Domenico Giannone Federal Reserve Bank of New York and CEPR

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The views expressed here do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System

Contraction of the terms Now and Forecasting

Meteorology Nowcasting

forecasting up to 6-12 hours ahead (long tradition, since 1860)

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Only recently introduced in economics:

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Why? Key variables released at low frequency and with long publication delays.

- Example, US GDP: Advanced estimate 4 weeks after end of the reference quarter
- Example, EA GDP: Flash estimate 6 weeks after end of the reference quarter

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Economic Nowcasting:

Forecasting the near future, the present and even recent past.

This Presentation

1 Nowcasting and the Real-Time Data-Flow with M. Bańbura, M. Modugno and L. Reichlin Handbook of Economic Forecasting, Volume 2, Elsevier-North Holland

Introducing the FRBNY Staff Nowcast Liberty Economics Blog, Federal Reserve Bank of New York

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- predicting the future: formal economic modeling of the relations among key macroeconomic aggregates
- predicting the present: simplified heuristic scrutiny of a variety of conjunctural data

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 forecasts are updated infrequently disregarding the high-frequency flow of conjectural information

quarterly updates (SPF and Central Banks), bi-annual updates (OECD, IMF)

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Research questions

How important is nowcasting relative to longer horizon forecasting?

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- How relevant is the conjectural information? How often should we update the predictions?

How important is nowcasting relative to longer horizon forecasting?

Very !!!!

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Forecasting GDP in real time MSFE relative to constant growth

Horizon	0	1	2	3	4
GB	0.87	1.03	1.16	1.23	1.29
SPF	0.85	1.03	1.00	1.06	1.06

Evaluation sample 1992Q1 through 2001Q4

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How can we predict the present? Can a machine replicate expert judgement?

How important is expert Judgement?



The Experts!



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Now-Casting US GDP: 10 years of Experience



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Learning from the Markets

Market participants can be viewed as now-casters

⇒ they obsessively monitor all macroeconomic data to get a view on current and future fundamentals and their effects on policy

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 - The relevant information on the state of the economy is conveyed to markets through the release of macroeconomic reports.
 - Market expectation for the headlines of these reports are collected up to the day before the actual release of the indicator and distributed by data providers (i.e. Bloomberg).

Learning from the Markets

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 - The relevant information on the state of the economy is conveyed to markets through the release of macroeconomic reports.
 - Market expectation for the headlines of these reports are collected up to the day before the actual release of the indicator and distributed by data providers (i.e. Bloomberg).
 - When realizations are different than these expectations, that is when the news are sizeable, the view of the market changes and this leads to changes in asset prices see (Andersen et al., 200; Flannery and Protopapadakis, 2002)), Boyd, Hu, and Jagannathan, 2005;



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21) 04/04 08:30 Description of an and the second se					
22) 04/03 08:30 🐗 📰 Initial Jobless Claims	Mar 29	319K	326K	311K	310K
23) 04/10 08:30 🛋 📶 Initial Jobless Claims			300K		
24) 04/17 08:30 🗆 🔤 📶 Initial Jobless Claims	Apr 12	315K		300K	
25) 04/24 08:30 🛋 📶 Initial Jobless Claims	Apr 19				
26) 04/30 14:00 🕬 🔤 📶 FOMC Rate Decision	Apr 30			0.25%	
27) 04/30 08:30 🐗 🖬 GDP Annualized QoQ	1Q A			2.6%	
28) 04/29 10:00 and Consumer Confidence Index	Apr			82.3	
29) 04/01 10:00 🐗 📶 ISM Manufacturing		54.0		53.2	
30) 04/11 09:55 and Univ. of Michigan Confidence	Apr P	81.0	82.6	80.0	
31) 04/25 09:55 🐗 📶 Univ. of Michigan Confidence		83.0			
32) 04/15 08:30 🕬 🔤 📶 CPI MoM	Mar	0.1%		0.1%	
33) 04/30 14:00 E 📑 Fed QE3 Pace				\$55B	
34) 04/30 14:00 🛛 📼 📶 Fed Pace of Treasury Pur	Apr			\$30B	
35) 04/30 14:00 🔄 📶 Fed Pace of MBS Purchases					
36) 04/02 07:00 🖛 📶 MBA Mortgage Applications	Mar 28		-1.2%	-3.5%	
37) 04/09 07:00 🛋 MBA Mortgage Applications			-1.6%	-1.2%	
38) 04/16 07:00 🗆 🔤 📶 MBA Mortgage Applications	Apr 11			-1.6%	
39) 04/23 07:00					
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40) 04/30 07:00 🕬 MBA Mortgage Applications	Apr 25				
41) 04/24 08:30 🜗 🔤 📶 Durable Goods Orders	Mar	1.0%		2.2%	
42) 04/23 10:00 🖛 🔤 📶 New Home Sales	Mar	460K		440K	
43) 04/01 09:45 🛛 🔤 📶 Markit US Manufacturing PMI	Mar F	56.0	55.5	55.5	
44) 04/23 09:45 🛛 🔤 📶 Markit US Manufacturing PMI	Apr P			55.5	
45) 04/14 08:30 🖝 📶 Retail Sales Advance MoM		0.9%	1.1%	0.3%	0.7%
46) 04/04 08:30 🛛 🔤 📶 Unemployment Rate	Mar	6.6%	6.7%	6.7%	
47) 04/16 08:30 📥 📶 Housing Starts				907K	
48) 04/16 09:15 🗆 💷 Industrial Production MoM	Mar	0.5%		0.6%	
49) 04/22 10:00 🛋 🖬 Existing Home Sales		4.55M		-4.60M	
50) 04/11 08:30 🗆 🖃 📶 PPI Final Demand MoM	Mar	0.1%	0.5%	-0.1%	
51) 04/02 10:00 🛋 🖬 Factory Orders		1.2%	1.6%	-0.7%	-1.0%
52) 04/21 10:00 🗆 🔤 📶 Leading Index	Mar	0.7%		0.5%	
3) 04/03 08:30 🗆 🖬 Trade Balance			-\$42.3B		
54) 04/15 08:30 🗆 🔤 📶 Empire Manufacturing	Apr	8.00		5.61	
55) 04/02 08:15 🐗 📶 ADP Employment Change					
5) 04/30 08:15 🗆 🖂 📶 ADP Employment Change	Apr			191K	
51 04/30 09:45 🚛 Chicago Purchasing Manager	Apr				
58) 04/09 10:00 🐗 🚽 Wholesale Inventories MoM	Feb	0.5%	0.5%	0.6%	0.8%
Australia 61 2 2777 8600 Brazil 351 2048 4500 Europe 44 20 733	2500 685	many 49 69 9	204, 1810, He	ng Kong OS	2 2227 6000
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Date Time	A MRT Event	Period	Surv(M)	Actual	Prior	Revised
59) 04/01 10:00	Construction Spending MoM	Feb	0.0%	0.1%	0.1%	-0.2%
60) 04/30 08:30	GDP Price Index	1Q A			1.6%	
61) 04/10 08:30	Import Price Index MoM	Mar	0.2%	0.6%	0.9%	
62) 04/17 10:00	🌗 🔤 📶 Philadelphia Fed Business Outloo	Apr	10.0		9.0	
63) 04/28 10:00	Pending Home Sales MoM	Mar			-0.8%	
64) 04/10 14:00	🐠 🔤 🚛 Monthly Budget Statement	Mar	-\$36.0B	-\$36.9B	-\$106.5B	
65) 04/15 08:30	CPI Ex Food and Energy MoM		0.1%		0.1%	
66) 04/03 10:00	🗆 🖂 🚛 ISM Non-Manf. Composite	Mar	53.5	53.1	51.6	
67) 04/24 08:30	Durables Ex Transportation		0.3%		0.2%	0.1%
68) 04/15 09:00	🕬 🖬 Net Long-term TIC Flows	Feb	\$22.5B		\$7.3B	
69) 04/30 08:30	🐠 📑 Employment Cost Index				0.5%	
70) 04/01 10:00	ISM Prices Paid	Man	59.5	59.0	60.0	
71) 04/03 09:45	Markit US Services PMI					
72) 04/03 09:45	🔤 🚛 Markit US Composite PMI	Mar F		55.7	55.8	
73) 04/25 09:45	🛛 🖬 Markit US Composite PMI					
74) 04/25 09:45	🔤 🚚 Markit US Services PMI	Apr P			55.3	
75) 04/22 10:00	💵 🔐 Richmond Fed Manufact. Index					
76) 04/04 08:30	🔤 🚚 Change in Manufact. Payrolls	Mar	7K	-1K	6K	19K
77) 04/03 08:30	Continuing Claims	Mar 22	2843K	2836K	2823K	2814K
Australia 61 2 9777	9600 Brazil 5511 2049 4500 Europe 44,20,7330	2500 685	many 49 69 9	202, 1810 H	ong Kong 05	2 2222 6000
Sapan 81 3 3201 890	0 010gapore 65 6212 1000 0.5. 1 212 SN	264096 ED	т амт-4.86	HIZE-121E-	14-Apr-20	14 09 92 56

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78) 04/10 08:30		ontinuing Claims		Mar 29	2835K	2776K	2836K	2838K
79) 04/17 08:30	Co	ontinuing Claims		Apr 5	2778K		2776K	
80) 04/24 08:30		ontinuing Claims		Apr 12				
81) 04/11 08:30	I PI	PI Final Demand	YoY	Mar	1.1%	1.4%	0.9%	
82) 04/30 08:30	E . P	ersonal Consump		10 A			3.3%	
83) 04/30 08:30	- C C						1.3%	
84) 04/22 09:00	49050 Fh	IFA House Price	Index MoM	Feb			0.5%	
85) 04/11 08:30	Pi at Pi		nergy MoM		0.2%	0.6%	-0.2%	
86) 04/11 08:30	🖂 💵 Pi	PI Ex Food and E	nergy YoY	Mar	1.1%	1.4%	1.1%	
87) 04/15 09:00	does 🚛 To						\$83.0B	
88) 04/14 08:30	📼 🚛 R.	etail Sales Ex Aut	o MoM	Mar	0.5%	0.7%	0.3%	
89) 04/16 08:30	- E . B							1014K
90) 04/03 09:45	495-2 Bl	loomberg Consur	ner Comfort	Mar 30		-30.0	-31.5	
91) 04/10 09:45	abrei 🚛 🖪	loomberg Consur						
92) 04/17 09:45	1	loomberg Consur	ner Comfort	Apr 13			-31.9	
93) 04/24 09:45	Apres 📶 🖪	loomberg Consur		Apr 20				
94) 04/16 09:15	🖂 💵 Ca	spacity Utilizatio		Mar	78.7%		78.8%	78.4%
95) 04/28 10:30	April Da	allas Fed Manf. A		Apr				
96) 04/21 08:30		nicago Fed Nat A	ctivity Index	Mar			0.14	
Australia 61 2 9777 Japan 81 3 3201 890	0 Braz	11 5511 3040 4500 E gapore 65 6212 1000	Urope 44 20 7330 U.S. 1 212 SN	318 2000 264096 ED	T GMT-4.00	204 1210 Ho ight 2014 B H178-1218-0	ng Kong 852 loomberg Fi 14-Apr-201	1 2977 6000 1 09 26 56

The markets



Mimicking Market behavior and Beyond

Nowcasting: Monitoring current economic conditions in real time

- Model-based counterpart to conjuctural analysis
- **Real-time** reading of the newsflow
- Continuously updated nowcast of GDP growth

A Big Data Analytics Framework

• High-dimensional data

Includes the **large** and **complex** data monitored by economists at central banks, trading desks, and in the media

Entirely automated

Mimics **best practice** without relying on any judgment or subjective prior information (free of judgement, mood, heading)

<u>Real-time</u>

Digests new information within minutes of the releases

Coherent analysis of the link between macro news and cyclical developments

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- Extract the news/surprise component from data
 Actual data minus model-based forecasts
- Translate the news in a common unit
 - What's the impact of news on GDP growth?

A model of Now-Casting

• y_t^Q : GDP at time t.

• Ω_{ν} : vintage of data (quarterly, monthly, possibly daily) available at time ν (date of a particular data release)

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Nowcasting of y_t^Q : orthogonal projection of y_t^Q on the available information: $\mathbb{E}\left[y_t^Q | \Omega_v\right],$

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Nowcasting of y_t^Q : orthogonal projection of y_t^Q on the available information: $\mathbb{E}\left[y_t^Q | \Omega_v\right],$

The information set Ω_{ν} has particular characteristics:

- it has a "ragged" or "jagged edge" [publication lags differing across series]
- it contains mixed frequency series, in our case monthly and quarterly
- it could be large

Spreadsheets in Real Time

-1.04	-9.75	-5.78	0.89	NaN	NaN	NaN	NaN	NaN
-0.28	-7.79	-1.54	-0.70	NaN	NaN	NaN	NaN	NaN
0.10	-0.05	0.57	0.47	0.54	-0.96	-0.10	0.32	-0.08
3.12	4.22	-0.93	1.45	-0.15	0.19	NaN	NaN	NaN
-0.43	0.43	-2.42	2.45	-0.22	0.80	NaN	NaN	NaN
0.06	-13.71	0.33	3.13	0.57	0.09	1.20	0.57	0.96
0.09	2.34	0.51	3.05	0.32	0.04	NaN	NaN	NaN
0.12	-13.15	0.64	1.70	-0.07	-1.47	NaN	NaN	NaN
-0.53	-8.77	-2.92	1.03	0.28	-1.10	0.30	0.87	0.24
-1.27	-8.21	-7.04	0.38	0.25	-0.75	NaN	NaN	NaN
-1.53	-7.94	-8.52	1.36	0.29	-0.74	NaN	NaN	NaN
-1.10	-9.46	-6.12	2.13	-0.06	-1.23	0.50	0.70	0.4
-0.69	2.48	-3.82	NaN	-0.24	4.70	NaN	NaN	NaN
-0.93	NaN	-5.17	NaN	NaN	NaN	NaN	NaN	NaN
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Further features

Projections need to be updated regularly

$$\mathbb{E}\left[\mathbf{y}_{t}^{Q}|\boldsymbol{\Omega}_{v}\right], \ \mathbb{E}\left[\mathbf{y}_{t}^{Q}|\boldsymbol{\Omega}_{v+1}\right], \dots$$

v, v + 1, ..., consecutive data releases

Typically the intervals between two consecutive data releases are short (possible couple of days or less) and change over time. Consequently, v has high frequency and it is irregularly spaced.

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News and nowcast revisions

New release ⇒ the information set expands (new releases): Ω_ν ⊆ Ω_{ν+1} [we are abstracting from data revisions]

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- Decompose new forecast in two orthogonal components:

$$\underbrace{\mathbb{E}\left[\mathbf{y}_{t}^{Q}|\Omega_{v+1}\right]}_{\text{new forecast}} = \underbrace{\mathbb{E}\left[\mathbf{y}_{t}^{Q}|\Omega_{v}\right]}_{\text{old forecast}} + \underbrace{\mathbb{E}\left[\mathbf{y}_{t}^{Q}|I_{v+1}\right]}_{\text{revision}},$$

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 $I_{\nu+1}$ information in $\Omega_{\nu+1}$ "orthogonal" to Ω_{ν}

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 $I_{\nu+1}$ information in $\Omega_{\nu+1}$ "orthogonal" to Ω_{ν}

• If we have a model that can account for joint dynamics of all variables, we can express the forecast revision as a weighted sum of *news* from the released variables:

$$\underbrace{\mathbb{E}\left[y_t^{Q}|\Omega_{\nu+1}\right] - \mathbb{E}\left[y_t^{Q}|\Omega_{\nu}\right]}_{\text{forecast revision}} = \sum_{j \in J_{\nu+1}} b_{j,t,\nu+1} \underbrace{(x_{j,T_{j,\nu+1}} - \mathbb{E}\left[x_{j,T_{j,\nu+1}}|\Omega_{\nu}\right])}_{\text{news}}.$$

For detailed derivation see Banubra and Modugno, 2008.

What kind of framework?

Three desiderata:

- 1 can capture joint dynamics of inputs and target
- 2 can be estimated on many series while retaining parsimony
- 3 can handle jagged edged data and mix frequency

Our approach:

- Dynamic factor model for large cross-section
 - Few factors capture the salient features of business cycle fluctuations

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- Flexibility, parsimony, robustness
- Filtering techniques
 - Efficient processing of real-time information
 - Mixed frequencies, jagged edges, missing data

Evans 2005 IJCB; Giannone, Reichlin and Small, 2008 JME

The dynamic factor model

$$x_t = \mu + \Lambda f_t + \varepsilon_t,$$

- *f_t*: (unobserved) common factors; ε_t: idiosyncratic components
- A factor loadings
- Factors are modelled as a VAR process:

$$f_t = A_1 f_{t-1} + \cdots + A_p f_{t-p} + u_t$$

Parsimonious and robust model for Big Data

- Diebold, Reichlin and Watson, World Congress of the Econometric Society, 2000
- Forni et al. (2000), Stock and Watson (2002), Bernanke and Boivin (2002), Bai (2003), Giannone et al (2005), Doz et al., (2011,2012)

Problems and solutions

Missing data

Naturally handled using Kalman filtering technique to obtain projections for any pattern of data availability in Ω_v as well as the *news l*_{v+1} and their impact *b*_{j,t,v+1}

Mixed frequency

Consider lower frequency variables as being periodically missing

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- Estimation: Quasi Maximum likelihood:
 - robust and feasible Doz, Giannone and Reichlin., 2008 REStat
 - handling missing data Banbura and Modugno, 2010

A quasi maximum Likelihood approach Doz et al, 2012 (Restat)

- The idea in a nutshell
 - For large cross-sections parametric estimation is feasible only if we impose some restrictions (on the cross-corr of elements of the idiosyncratic)

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- On the other hand
 - Superimposed restrictions are the most significant source of model **misspecification**, especially when the cross-section is large!
 - No consensual way to model the cross-sectional correlation among idiosyncratic terms (there is non natural order in the cross-section)

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- The idea in a nutshell
 - For large cross-sections parametric estimation is feasible only if we impose some restrictions (on the cross-corr of elements of the idiosyncratic)
- On the other hand
 - Superimposed restrictions are the most significant source of model **misspecification**, especially when the cross-section is large!
 - No consensual way to model the cross-sectional correlation among idiosyncratic terms (there is non natural order in the cross-section)
- Our Approach
 - Define a miss-specified (Quasi) Likelihood imposing ad hoc orthogonality restrictions (**exact** factor model)
 - Look at the approximation error when the model is approximate

... Maximum Likelihood Estimation: the main result

Define:

- $\hat{\theta}$ the maximum likelihood estimates under our approximating model...

- $\textbf{F}=(\textbf{f}_1,...,\textbf{f}_{\mathcal{T}})'$ true common factors
- $\mathbf{F}_{\hat{\theta}} = (\mathbf{f}_{\hat{\theta},1},...,\mathbf{f}_{\hat{\theta},T})'$ expected common factors estimated under $\hat{\theta}$

Proposition Under the assumption of an approximate factor structure

$$\frac{1}{T}\mathrm{Tr}(\mathbf{F}-\hat{H}\hat{\mathbf{F}}_{\hat{\theta}})'(\mathbf{F}-\hat{H}\hat{\mathbf{F}}_{\hat{\theta}}) = O_{p}\left(\frac{1}{\Delta(n,T)}\right) \text{ as } n, T \to \infty$$

where
$$\Delta_{nT} = \min\left\{\sqrt{T}, \frac{n}{\log(n)}\right\}$$

and
 $\hat{H} = \left(\hat{\mathbf{F}}_{\hat{\theta}}\hat{\mathbf{F}}_{\hat{\theta}}\right)^{-1}\hat{\mathbf{F}}_{\hat{\theta}}\mathbf{F}$ is the coefficient of the OLS projection of \mathbf{F} on $\hat{\mathbf{F}}_{\hat{\theta}}$.

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... Maximum Likelihood Estimation: the main result

Some comments...

 General maximum likelihood estimates are consistent to the common factors in a large cross-section and under an approximate factor structure...

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Consistency is achieved along any path n, T → ∞
 ⇒ suitable for large cross-section (even for n >> T)

Alternative models?

Vector Autoregression (VAR) instead of dynamic factor model

 Estimation: use Shrinkage (informative prior) to make it work with Big Data ⇒ Large Bayesian VAR

De Mol et al., 2008; Banbura et al,. 2010; Koop, 2013; Karlsson, 2102; Giannone et al, 2015

- · Handling mixed frequencies: blocking, unobserved components
 - Theory: cross-fertilization between system identification
 and econometric

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Andersson, Deistler and co-authors

Applications

Schorfheide and Song (2011), McCracken, Owyang, Sekhposyan (2013)

Bayesian Shrinkage and Comovement

- Homogenous shrinkage on observables implies less shrinkage on important common factors
- If few common factors dominate the induced by the prior becomes negligible for large models (double asymptotics) See Demol et al., 2008 (JoE).
- Intuition: comovement implies that sample informations in all variable massively points in the same direction against prior.

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State space representation with mixed frequencies

Example: Let Y_t^Q denote the vector of (log of) the quarterly flow series.

We assume that Y_t^Q is the sum of daily contributions X_t

$$Y_t^Q = \sum_{s=t-k+1}^t X_s, \qquad t = k, 2k, \ldots.$$

Hence we will have that the stationary series $y_t^Q = Y_t^Q - Y_{t-k}^Q$ can be written as:

$$y_t^Q = k \left(\sum_{s=t-k+1}^t \frac{t+1-s}{k} x_s + \sum_{s=t-2*(k-1)}^{t-k} \frac{s-t+2*k-1}{k} x_s \right), \qquad t=k, 2k,$$

where $x_s = X_s - X_{s-1}$ can be thought of as an unobserved daily growth rate (or difference).

No	Name	Frequency	Publication delay
			(in days after reference period)
1	Real Gross Domestic Product	quarterly	28
2	Industrial Production Index	monthly	14
3	Purchasing Manager Index, Manufacturing	monthly	3
4	Real Disposable Personal Income	monthly	29
5	Unemployment Rate	monthly	7
6	Employment, Non-farm Payrolls	monthly	7
7	Personal Consumption Expenditure	monthly	29
8	Housing Starts	monthly	19
9	New Residential Sales	monthly	26
10	Manufacturers' New Orders, Durable Goods	monthly	27
11	Producer Price Index, Finished Goods	monthly	13
12	Consumer Price Index, All Urban Consumers	monthly	14
13	Imports	monthly	43
14	Exports	monthly	43
15	Philadelphia Fed Survey, General Business Conditions	monthly	-10
16	Retail and Food Services Sales	monthly	14
17	Conference Board Consumer Confidence	monthly	-5
18	Bloomberg Consumer Comfort Index	weekly	4
19	Initial Jobless Claims	weekly	4
20	S&P 500 Index	daily	1
21	Crude Oil, West Texas Intermediate (WTI)	daily	1
22	10-Year Treasury Constant Maturity Rate	daily	1
23	3-Month Treasury Bill, Secondary Market Rate	daily	1
24	Trade Weighted Exchange Index, Major Currencies	daily	1

Daily factor, GDP and its common component



See also Stock and Watson, 1991; Aruoba, Diebold, Scotti, 2009

Filter uncertainty, GDP



Forecasting the Great Recession



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Does information help improving forecasting accuracy?

Root Mean Squared Forecast Error (RMSFE)



S&P 500 and its common component at different levels of time aggregation



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Now-Casting and the Real-Time Data-Flow

Research questions

- How important is nowcasting relative to longer horizon forecasting?
- Can we predict the present? How relevant is informal judgement?
- How relevant is the conjectural information? How often should we update the predictions?

What have we learned

- Nowcasting is key! Little predictability beyond current quarter!
- We can predict the present without the need of informal judgement?.
- It is worth to obsessively monitor conjectural information! Accuracy improves significantly and continuously.