Nowcasting: The Real-Time Informational Content of Macroeconomic Data*

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Abstract

A formal method is developed for evaluating the marginal impact that intra-monthly data releases have on current-quarter forecasts (nowcasts) of real GDP growth. The method can track the real-time flow of the type of information monitored by central banks because it can handle large data sets with staggered data-release dates. Each time new data are released, the nowcasts are updated on the basis of progressively larger data sets that, reflecting the unsynchronized data-release dates, have a "jagged edge" across the most recent months.

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1 Introduction

Monetary policy decisions in real time are based on assessments of current and future economic conditions using incomplete data. Because most data are released with a lag and are subsequently revised, both forecasting and assessing current-quarter conditions (nowcasting) are important tasks for central banks. Central banks (and markets) pay particular attention to selected data releases either because the data are released early relative to other variables or because they are directly tied to a variable the central banks want to forecast (e.g. employment or industrial production for nowcasting GDP). In principle, however, any release, no matter at what frequency, may potentially affect current-quarter estimates and their precision. From the point of view of the short-term forecaster, there is no reason to throw away any information, but it is of course relevant to understand how reliable each release is as a signal of current economic conditions.

In nowcasting current-quarter GDP growth, qualitative judgment is typically combined with simple small-scale models that sometimes are called "bridge equations." The idea is to use small models to "bridge" the information contained in one or a few key monthly data with the quarterly growth rate of GDP, which is released after the monthly data. For example, see Baffigi, Golinelli, and Parigi (2004), Runstler and Sédillot (2003) and Kitchen and Monaco (2003).

In this paper, we develop a formal forecasting model that addresses several key issues that arise when using a large number of data series that are released at alternative times and with different lags. Moreover, we combine the idea of "bridging" monthly information with the nowcast of quarterly GDP and the idea of using a large number of data releases within a single statistical framework. The framework formalizes the updating of the GDP nowcast as monthly data are

released throughout the quarter. This approach can be used not only to nowcast GDP but also to evaluate the marginal impact of each new data release on the nowcast and its accuracy. The framework can be understood as a large bridge model that combines three aspects of nowcasting: i) it uses a large number of data series; ii) it updates nowcasts and measures of their accuracy in accordance with the real-time calendar of data releases; and iii) it "bridges" monthly data releases with the nowcast of quarterly GDP.[1]

Because the model exploits information in a large number of data releases, it must be specified in a parsimonious manner in order to retain forecasting power. This is achieved by summarizing the information of the many data releases with a few common factors. The nowcast is then defined as the projection of quarterly GDP on the common factors estimated from the panel of monthly data ("bridging with factors").

The use of factor models for macroeconomic forecasting is now standard at central banks and other institutions. Many authors have shown that these models are successful in this regard (Boivin and Ng 2005, Forni, Hallin, Lippi, and Reichlin 2005, D'Agostino and Giannone 2006, Giannone, Reichlin, and Sala 2004, Marcellino, Stock, and Watson 2003, Stock and Watson 2002a, Stock and Watson 2002b), but factor models have not been used specifically for the problem of nowcasting in real time.

In real time, some data series have observations through the current period, whereas for others the most recent observations may be available only for a month or quarter earlier. Consequently, the underlying data sets are unbalanced. Appro-

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[1]The replicating files and appendix are available at http://homepages.ulb.ac.be/ dgiannon/ and http://homepages.ulb.ac.be/ lreichli/. The data set has been constructed with the help of economists at the Board of Governors of the Federal Reserve System within a project that is evaluating our model on an ongoing basis.

priately dealing with this "jagged edge" feature of the data is key for producing a nowcast that, by exploiting information in the most recent releases, has a chance to compete with judgmental nowcasts.

To deal with this problem, we adapt the large factor model typically used in the literature. In the first step, the parameters of the model are estimated from an OLS regression on principal components extracted from a balanced panel, which is created by truncating the data set at the date of the least timely release. In the second step, the common factors are extracted by applying the Kalman smoother on the entire data set. We have used the same model in a related paper that focuses on the structural interpretation of forecasting errors rather than on the real-time differences in the timing of data releases (Giannone, Reichlin, and Sala 2004). The consistency properties of this procedure are studied in Doz, Giannone, and Reichlin (2006).

The model is used to produce nowcasts based on about two hundred time series for the US economy typically used by short-term forecasters. By tracking the calendar of data releases throughout each quarter, we produce a nowcast of GDP corresponding to each data release. This sequence of nowcasts is used to evaluate the nowcasts' forecasting accuracy as the conditioning information set evolves over time and to assess the real-time marginal impacts that different types of economic information have on the nowcast of GDP.

The problem addressed in this paper relates to the general problem of analyzing the economy in real time. The literature, however, has almost exclusively focused only on the problem of data revisions and its implication for statistical and policy analysis (Croushore and Stark 2001, Koenig, Dolmas, and Piger 2003, Orphanides 2002) and has payed little attention to the fact that, in

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real time, the forecast has to be conducted on the basis of data sets that, due to different publication lags, are unbalanced at the end of the sample. This problem is of first-order importance whenever, as is typically the case for forecasting, one performs the analysis on the basis of multivariate information, rather than focusing on only one series.

Our approach is closely related to Evans (2005) who, as in this paper, constructs a model for the updating of the nowcast of GDP as new information become available. However, his framework can handle only a limited number of series. The advantage of our method is that the nowcast can be conditioned on a large number of variables, possibly on all the indicators examined routinely by the experts at central banks. This allows for estimates of the impact of each data release to be conditioned on more realistic informational assumptions and for a detailed analysis of the marginal impacts of different data releases on those estimates as time evolves throughout the quarter.

Finally, the problem of obtaining a timely nowcast of quarterly GDP growth should be distinguished from that of extracting a coincident index of economic activity, for which factor models have been successfully applied (see, for example, the Eurocoin, CEPR-Bank of Italy coincident indicator for the Euro area activity and the Chicago Fed index of the US activity). A coincident index is typically a filter on current-quarter GDP (Altissimo, Bassanetti, Cristadoro, Forni, Hallin, Lippi, and Reichlin 2001) or a weighted average of several monthly indicators (FED 2001) and is not aimed at obtaining an accurate nowcast of current-quarter GDP growth.

The paper is organized as follows. Section 2, describes the nowcasting problem and the structure of the staggered data releases in the United States. Section 3

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introduces the model and estimation technique. Section 4 describes the empirical analysis and comments on the results. Section 5 concludes.

2 The Nowcasting Problem and the Real-Time Data Flow

Our aim is to evaluate the current-quarter nowcast of real economic activity, measured by the growth rate of Gross Domestic Product (GDP), on the basis of the flow of information that becomes available during the quarter.

Within each quarter, q, the contemporaneous value of GDP growth, y_q, is not available, but can be estimated using higher-frequency variables that are published in a more timely manner. As time goes by, the data set relevant for calculating a given nowcast changes. A particular feature of these evolving data sets is that, when considering the most recent time periods, they exhibit a "jagged edge" along which some variables have data entries and others have no observations.

As a simple example, define the relevant information set at month v as Ω_v^n, which includes the relevant n monthly time series up through month v. Then compute the following projection:

$$\text{Proj}[y_q \mid \Omega_v^n].$$

Let us assume that Ω_v^n is composed of two blocks $[\Omega_v^{n_1} , \ \Omega_v^{n_2}]$ and that the month-v values for variables in $\Omega_v^{n_1}$ are released in month v, while those in $\Omega_v^{n_2}$ are released with a one-month lag. This implies that, in month v, variables in $\Omega_v^{n_1}$ are available up through month v, while variables in $\Omega_v^{n_2}$ are available only

up through month $v - 1$. In this sense, the data set is unbalanced or "jagged." The nowcasting exercise must be able to handle such data sets in order to use all available information. Our nowcasting problem is the generalization of this simple case.

The conditioning set we use in the projection is a large panel of monthly time series, consisting of about 200 series for the US economy, broadly those examined closely by the staff of the Federal Reserve when making its forecasts. The data considered are published in thirty five releases per month and consist of direct measures of both real economic activity and prices and of aggregate and sectoral variables. Moreover, they include indirect measures of economic developments, such as surveys and financial prices, and measures of money and credit.

To set the notation, we denote the information set by

$$\Omega_{v_j} = \left\{ X_{it|v_j}; \ \ i = 1, ..., n; \ \ t = 1, ..., T_{iv_j} \right\}.$$

This data set is composed of n variables, $X_{it|v_j}$, where $i = 1, ..., n$ identifies the individual time series and $t = 1, ..., T_{iv_j}$ denotes time in months from the first observation to the last available one, which varies across variables and vintages. Accordingly, T_{iv_j} indicates the last period for which series i in vintage v_j has an observed value. For example, given the nature of data releases in the U.S., when industrial production is released in month v, the most recent observation is for the previous month, and $T_{iv_j} = v - 1$. However, when surveys are released, the most recent observation is for the month of the release, and $T_{iv_j} = v$.

Notice that the new information set differs from the preceding one for two reasons. First, there are new, more recent, observations: $T_{iv_j} \geq T_{iv_{j-1}}, i \in I_{v_j}$,

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while $T_{iv_j} = T_{iv_{j-1}}, i \notin I_{v_j}$.[2] Second, old data are revised, with the data revisions given by $X_{it|v_j} - X_{it|v_{j-1}}, i \in I_{v_j}$. In absence of data revisions $\Omega_{v_{j-1}} \subseteq \Omega_{v_j}$, i.e. the information set is expanding over time.

Because GDP is a quarterly series while the information we use for nowcasting is monthly, we introduce some additional notation to set the timing conventions. We let a quarter q be dated by its last month (for example, the first quarter of 2005, is dated by q =March05). Assuming that the first month in the sample corresponds to the beginning of a quarter (that is $t = 1$ is either January, April, July or October), we have $q = 3k$ where $k = 1, 2, ...$ Within each quarter $q = 3k$, the monthly data release j is published three times, generating the three data sets Ω_{v_j}, where $v = 3k - 2, 3k - 1$ and $3k$ in the first, second and third months of quarter, respectively. At v_j, a set of variables $X_{i,t}, i \in I_{v_j}$ is released and the information set expands from $\Omega_{v_{j-1}}$ to Ω_{v_j}.

For each information set within a given quarter, the nowcast is computed as the expected value of GDP conditional on the available information. Denoting y_{3k} as GDP growth rate, which is measured at quarterly frequency, we have:

$$\widehat{y}_{3k|v_j} = \mathrm{E}\left[y_{3k}|\Omega_{v_j}; \mathcal{M}\right], \quad v = 3(k-h) - 2, 3(k-h) - 1, 3(k-h), \quad j = 1, ..., J$$

where $\mathcal{M}$ denotes the underlying model according to which the expectation is taken. The forecast h quarters ahead corresponds to the estimates made during the months $v = 3(k-h) - 2, 3(k-h) - 1, 3(k-h)$. For $h = 0$ we have the nowcast. This is our "bridge equation." Notice that the "bridging" equation exploits monthly information to obtain a better nowcast of quarterly GDP, rather

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[2]The set I_{v_j} lists the set of variables released as of date v_j.

than interpolating quarterly GDP to obtain a monthly GDP indicator as, for example, in Chow and Lin (1971).

The uncertainty associated with this projection is measured by

$$V y_{3k|v_j} = \mathrm{E}[(\widehat{y}_{3k|v_j} - y_{3k})^2; \mathcal{M}].$$

Abstracting from data revisions, the intra-month flow of data is mainly reflected in the increase of the cross-sectional information since data are released at different dates of the month. In particular, at each release date v_j the information set expands because of the inclusion of new information. Because the data set is expanding $V y_{3k|v_j} \leq V y_{3k|v_{j-1}}$ (i.e., uncertainty is expected to decrease as time passes by). The evolution of this measure of uncertainty across data releases indicates the extent to which each release helps reduce uncertainty of the nowcast. The reduction of uncertainty provides a measure of the marginal information content of the jth data release.

3 The Model and Estimation Technique

To compute the conditional expectations above, we have to specify a model. Since the variables in the information set are numerous, estimating a full model would limit the degrees of freedom and hence the model would perform poorly in forecasting because of the large uncertainty in the parameters' estimation ("the curse of dimensionality"). The fundamental idea of our approach is to exploit the collinearity of the series in our panel by summarizing all the available information in few common factors. Due to collinearity, a projection on the space of the common factors is able to capture the bulk of the dynamic interaction among

the series and to provide a parsimonious model that works well in forecasting.[3] The parsimonious approximation of the information set by a limited number of common factors makes the projection feasible since it requires the estimation of only a limited number of parameters.

To specify the factor model, let $x_{it|v_j}$ denote the generic stationary monthly indicator available for the vintage v_j and transformed so as to correspond to a quarterly quantity when observed at the end of the quarter[4], that is when $t = 3k$ for $k = 1, 2, ..., \lfloor T_{i,v_j}/3 \rfloor$. We assume the following factor structure for the transformed monthly indicators:

$$x_{i,t|v_j} = \mu_i + \lambda_{i1} f_{1,t} + ... + \lambda_{ir} f_{r,t} + \xi_{i,t|v_j}, \quad i = 1..., n$$

where μ_i is a constant, and $\chi_{it} \equiv \lambda_{i1} f_{1k} + ... + \lambda_{ir} f_{rk}$ and ξ_{it} are two orthogonal unobserved stationary stochastic processes. We assume that the processes χ_{it} (the common components) are linear functions of a few $r << n$ unobserved common factors that capture "almost all" comovements in the economy, while the linear processes ξ_{it} (the idiosyncratic components) are driven by variable-specific shocks.

Let us rewrite the model in matrix notation:

$$x_{t|v_j} = \mu + \Lambda F_t + \xi_{t|v_j} = \mu + \chi_t + \xi_{t|v_j} \qquad (1)$$

where $x_t = (x_{1t|v_j}, ..., x_{nt|v_j})'$, $\xi_{t|v_j} = (\xi_{1t|v_j}, ..., \xi_{nt|v_j})'$, $F_t = (f_{it}, ..., f_{rt})'$ and Λ is a $n \times r$ matrix of the factor loading with generic entry λ_{ij}.

Assuming that GDP does not depend on variable-specific dynamics, projecting on the common factors (instead of projecting on all the variables) is not only

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[3]For an extensive discussion on this point, see Forni, Hallin, Lippi, and Reichlin (2005), Giannone, Reichlin, and Sala (2004), Stock and Watson (2002a), and Stock and Watson (2002b).
[4]The appendix describes the data transformations.

parsimonious and feasible but it also provides a good approximation for the full, but unfeasible and over-parameterized, projection on all the variables. Under the additional assumption that GDP growth and the monthly indicators are jointly normal, we obtain that the nowcast of GDP growth is a linear function of the expected common factors:

$$\widehat{y}_{3k|v_j} = \alpha + \beta' \hat{F}_{3k|v_j} \tag{2}$$

where $\hat{F}_{3k|v_j} = \mathrm{E}\left[F_{3k}|\Omega_{v_j}; \mathcal{M}\right]$ for $v = 3k, 3k - 1, 3k - 2$.

Recent literature has shown that the unobserved common factors F_t can be consistently estimated by principal components on the observable variables.[5] In our case, however, the problem is more complicated because, when extracting the common factors in real time, we want to take into consideration and exploit the timeliness of the releases of the monthly indicators, which requires dealing with missing data at the end of the sample.

The methodology we propose here is the two-step estimator studied by Doz, Giannone, and Reichlin (2006) and applied by Giannone, Reichlin, and Sala (2004) to identify macroeconomic shocks in real time. This framework combines principal components with Kalman filtering techniques, where the Kalman smoother is used to compute recursively the expected value of the common factors. This parametric version of the factor model can also be used to derive explicit measures of the precision of the common factors estimates.

To apply Kalman filtering techniques for the extraction of the common factors, we have to further specify the structure of the model. First, we parameterize the dynamics of the common factors as a vector autoregression:

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[5]See Bai (2003), Bai and Ng (2002),Forni, Giannone, Lippi, and Reichlin (2005), Forni, Hallin, Lippi, and Reichlin (2005), Stock and Watson (2002a).

$$F_t = AF_{t-1} + Bu_t; \quad u_t \sim WN(0, I_q) \tag{3}$$

where B is a $r \times q$ matrix of full rank q, A is a $r \times r$ matrix with all roots of $\det(I_r - Az)$ outside the unit circle, and u_t is the q dimensional white noise process of the shocks to the common factors. In such a model, a number of common factors (r) that is large relative to the number of common shocks (q) aims at capturing the lead and lag relations among variables along the business cycle (cfr. Forni, Giannone, Lippi, and Reichlin (2005) for details).

We then parameterize the idiosyncratic components by specifying that, for available vintages, the idiosyncratic components are cross-sectionally orthogonal white noises:

$$\text{E}(\xi_{t|v_j}\xi'_{t|v_j}) = \Psi_{t|v_j} = \text{diag}(\tilde{\psi}_{1,t|v_j}, ..., \tilde{\psi}_{n,t|v_j}) \tag{4}$$

$$\text{E}(\xi_{t|v_j}\xi'_{t|v_j}) = 0, s > 0 \text{ for all } v, j. \tag{5}$$

We also assume that $\xi_{it|v_j}$ is orthogonal to the common shocks u_t:

$$\text{E}(\xi_{t|v_j}u'_{t-s|v_j}) = 0, \text{ for all } s, v, j. \tag{6}$$

To handle missing observations at the end of the sample produced by the non-synchronous real-time data flow, we parameterize the variance of the idiosyncratic component as:

$$\tilde{\psi}_{i,t|v_j} = \begin{cases} \psi_i & \text{if } x_{it|v_j} \text{ is available} \\ \infty & \text{if } x_{it|v_j} \text{ is not available.} \end{cases} \tag{7}$$

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With the additional assumption that the errors are Gaussian, equations 1 through 7 fully characterize the model.

The parameters are estimated from an OLS regression on principal components extracted from a balanced panel that has truncated at the date of the least timely release. At each vintage v_j, the balanced data set uses the sample through $\min\{T_{1v_j}, ..., T_{nv_j}\}$.[6]

We denote the model as $\mathcal{M}_\theta$, where all parameters are collected in θ. If we replace the parameters by their consistent estimates and collect them in $\hat{\theta}$, we can estimate the common factors and their accuracy as:

$$\hat{F}_{t|v_j} = \text{E}[F_t \mid \Omega_{v_j}; \mathcal{M}_{\hat{\theta}}] \tag{8}$$

$$\hat{V}_{v_j} = \text{E}[(F_t - \hat{F}_t)(F_t - \hat{F}_t)'; \mathcal{M}_{\hat{\theta}}]. \tag{9}$$

Both of these measures can be computed recursively using the Kalman smoother since the model is in a state space form.

The way missing observations are treated implies that the filter, through its implicit signal extraction process, will put no weight on missing observations in the computation of the factors. In this way, when no observation is available, the filter produces a forecast of the common factors.

Notice that the two-step estimator of the common factors, beside being able to deal with missing observations, exploits the dynamics of the common factors and the cross-sectional heteroscedasticity of the idiosyncratic components, thereby providing efficiency improvements over simple principal components.[7]

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[6]See the appendix for details of the estimation.

[7]The relation of our model to that used in estimating principal components is discussed in the appendix.

Doz, Giannone, and Reichlin (2006) have shown that the two-step estimator for the common factors is consistent when the cross-section size, n, and the sample size, T, are both large. Although the model does not allow for cross-sectional and serial correlation of the idiosyncratic component, consistency is achieved under more general assumptions. The key insight to understand this robustness property of the estimator is the same as for simple principal components: due to the law of large numbers, the idiosyncratic component becomes negligible as the cross-sectional dimension increases. As a consequence, as far as it is confined to the idiosyncratic part, the misspecification of the model does not compromise consistency. For the same reason, the estimates of the common factors are likely to be robust to the presence of data revisions provided the revision errors are weakly cross-correlated.[8]

Given the estimates of the common factors, the nowcast of GDP can hence be computed by estimating the coefficients α and β of equation (2) by OLS regression of GDP, y_{3k}, on the quarterly common factors, $\hat{F}_{3k|v_j}$, using the sample for which GDP growth is observed, $k = 1, ..., \lfloor T_{yv_j}/3 \rfloor$ where T_{yv_j} is the last month for which GDP is available for the vintage v_j. The estimate for GDP is hence given by:

$$\widehat{y}_{3k|v_j} = \gamma_0 + \hat{\gamma}' \hat{F}_{3k|v_j}.$$

The forecast h quarters ahead corresponds to the estimates made during the months $v = 3(k-h) - 2, 3(k-h) - 1, 3(k-h)$. For $h = 0$ we have the nowcast, that is the estimate of GDP made during the current quarter.

The degree of precision of the estimate is computed as:

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[8]See the appendix for details.

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$$V y_{3k|v_j} = \hat{\gamma}' \hat{V}_{0|v_j} \hat{\gamma} + \widehat{\text{Var}(\hat{e}_{3k|v_j})},$$

where $\hat{e}_{3k|v_j} = y_{3k} - \hat{y}_{3k|v_j}$ are the estimated residuals.

Notice that in our specification we do not include lagged GDP as predictor. The reason is that, as we will show in the next Section, the common factors are not only able to capture the bulk of dynamic interaction among monthly indicators, but also the bulk of dynamics in GDP. This suggests that the sources of GDP dynamics are common to those of the monthly series.

4   Empirics

As indicated in Section 2, the data set consists of about 200 macroeconomic indicators for the US economy, including real variables (such as industrial production and employment), financial variables, prices, wages, money and credit aggregates, surveys from other sources, and other conjunctural indicators. Data are collected in March 2005 with the sample starting in January 1982. They are transformed to induce stationarity and to insure that the transformed variables correspond to a quarterly quantity when observed at the end of the quarter. Details on data transformations for individual series are reported in the appendix.

To examine the perfomance of the model, we perform two sets of exercises. In the first, we provide an evaluation of the overall performance of the model. We check how well the projection on the common factors tracks current-quarter GDP, that is we look at the in-sample fit of the model. Moreover, we establish the overall out-of-sample forecasting performance of the model using the information available at the middle of each quarter.

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In the second exercise, we study the effect of each release during the quarter on the forecast accuracy; i.e., we analyze the evolution of the forecast in relation to the flow of information throughout the quarter (we have 35 distinct data releases in the quarter). We compute not only the model-based measure of accuracy but also an out-of-sample measure that reflects model uncertainty.

For both exercises we aggregate the 35 releases in a stylized monthly calendar of 15 releases. This is done because dates of publications are sometimes overlapping. As will be detailed later, the calendar generally identifies a block of data releases by both a publication date and an economic classification (all industrial production series, labor and wage series, surveys and so on).

Because real-time vintages for all the series in the panel are not available, we cannot perform a pure real-time evaluation. Therefore, the simulated out-of-sample analysis is "pseudo" real time. The design of the exercise can be described as follows. Because the timing and order of data releases vary only slightly from month to month, we assume that the pattern of data availability is unchanged throughout the evaluation sample. [9] More precisely, starting from January 1995 and until December 2004, each month the 15 real-time vintages are constructed by replicating the pattern of data availability implied by the stylized calendar of the 15 data releases. Notice that, since we use data collected in March 2005, we are not able to track data revisions. In this sense our vintages are "pseudo" real-time vintages rather than fully real time vintages.[10] We estimate the model recursively using only information available at each point the nowcasts are computed.

We parameterize the model with two static factors and two common shocks:

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[9]This assumption is not too unrealistic since the variation of the calendar over time are only minor.

[10]In the Appeniix, we compare the results on the performance of the nowcasts obtained using "pseudo" real-time vintages with those obtained by using real-time GDP vintages. It is shown that using real-time GDP rather than revised GDP does not change the results qualitatively.

Figure 1: Realized GDP Growth versus Nowcast
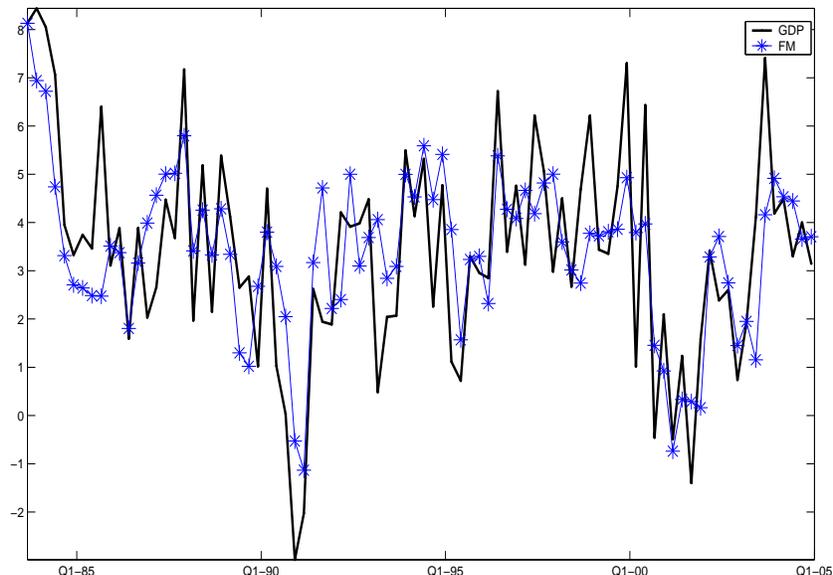
$q = 2, r = 2$. This parametrization will be kept throughout the empirical exercise. A robustness check using out-of-sample results for different choices of q and r is provided in the appendix. As shown, our qualitative results are roubst with respect to alternative values for these parameters.

4.1   Overall evaluation of the model

As shown in the previous section, the nowcast of current-quarter GDP growth is obtained as a projection on the common factors. To verify that this procedure provides a good in-sample fit, Figure 1 plots GDP growth against our nowcast. As shown, our model tracks GDP growth quite well. In particular, it is effective in capturing the two recessions of the sample – in the early 90s and at the beginning of the new millennium.

Table 1 reports the autocorrelation function of the residuals of the projection. The results indicate that only the autocorrelation at two quarters is marginally

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significant and hence the residuals cannot be statistically distinguished from white noise. This suggests that the few common factors extracted from our large database of monthly indicators capture the bulk of GDP dynamics.

We now perform the out-of-sample evaluation of the model, comparing the performance of our model with that of the the Survey of Professional Forecasts (SPF). SPF forecasts are collected at the middle of each quarter. To make sure that the results from our model are based on an information set comparable to that available to the SPF forecasters, our model outcomes are based on data available up to the end of the first week of the second month of each quarter, just after the release of the Employment Report.

Forecast accuracy is measured by the Mean Square Forecast Error (MSFE). The evaluation sample starts in the first quarter of 1995 and ends in the last quarter of 2004. As a benchmark of non-predictability, we compute the forecasts for a naive constant growth model.

Table 2 below reports the MSFE of the factor model and of the SPF relative to the naive constant-growth model. A number below one indicates that the forecasts are more accurate than those produced by the naive benchmark.

Results indicate that, beyond the first quarter, neither the SPF nor the factor model are more accurate than the naive constant-growth model. Moreover, the longer the forecast horizon, the worse is the relative forecast.[11] Concerning the current-quarter estimate (nowcast), some improvement over the naive model is obtained by both the SPF and the factor model.

Figure 2 plots quarterly GDP growth against the constant growth model, the factor model nowcast (FM), the SPF nowcast and the nowcast produced by the

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[11]Giannone, Reichlin, and Sala (2004) find similar results in different sub-samples, indicating that our findings are robust.

Figure 2: Comparative Nowcast Results
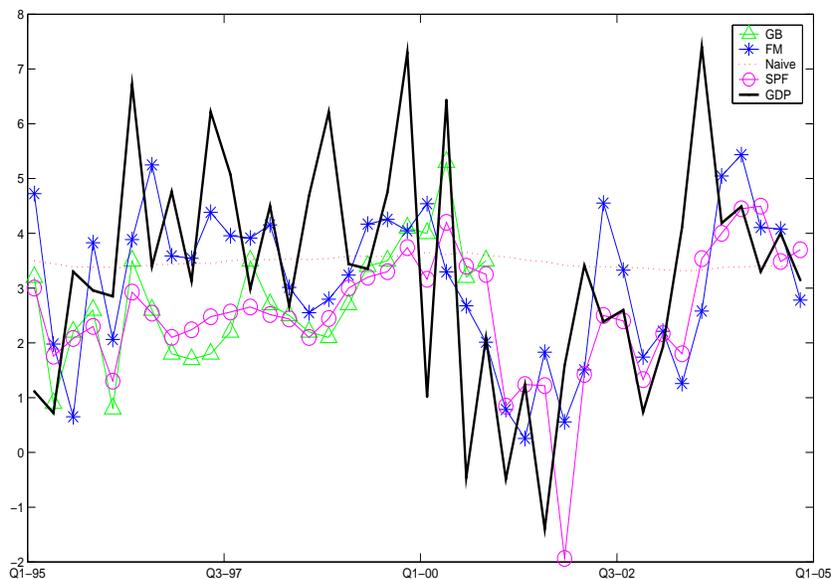
Board of Governors of the Federal Reserve, the Greenbooks (GB), available to the public only until the last quarter of 2000.

As is evident, our nowcast is effective in tracking GDP growth also when estimated in real time. Moreover it compares well with both the Greenbook's and the SPF forecasts. The slow growth phase starting in 2001 is captured equally well by both the SPF and our model. In the second half of the 90s, the Greenbook and the SPF perform relatively poorly as they underestimate the surge in growth associated with the boom in productivity, while the factor model has no bias over this period.

We conclude that our estimates of current-quarter GDP growth have good in-sample and out-of-sample performances. Hence, the model is well supported by the data. It should be stressed that the model performs well at the horizon where institutional forecasts, such as Greenbook's and the SPF forecasts, have been shown to outperform a simple constant growth model (Giannone, Reichlin,

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and Sala 2004). At horizons longer than the current quarter, there is very little forecastability for GDP (D'Agostino, Giannone, and Surico 2006). Clearly, the current quarter is the horizon at which the timely exploitation of the early releases matters most.

4.2 The marginal impacts of data releases on the accuracy of the nowcast

Before conducting an analysis of the marginal impacts of individual data releases, the calendar of data releases is reviewed in detail because the order of the releases importantly affects their marginal impacts.

Stylized Calendar

The timing and structure of the data flows are described in Table 3. The 15 blocks into which the data releases have been are aggregated are listed in column 1, while the 35 individual releases are listed in column 2.[12] Different blocks of releases are published at different dates throughout a month (column 3) and may refer to different dates (column 4). Typically, surveys have very short publishing lags and often are forecasts for future months or quarters; while GDP, for example, is released with a relatively long delay.[13] Industrial production, prices, and other variables are intermediate cases.

We start the month with the Chicago Report of the National Association of Purchasing Management, which is released the first business day of the month. We name this block "Survey 2" in the table. The next block comprises miscella-

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[12]The source of each data release and the individual series in each release (and block) are reported in the appendix.

[13]The releases of the GDP and Income block for the first, second and third months of the quarter contain the GDP and Income data from the "advance," "preliminary," and "final" releases; respectively.

neous releases, such as construction spending and the advanced report on durable goods manufacturers ("Mixed3"). "Mixed 3" is followed by "Money and Credit" and so on.

Following the notation introduced in Section 2, v_1 indexes the vintage after the release of "Survey 2" and before the release of the second block "Mixed 3". Just after the inclusion of the "Financial" block, we have the last vintage of the month, indexed by v_{15}.

Because the data blocks defining the vintages are in the same order each month, we use v_j to index both the vintage and the time at which they are released. We say that variables in the first block ("Survey 2") are updated in vintage v_1 and are released at time v_1.

The treatment of financial variables deserves a comment. Financial variables and interest rates are the most timely of all the variables since they are available on a daily basis. Because the bulk of our data are monthly, we disregard information from financial variables at frequencies lower than the month and let these variables enter the model as monthly averages. We make the arbitrary assumption that they become available only at the end of the month, which implies that their impact on the estimation of the nowcast and its uncertainty will be understated.

Because the stylized release calendar of 15 blocks roughly preserves the time varying real-time release calendar and because the blocks include data series of a similar economic content, our vintage data sets can be used sequentially to examine the marginal impact of macroeconomic data releases on the nowcasts of GDP growth.

The analysis

We now present two sets of results. First, we evaluate the in-sample evolution of uncertainty over the quarter in relation to each release in the stylized calendar. For each month of the current quarter $v = 3k - 2, 3k - 1, 3k$ and for all data releases within the month $j = 1, ..., 15$, we define uncertainty as:

$$V y_{3k|v_j} = \mathrm{E}[(\widehat{y}_{3k|v_j} - y_{3k})^2],$$

where $\widehat{y}_{3k|v_j}$ is the nowcast computed on the basis of the (incomplete) data at date v_j and y_{3k} is realized current-quarter GDP growth. Because of the stationarity assumption, our measure is invariant to the quarter in which we compute the forecast. The measure depends only on the estimated parameters and on the real-time data flow, which, accordingly to the stylized calendar, is the same in every quarter. We evaluate it using parameters estimated over the entire sample.

Using the notation of Section 2, the nowcasts for quarter k are denoted by $\hat{y}_{3k|v_j}$ for the three months of the quarter, $v = 3k - 2, 3k - 1, 3k$ and for each time new macroeconomic data are released, $j = 1, ..., J$.

Second, we compute corresponding out-of-sample measures in order to check for the robustness of the first set of results. Out-of-sample uncertainty, unlike the corresponding in-sample measure, is influenced by model uncertainty and can be taken as a further and tougher validation check of our model. In particular, we look at the evolution of the MSFE for the nowcasts computed after each data release within the quarter when GDP growth is projected on many monthly data series. That is,

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$$\frac{1}{K_1 - K_0 + 1} \sum_{k=K_0}^{K_1} \left(\hat{y}_{3k|v_j} - y_{3k} \right)^2 \qquad v = 3k - 2, 3k - 1, 3k; \quad j = 1, ..., 15$$

where the forecasts are computed recursively using only information available at the time the nowcast is made. Unlike for the overall forecasting evaluation, where the nowcast is computed at the end of the first week of the second month of each quarter, here we track the evolution of the uncertainty of such nowcasts throughout the quarter.

These two measures are derived from the analysis of the data releases in their natural chronological order and thus correspond to the exercise in which the forecaster updates her nowcasts after the release of each data block.

Results for the in-sample measure are reported in Figure 3, where uncertainty is expressed relatively to the variance of GDP growth. The chart shows that intra-month information matters. Data releases throughout the quarter convey new information that is relevant because the uncertainty decreases uniformly through the quarter.

The release that has the largest impact on the nowcast and its precision is the "Mixed 2" block. "Mixed 2" is composed of two series from the "New Residential Construction" release and nine series from the "Philadelphia Business Outlook Survey". By way of the Philadelphia survey, "Mixed 2" is the most timely release since it is the first block containing data relating to the current month.

Results from the out-of-sample measure are described in Figure 4, which reports the MSFE of the factor model relative to the constant-growth benchmark. A value below one (dotted line), indicates that the nowcast from the factor model outperforms that of the constant-growth model. The out-of-sample exercise con-

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Figure 3: MSFE Across Data Blocks (In Sample)
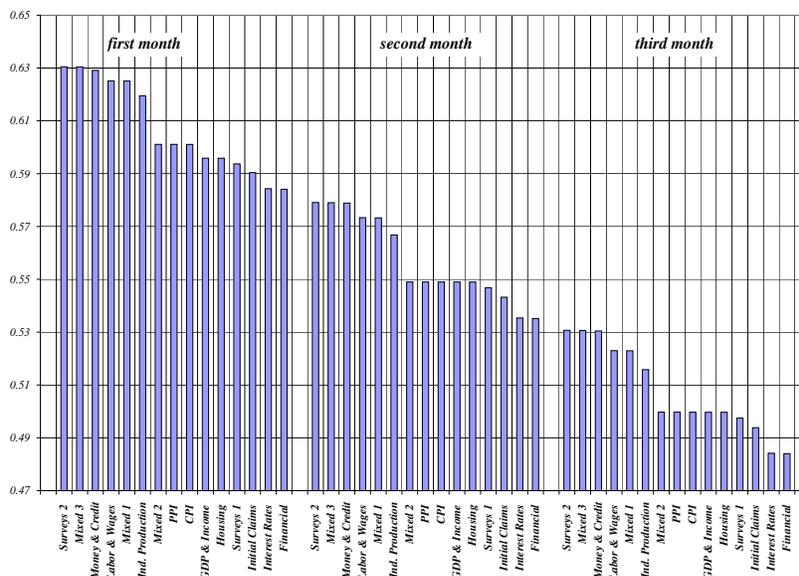
firms that, as more information becomes available throughout the quarter, uncertainty declines.

Notice that uncertainty corresponding to releases during the first month should be seen as uncertainty around a forecast rather than nowcast uncertainty since, in the first month, the only data release referring to the current quarter are the Philadelphia Surveys ("Mixed 2"). During the first month, uncertainty around the factor model forecasts is higher than that corresponding to the naive constant growth model and the model is therefore not very reliable. This can also be seen by the fact that, in the first month, the industrial production release (referring to the previous month) increases uncertainty rather than reduces it.

From the second month onward, however, we confirm the feature of the in-sample analysis where new information has a monotonic and negative effect on uncertainty. In the first month, the distortion induced by "Industrial Production" is corrected by "Mixed 2," which, as in the in-sample evaluation, has a large

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Figure 4: MSFE Across Data Blocks (Out of Sample)
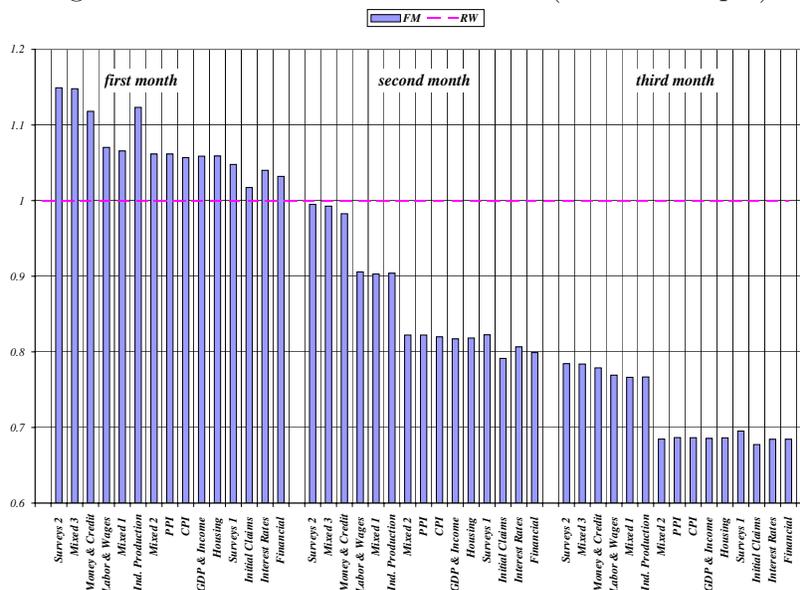
impact on the nowcast. In the second month; the "Labor and Wages" release, which contains the first hard data relating to the current quarter, has a large effect. In fact, only when the report on the employment situation of the second month of the quarter (from the Bureau of Labor Statistics) is incorporated in the estimates does the factor model become more accurate than the naive model. Starting from that moment, results of the out-of-sample exercise confirmed what was seen for the in-sample measure of forecast accuracy.[14]

In particular, these out-of-sample results confirm the earlier in-sample ones showing the importance of "Mixed 2" and the fact that information contained in industrial production does not have a role in reducing uncertainty because it arrives relatively late in the quarter. Conditional on data released earlier, industrial production does not induce a marginal reduction of uncertainty. This highlights the importance of taking into account "timeliness" when measuring

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[14]It is worth recalling that the nowcasts and the forecasts in Table 2 are computed just after the "Labor and Wages" release at the beginning of the second month.

the impact of data releases.

In summary, the results from the in-sample measure of accuracy are broadly confirmed and they indicate that, in real time, the surveys are the most relevant source of information for current quarter estimates of GDP. The out-of-sample exercise attributes a larger role to "Labor and Wages" than what was seen in the in-sample exercise, in particular at the beginning of the second month of the quarter. Finally, both evaluation exercises have shown that**more** information helps in reducing uncertainty.[15]

5   Summary and Conclusion

This paper has addressed a standard problem of real-time conjunctural analysis: the forecast of current-quarter GDP growth in relation to the flow of data releases. This problem has been analyzed with a non-standard tool that exploits the information in a large number of monthly variables, released in an asynchronous way. The nowcasts are updated, each time new data are published, on the basis of data sets with a "jagged edge" and which become progressively larger as time evolves. In this way we offer a formal procedure to perform an exercise that, in conjunctural analysis, is typically conducted on the basis of informal judgment.

The econometric model used in this analysis is a dynamic factor model where

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[15]Other studies have evaluated the marginal impact of a block of variables by evaluating a forecast including or excluding the variables in question. Our exercise is different and more meaningful to handle the real time aspect of data flow, in particular when data are nearly collinear as it is the case for macroeconomics series. For example, in the extreme case in which two blocks of variables are perfectly collinear, using each block separately would produce the same forecasts indicating that the two blocks are equally important. In real time, however, the marginal contribution of a particular block depends on the order of data arrival. In the example above of perfectly collinear blocks of variables, only the block that is released first has information content since, by the time the later release is published, its informational content is already incorporated in the forecast.

the factors are estimated in two steps: first computing principal components and then using the Kalman smoother. The consistency properties of this methodology have been shown by Doz, Giannone, and Reichlin (2006).

This paper provides an out-of-sample empirical evaluation that shows the model fares well relative to several benchmarks. We use that method to evaluate quantitatively how information from various sources affects our assessment of current economic conditions by estimating the effect of each release on the accuracy of the nowcast.

Empirical results show that within-quarter data flows matter in the sense that the precision of the nowcast generally increases monotonically as new information becomes available during the current quarter. This result lends support to the idea that exploiting rich data sets is very relevant for real-time data analysis. We also show that the timing of releases is a key determinant of the size of the release's marginal predictive power. In particular, the Philadelphia Federal Reserve Bank surveys, which are released early in the month, have a large positive effect on forecasting accuracy. Our out-of-sample exercise shows that this is also true for the report on the employment situation.

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Table 1: Tracking GDP Growth with the Factor Model: ACF of the Residuals

lag (m)	1	2	3	4
acf	-0.01	0.22	0.03	0.03
p-value	0.93	0.05	0.81	0.81

Autocorrelation function of the residual of the projection of GDP growth on the common factors. P-values refer to the Ljung-Box Q-statistics for the null of no serial correlation up to order m.

Table 2: Nowcasts and Forecasts of GDP: Out-of-Sample Evaluation.

Horizon	0	1	2	3	4
FM	0.91	1.05	1.10	1.25	1.18
SPF	0.94	1.15	1.29	1.29	1.36

Mean Squared Forecast Errors of GDP growth for the Factor Model (FM) and Survey of Professional Forecasters (SPF) relative to a naive constant growth model for GDP. Evaluation sample: 1995q1-2004q4.

Table 3: Calendar of Data Releases within the Month

Block Name (1)	Release (2)	Timing (approx.) (3)	Publishing Lag (4)	Frequency of data (5)
Surveys 2	PMGR-Manufacturing	1st business day of month	one month	Monthly
Mixed 3	Commercial Paper outstanding	1st bus. day of month	one month	Monthly
Mixed 3	Construction Put in Place	1st bus. day (or slightly before)	two months	Monthly
Mixed 3	Advance Report on Durable Goods Manufacturers Shipments, Inventories and Orders	1st. bus. day (or slightly before)	one month	Monthly
Mixed 3	Full Report on Durable Goods Manufacturers Shipments, Inventories and Orders	5 days after Advance Durables	two months	Monthly
Money & Credit	Consumer Delinq. Bulletin	Quarterly (series is monthly)	two quarters	Monthly
Money & Credit	Aggregate Reserves of Depository Institutions and the Monetary Base	1st Thurs. of month	one month	Monthly
Money & Credit	Money Stock Measures	2nd Thurs. of month	one month	Monthly
Money & Credit	Assets and Liabilities of Commercial Banks in the United States	1st Fri. of month	two months	Monthly
Labor & Wages	Employment Situation	1st Fri. of month	one month	Monthly
Mixed 1	Consumer Credit	5th business day of month	two months	Monthly
Mixed 1	Advance Monthly Sales For Retail and Food Services	11-15th of month	one month	Monthly
Mixed 1	Monthly Treasury Statement of Receipts and Outlays of the U.S. Government	Middle of month	one month	Monthly
Mixed 1	FT900 U.S. International Trade in Goods and Services: Exhibit 5	2nd full week of month	two months	Monthly
Ind. Production	Industrial Production and Capacity Utilization	15th to 17th of month	one month	Monthly
Mixed 2	New Residential Construction	16th to the 20th of month	one month	Monthly
Mixed 2	Business Outlook Survey: Federal Reserve Bank of Philadelphia	3rd Thursday of month	current month	Monthly
PPI	Producer Prices	Middle of month	one month	Monthly
CPI	Consumer Prices	Middle of month	one month	Monthly
GDP & Income	GDP - detail: inventories and sales	Day after GDP - release	two months	Monthly
GDP & Income	GDP - release: GDP and GDP deflator	Last week of month	one quarter	Quarterly
GDP & Income	Personal Income and Outlays	Day after GDP - release	one month	Monthly
Housing	Manufactured Homes Survey	3rd to last bus. day of month	one month	Monthly
Housing	New Residential Sales	Last week of month	one month	Monthly
Surveys 1	Chicago Fed Midwest Manufacturing Index	Last week of month	one month	Monthly
Surveys 1	Consumer Confidence Index	Last Tues. of month	current month	Monthly
Surveys 1	Michigan Survey of Consumers	Last Fri. of the month	current month	Monthly
Initial Claims	Claims, Unemployment Insurance Weekly Claims Report	Last Thurs. of month: Monthly ave.	current month	Weekly
Interest Rates	Freddie Mac Primary Mortgage Survey	Last Wed. of month: Monthly ave.	current month	Weekly
Interest Rates	Selected Interest Rates	Last day of month: Monthly ave.	current month	Daily
Financial	Foreign Exchange Rates	Last day of month: Monthly ave.	current month	Daily
Financial	London Gold PM Fix	Last day of month: Monthly ave.	current month	Daily
Financial	New York Stock Exchange	Last day of month: Monthly ave.	current month	Daily
Financial	S&P Indices	Last day of month: Monthly ave.	current month	Daily
Financial	Wilshire Index	Last day of month: Monthly ave.	current month	Daily

Data releases are indicated in rows. Column 1 reports the block in which the released data are included. Column 2 indicates the releases. Column 3 indicates the official dates of the publication. Column 4 report the period up to which the data are reported. The native frequency of the data is reported is Column 5. Typically, surveys have very short publishing lags and often are forecasts for future months or quarters, while GDP, for example, is released with a relatively long delay.[a]