Nowcasting in Real-Time*

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1 Introduction

Nowcasting: Whether it is done with formal models or judgmentally, forming estimates of the current-quarter state of the economy (nowcasting) is done at virtually all major central banks.

1. A formal approach to nowcasting was established in by Giannone, Reichlin and Small (Journal of Monetary Economics, May 2008)

2. There has been an explosion of interest and research in nowcasting.

(a) At central banks:
   i. ECB (Monthly Bulletin, April 2008, European Central Bank)
   ii. Ireland (D’Agostino, McQuinn, and O’Brien, 2008)
   iii. New Zealand (Matheson, 2010)
   iv. Norway (Aastveit and Trovik, 2008)

(b) Review of Literature: “Nowcasting” by Banbura, Giannone, Reichlin
   ii. Available at: www.cepr.org/pubs/dps/DP7883.aps
This Paper: Extends the work of GRS and the current status of nowcasting in the profession at large in three ways:

1. Over the past five years, we have been running nowcasts every Friday – allowing us to:

   (a) Show the real-time performance of the GRS model.

   (b) Collect weekly real-time vintages of our dataset of almost 200 data series starting in March 2005.

2. Publicly Available Data Sets:

   (a) Pick your DVD up after this presentation.

   (b) Periodical updates will be available.

3. Also take into account recent advances in estimation methodology by Banbura and Modugno(2010).

   (a) Full Maximum Likelihood Estimation

   (b) Provides a way to construct the “news” in new data releases.
2 Information Flows and Data Sets

GDP is released with a lag (Advanced estimate)

GDP for a given quarter is updated twice (Second and Third estimates)

Figure 1: GDP Releases
Data that are components of GDP and that are useful for forecasting GDP are released with lags

1. Differing lags producing a ragged edge reflecting differing timeliness.

Figure 2: Data Releases

<table>
<thead>
<tr>
<th>Release</th>
<th>Pub lag</th>
<th>Timing (approx.)</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business Outlook Survey: FRB Philadelphia</td>
<td>current month</td>
<td>3rd Thursday of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Claims</td>
<td>current month</td>
<td>Last Thurs of month</td>
<td>Weekly</td>
</tr>
<tr>
<td>Freddie Mac Primary Mortgage Survey</td>
<td>current month</td>
<td>Last Monday of month</td>
<td>Weekly</td>
</tr>
<tr>
<td>Michigan Survey of Consumers: Consumer Conf.</td>
<td>current month</td>
<td>Last Fri. of the month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Selected Interest Rates</td>
<td>current month</td>
<td>Last day of month: Monthly ave.</td>
<td>Daily</td>
</tr>
<tr>
<td>Foreign Exchange Rates</td>
<td>current month</td>
<td>Last day of month: Monthly ave.</td>
<td>Daily</td>
</tr>
<tr>
<td>Adv. Monthly Sales for Retail and Food Services</td>
<td>one month</td>
<td>11-15th of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Aggregate Reserves</td>
<td>one month</td>
<td>1st Thurs. of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Assets and Liabilities of Commercial Banks</td>
<td>one month</td>
<td>1st Fri. of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Commercial Paper Outstanding</td>
<td>one month</td>
<td>1st business day of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Consumer Prices</td>
<td>one month</td>
<td>Middle of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Employment Situation</td>
<td>one month</td>
<td>1st Fri. of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Industrial Production and Capacity Utilization</td>
<td>one month</td>
<td>15th to 17th of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Money Stock Measure</td>
<td>one month</td>
<td>2nd Thurs. of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Monthly Treasury Statement</td>
<td>one month</td>
<td>Middle of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>New Residential Construction</td>
<td>one month</td>
<td>16th to the 20th of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>New Residential Sales</td>
<td>one month</td>
<td>Last week of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Personal Income and Outlays</td>
<td>one month</td>
<td>Day after GDP - release</td>
<td>Monthly</td>
</tr>
<tr>
<td>PMGR-Manufacturing</td>
<td>one month</td>
<td>1st business day of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Producer Prices</td>
<td>one month</td>
<td>Middle of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Adv. Report on Durables</td>
<td>one/two months</td>
<td>24th-28th (approx)</td>
<td>Monthly</td>
</tr>
<tr>
<td>Chicago Fed Midwest Manufacturing Index Survey</td>
<td>one/two months</td>
<td>Last week of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Construction Put in Place</td>
<td>two months</td>
<td>1st business day of month (approx)</td>
<td>Monthly</td>
</tr>
<tr>
<td>Consumer Credit</td>
<td>two months</td>
<td>5th business day of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>Full Report Durables</td>
<td>two months</td>
<td>5 days after Advance Durables</td>
<td>Monthly</td>
</tr>
<tr>
<td>GDP - detail</td>
<td>two months</td>
<td>Day after GDP - release</td>
<td>Monthly</td>
</tr>
<tr>
<td>Manufactured Homes</td>
<td>two months</td>
<td>3rd to last bus. day of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>U.S. Intern. Trade (FT900)</td>
<td>two months</td>
<td>2nd full week of month</td>
<td>Monthly</td>
</tr>
<tr>
<td>GDP - release</td>
<td>one quarter</td>
<td>Last week of month</td>
<td>Quarterly</td>
</tr>
</tbody>
</table>
3 Nowcasting: the general problem

The problem:

- $\Omega_v$: vintage of available data. Quarterly, Monthly, possibly daily. $v$ refer to the date of a particular release, e.g. first Friday of each month employment report.

- Denote GDP growth at time $t$ as $y_t^Q$.

Nowcasting GDP: the projection of $y_t^Q$ on the available information

$$\mathbb{P} \left[ y_t^Q | \Omega_v \right]$$

The dataset $\Omega_v$ has three characteristics:

1. it has jagged edges (publication lags differing across series)

2. it contains mixed frequency series, monthly and quarterly in our case

3. it is possibly large
4 Sequences of updates

We have a sequence of projection:

\[ P \left[ y_t^Q | \Omega_v \right], \; P \left[ y_t^Q | \Omega_{v+1} \right], \ldots \]

\( v, v+1, \ldots \) refer to the dates in which the forecast is made. It can have high frequency and can be irregularly spaced.

The intervals between updates can be very short, possibly every data release and can change over time.

In our case it is every Friday at 6 PM
5  What is new? Keep track of “news”

- The information set expands (new releases): $\Omega_v \subseteq \Omega_{v+1}$

Abstracting from data revisions

- Decompose each forecast in two components

$$\mathbb{P} \left[ y_{t} | \Omega_{v+1} \right] = \mathbb{P} \left[ y_{t} | \Omega_{v} \right] + \mathbb{P} \left[ y_{t} | I_{v+1} \right]$$

- $I_{v+1}$: NEWS, the subset of $\Omega_{v+1}$ that is orthogonal to $\Omega_v$

- The only element that might lead to a change in the nowcast is the unexpected part of the data release, $I_{v+1}$, the news

**Tracking the effects of the “news”**

- If we have a model that can forecast all the data, we can express the forecast revision as a weighted sum of news about the newly released data:

$$\mathbb{P} \left[ y_{t} | \Omega_{v+1} \right] - \mathbb{P} \left[ y_{t} | \Omega_{v} \right] = \sum_{j \in J_{v+1}} b_{j,t,v+1} \left( x_{j,T_{j,v+1}} - \mathbb{P} \left[ x_{j,T_{j,v+1}} | \Omega_{v} \right] \right)$$

- $J_{v+1}$: set of variables being released at time $v + 1$

- The magnitude of the forecast revision depends on the size of the “news” and on its relevance for the GDP growth as quantified by the weights $b_{j,t,v+1}$

For details, see Banbura and Modugno, 2010.
6 The model: Specification

Three desiderata

1. can capture the joint dynamic of GDP and all the data releases
2. can be estimated on many data while retaining parsimony
3. can handle jagged edges data and mixed frequencies

$\Rightarrow$ Factor Model

\[ x_t = \mu + \Lambda f_t + \varepsilon_t \]

• \( x_t \): \( n \times 1 \) vector observables (the data)

• \( f_t \): \( r \times 1 \) vector of (unobserved) common factors

\[ f_t = A_1 f_{t-1} + u_t \]

• \( A \): \( n \times r \) matrix of factor loadings

• \( \varepsilon_t \): \( n \times 1 \) vector of idiosyncratic components (cross-sectionally orthogonal)

\[ \varepsilon_{i,t} = \rho_i \varepsilon_{i,t-1} + e_{i,t} \]

The model has a \textbf{state space} representation:

Jagged edges, Mixed frequencies and missing data can be naturally dealt with by using \textbf{Kalman filtering} techniques.
7 The model: Estimation

Factor Model

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Estimation


• Banbura and Modugno (2010): full maximum likelihood essentially iterating the two step above.
Robustness

The model we are using is surely miss-specified (for instance, it ignores cross-sectional correlation among the idio terms, conditional heteroskedasticity in the disturbances, and so forth).

Result: when \( n \) and \( T \) are large, the factor estimates from the simpler model are consistent despite potential misspecification.

See Doz, Giannone and Reichlin (2006a,b)
8 Results

The nowcasting performances of the factor model as estimated by GRS (FM) and as estimated by Banbura and Modugno (EM) are shown in Figure 3.

1. The two estimation techniques produce similar nowcast results

2. The nowcasts track the growth of real GDP
   (a) Overpredict in early-mid 2006 and in fall of 2008
   (b) Catch Great Recession of early 2009 and rebound in fall of 2009.

3. Note the dating convention: It is in the form YYYYMMDD without the first three Ys. So 20051014 becomes 51014.

Figure 3: Nowcasting: Five Years of Experience
Using these nowcasts, the value of updating nowcasts in real time can be seen by calculation mean-squared-forecast-errors for the first, second, third and etc, weeks of a quarter.

The naive model is the ten-year moving average of Real GDP growth.

As shown in Figure 3, for both estimation techniques, the MSFE generally declines as more information becomes available.

Figure 4: Real-Time Informational Content of Data Releases
To provide a closer look at the performance of these models, in Figure 5:

1. The two years of 2008 and 2009 are examined closer up.

2. We show the nowcasts from the Survey of Professional Forecasters (SPF)

Examination of Figure 5 indicates:

1. The models performed well relative to the SPF.

2. The timeliness of these nowcasting models is shown in October of 2008, when they starting indicating economic weakness before the following SPF was released.
As indicated previously, the factor models can be used to evaluate the impact of the news associated with each data release.

Figure 6 shows how the news associated with various data releases affected the nowcast during 2008:Q4

1. Virtually all the news was negative

2. The “hard” data such as Industrial Production and “Labor and Wages” was significant and negative.

3. “Soft” information such as the “Surveys” component are also informative.

   (a) The importance of surveys stems, in large part, from their timeliness—early information on the current quarter.
9 Conclusion

1. Real-time nowcasting can provide useful and timely updates to the estimate of the current quarter.

2. Real-time datasets available for public use

3. Improvements continue in estimation of factor models