_t,\Lambda} \sum_{t=1}^{T}\sum_{i=1}^{n}(z_{it-\Lambda_i Ft})^2$$

The correlation matrix of the observables (y_t) can be defined as:

$$S = \frac{1}{T}\sum_{t=1}^{T} x_t x_t'$$

Let's define D the $r \times r$ diagonal matrix with diagonal elements given by the r largest eigenvalues of S and V the $n \times r$ matrix of the corresponding eigenvectors subject to the normalization $V'V = I_r$. Factors are estimated as:

$$\tilde{F}_t = \Lambda x_t$$

and the factor loadings $\hat{\Lambda}$ are estimated by regressing the variables on the estimated factors:

$$\hat{\Lambda} = \sum_{t=1}^{T} x_t \tilde{F}_t' (\sum_{t=1}^{T} \tilde{F}_t \tilde{F}_t{}')^{-1}$$

and the covariance matrix of the idiosyncratic component is estimated as:

$$\hat{\Sigma}_\xi = diags(S - VDV)$$

The other parameters $\hat{A}$ and Σ are estimated by running a VAR on the estimated factors:

$$\hat{A} = \sum_{t=2}^{T} \tilde{F}_t \tilde{F}_{t-1}' (\sum_{t=2}^{T} \tilde{F}_{t-1} \tilde{F}_{t-1}')^{-1}$$

$$\hat{\Sigma} = \frac{1}{T-1}\sum_{t=2}^{T} \tilde{F}_t \tilde{F}_t' - \hat{A}(\frac{1}{T-1}\sum_{t=2}^{T} \tilde{F}_{t-1}\tilde{F}_{t-1}')\hat{A}'$$

Finally, P is defined as the $q \times q$ diagonal matrix with the entries given by the largest q eigenvalues of $\hat{\Sigma}$ and by M the $r \times q$ matrix of the corresponding eigenvectors, then:

$$\hat{B} = MP^{\frac{1}{2}}$$

Table 1: List of Variables used in the Factor Analysis

Name	Frequency	Timeliness (approx. days)	Source
Live Register	M	10	www.cso.ie/prlabfor.htm
Retail Sales	M	40	www.cso.ie/prservices.htm
Car Sales	M	10	www.cso.ie/prtransport.htm
Unemployment Rate	M	10	www.cso.ie/prlabfor.htm
Industrial Production	M	40	www.cso.ie/prind.htm
Real M1	M	30	www.centralbank.ie
Real M3	M	30	www.centralbank.ie
Real Private Sector Credit	M	30	www.centralbank.ie
CPI sub-indices (7 series)	M	30	www.cso.ie/prprices.htm
House Completions	M	20	www.environ.ie/
House Registrations	M	20	www.environ.ie/
Consumer sentiment index	M	8	www.esri.ie/
Index of consumer expectations	M	8	http://www.esri.ie/
Euro sterling exchange rate	M	0	www.centralbank.ie
Euro dollar exchange rate	M	0	www.centralbank.ie
Euro area consumer and business surveys (11 series)	M	3	http://ec.europa.eu/
Extra euro area demand for Irish exports	Q	variable	ECB
Intra euro area competitors' prices on export side	Q	variable	ECB
Gross Domestic Product	Q	90	www.cso.ie

Table 2: Mean Absolute Deviations of Year-on-Year Growth Rates by Sector

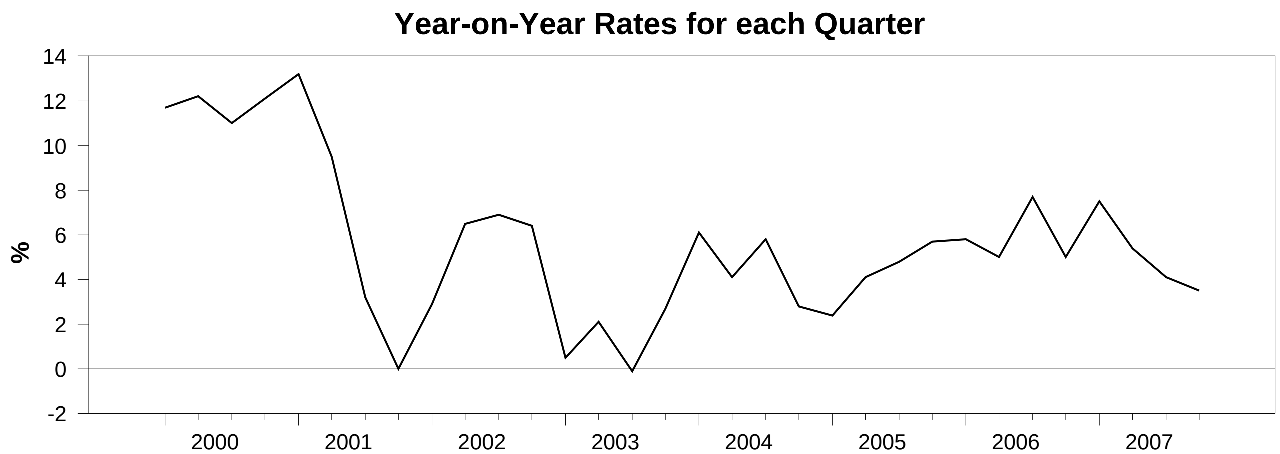
	Mean Absolute Deviation	Share of GDP at Factor Cost
Agriculture	28.0	2.3
Industry (excl. Construction)	31.4	25.1
Building and Construction	16.7	8.5
Distribution, Transport and Communication	8.0	15.6
Public Administration and Defence	2.4	3.4
Other Services	8.1	46.2

Note: Shares are approximate, due to non-additivity of the chained-linked data, and do not add to 100.

Table 3: Mean Squared Errors (MSE) for Backcasts and Nowcasts

Model	MSBE	MSNE
1st Month	5.317	6.145
2nd Month	5.034	5.570
3rd Month		5.475
Benchmark	8.189	8.361

Figure 1: Irish GDP Growth Rates 2000 - 2007



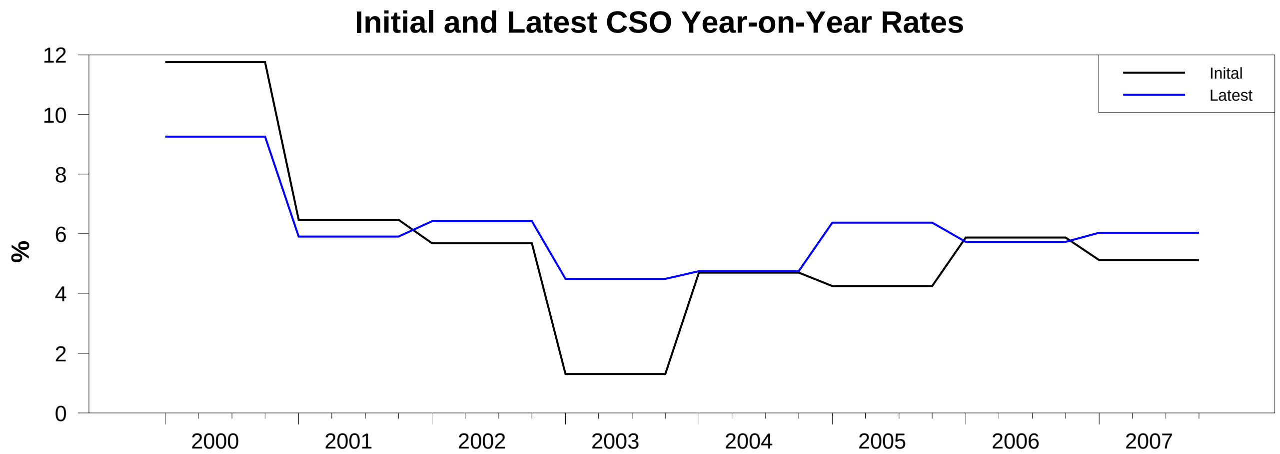


Figure 1: *Comparison of Backcasting Performance*

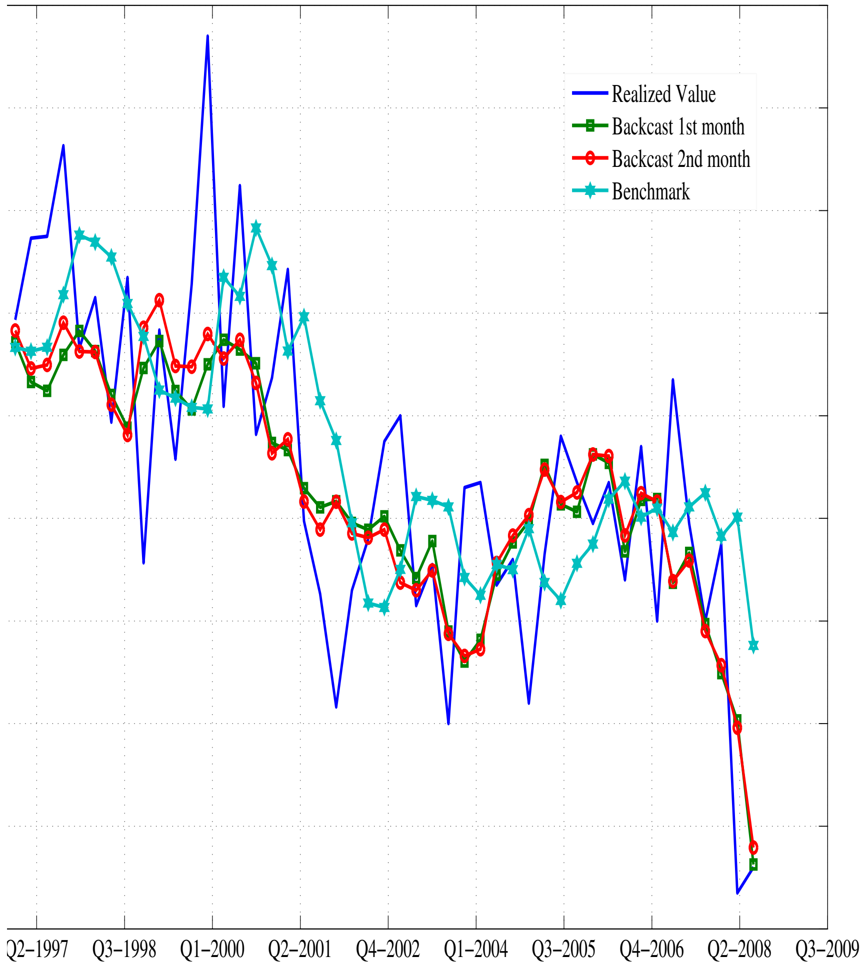


Figure 2: *Comparison of Now-Casting Performance*

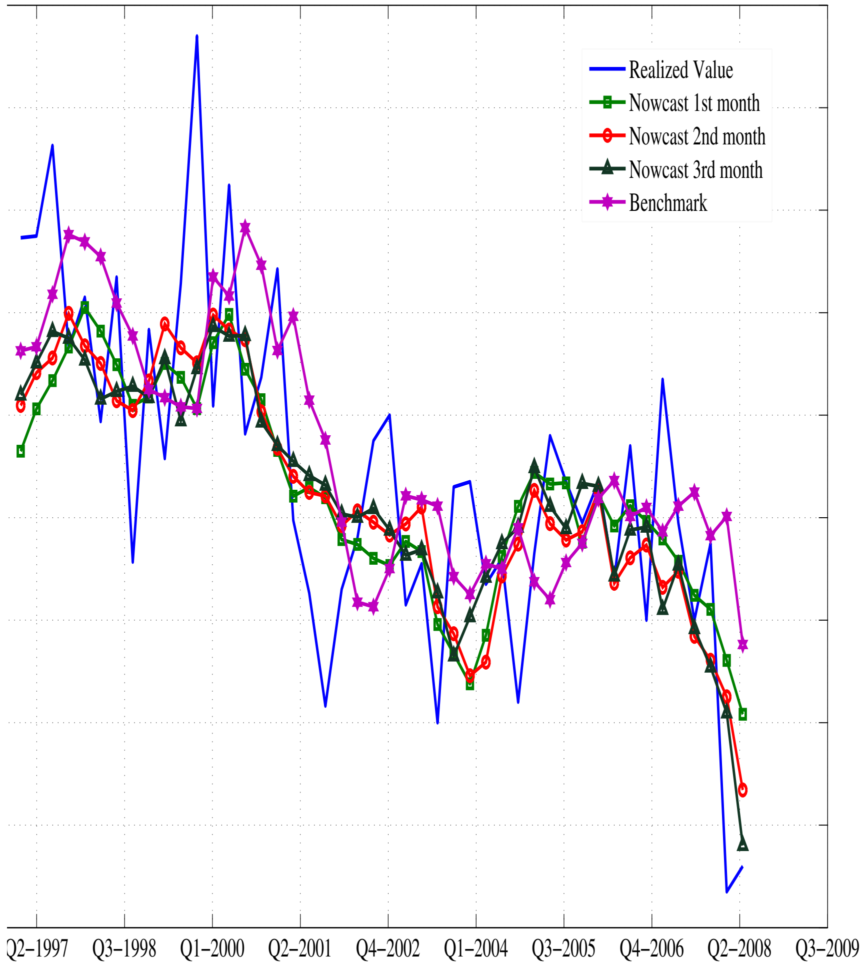


Figure 4

Impact of Data Releases on Forecast Accuracy