On the Estimation of Common Factors in the Presence of Block Structures

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MFC 2009, Rome March 27, 2009

In this paper

- Factor models in which the idiosyncratic component is characterized by local cross-correlation due to 'block-specific' factors

  $\Rightarrow$ block-specific = not common to all units, not idiosyncratic, but common to groups of units

- explicitly model the block-specific factors

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$$X_t = \text{common component} + \text{block-specific component} + \text{idiosyncratic component}$$

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Motivations

- data structures likely generating block-specific factors are very common in the empirical literature on common factor models
- block structures, if not modelled, may have negative effects on the estimation of the common factors, especially in finite samples (see Bai and Ng, 2006 and Onatski, 2007)
  $\Rightarrow$ worth investigating!

Related literature

- empirical literature:
  see as an example Forni and Reichlin (2001, EER); Kose, Otrok and Whiteman (2003, AER); Brooks and Del Negro (2004, FRBA WP); Beck, Hubrich and Marcellino (2006, ECB WP)

- theoretical literature:
  see mainly Ng, Moench and Potter (2008), Haalin and Liska (2008) and Onatski (2007)

Main contributions

- → estimation of the model with block-specific factors by exact maximum likelihood (restricted EM algorithm)
- → study of the influence of block-structures on the estimation of the common factors (Monte Carlo simulations)
- → empirical application: evaluation of the forecasting performance of alternative business survey indicators based on both aggregate and sectoral data, to assess:
  - importance of data aggregation method
  - importance of sectoral heterogeneity
  - importance of timely information
  - advantage of direct aggregate forecast vs aggregation of sectoral forecasts

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The model

$$\mathbf{x}_t = \Lambda^{\mathrm{c}} \mathbf{f}_t^{\mathrm{c}} + \Lambda^{\mathrm{b}} \mathbf{f}_t^{\mathrm{b}} + \mathbf{e}_t$$

- static model
- $\Lambda^{\mathrm{c}} \mathbf{f}_t^{\mathrm{c}}$ and $\mathbf{e}_t$ are, respectively, the common and the idiosyncratic components
- $\Sigma_{\mathbf{e}} = E(\mathbf{e}_t \mathbf{e}_t')$ is a diagonal matrix
- $\Lambda^{\mathrm{b}} \mathbf{f}_t^{\mathrm{b}}$ is the block-specific component, identified by the following restrictions on the factor loadings:

$$\Lambda_{ik}^{\mathrm{b}} = \begin{cases} \textit{unconstrained} & \text{if } i \text{ is in block } k,\ i = 1, \cdots, n \\ 0 & \text{otherwise} \end{cases}$$

and $\mathbf{f}_t^{\mathrm{b}}$ is the $r^{\mathrm{b}} \times 1$ vector of block-specific factors

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Estimation of the model

- following Doz, Giannone and Reichlin (2006), the model with block-specific factors is estimated by exact maximum likelihood (EML) by using the Expectation Restricted Maximization (ERM) algorithm

$\longrightarrow$ computationally feasible

$\longrightarrow$ consistent estimates of block-specific factors

$\longrightarrow$ consistent estimates of common factors

Estimation of the common factors

If block-specific factors are not modelled explicitly, the covariance matrix of the idiosyncratic component is not diagonal

We can distinguish two cases:

- $n_b/n \nrightarrow 0 \Rightarrow$ off-diagonal elements do not die out with the cross-section

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PC and QML estimators of the common factors are not consistent (see DGR, 2006), while exact maximum likelihood (EML) is

- $n_b/n \rightarrow 0 \Rightarrow$ the model is approximate factor model

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PC, QML and EML provide consistent estimates of the common factors but, we claim, EML may be more precise

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Monte Carlo design

- simulate a model with block-specific factors and compute the following estimates of the common factors:
  - principal components (SW, 2002)
  - quasi maximum likelihood (DGR, 2006)
  - exact maximum likelihood
- compare their precision using the trace statistic:

$$TR_{(m)} = \frac{\mathrm{Tr}\left(\mathbf{F}'\hat{\mathbf{F}}_{(m)}(\hat{\mathbf{F}}_{(m)}{}'\hat{\mathbf{F}}_{(m)})^{-1}\hat{\mathbf{F}}_{(m)}{}'\mathbf{F}\right)}{\mathrm{Tr}(\mathbf{F}'\mathbf{F})}$$

(Boivin and Ng, 2006 and DGR, 2006)

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Monte Carlo design

- static model with one common factor
- units are grouped in r_{b} blocks of size n_{b}
- cross-correlation within each block is generated by one block-specific factor ($\Rightarrow$ number of block-specific factors = r_{b})
- all the blocks have the same size, which is kept fixed when n grows ($n_{\mathrm{b}}/n \rightarrow 0$)
- each of the three components - common, block-specific and idiosyncratic - explains one third of the variance in the data

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Monte Carlo results

Baseline Monte Carlo experiment results*. $r = 1$, $n^{\mathrm{b}} = 5$.

$TR_{(EML)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$T = 50$	0.92	0.96	0.97	0.97	0.97	0.97
$T = 100$	0.93	0.97	0.98	0.98	0.99	0.99
$T = 150$	0.94	0.97	0.98	0.99	0.99	0.99

$TR_{(EML)}/TR_{(PC)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$T = 50$	1.082	1.025	1.011	1.007	1.005	1.004
$T = 100$	1.076	1.023	1.011	1.007	1.005	1.004
$T = 150$	1.076	1.023	1.010	1.007	1.005	1.004

$TR_{(EML)}/TR_{(QML)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$T = 50$	1.073	1.021	1.009	1.006	1.004	1.004
$T = 100$	1.062	1.019	1.009	1.006	1.004	1.003
$T = 150$	1.058	1.019	1.008	1.006	1.004	1.003

* Medians across 1000 repetitions

Monte Carlo results

The effect of the block-size*. $T = 100$, $r = 1$

$TR_{(EML)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$n^b = 10$	0.94	0.97	0.98	0.98	0.99	0.99
$n^b = 5$	0.93	0.97	0.98	0.98	0.98	0.99
$n^b = 2$	0.92	0.96	0.98	0.98	0.98	0.99

$TR_{(EML)}/TR_{(PC)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$n^b = 10$	1.286	1.035	1.014	1.009	1.006	1.005
$n^b = 5$	1.076	1.023	1.011	1.007	1.005	1.004
$n^b = 2$	1.033	1.012	1.006	1.004	1.003	1.003

$TR_{(EML)}/TR_{(QML)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$n^b = 10$	2.018	1.027	1.012	1.007	1.005	1.004
$n^b = 5$	1.062	1.019	1.009	1.006	1.004	1.003
$n^b = 2$	1.033	1.009	1.005	1.003	1.002	1.002

* Medians across 1000 repetitions

Empirical application

- The aim is to assess the out of sample forecasting performances of business survey based indicators
- and, in particular whether
  - they do help forecasting the manufacture production index
  - timeliness with respect to official data is important
  - the aggregation method used to compute the indicators makes any difference
  - sectoral heterogeneity provides useful information
  - aggregation of sectoral forecasts beats direct aggregate forecasts

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Data

- survey data: Italian balances of opinions, both at an aggregate (manufacture) and at a sectoral level (subsections, NACE Rev1.1) of:
  - production expectations
  - order books
  - stock of finished products
  - export order books
  - production level

  covering the period Jan-91 through Jan-07

- last available release of the aggregate and sectoral production indexes (Jun-08) → nearly definite data for the evaluation period

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Survey based indicators considered

- Balances of opinions of production expectations and production level, both aggregate and sectoral
- Industrial Confidence Indicators, both aggregate and sectoral
- Business Climate Indicators, both aggregate and sectoral
- Common and sector-specific factors estimated by exact maximum likelihood
- Principal Component Indicator (only aggregate)
- Common factor estimated by QML (only aggregate)

Forecast equations

- $\widehat{Y}_{T^*+h} = \widehat{c}$ (benchmark)
- $\widehat{Y}_{T^*+h} = \widehat{c} + \widehat{A}(L)Y_{T^*}$
- $\widehat{Y}_{T^*+h} = \widehat{c} + \widehat{A}(L)Y_{T^*} + \widehat{B}(L)\Pi_{T'}$
- $\widehat{Y}_{T^*+h}$ = aggregation of sectoral forecasts obtained through

$$\widehat{Y}_{s,T^*+h} = \widehat{c} + \widehat{A}(L)Y_{s,T^*} + \widehat{B}(L)\Pi_{T'} + \widehat{C}(L)\Pi_{s,T'}$$

- lag selection by AIC criterion
- forecasts are evaluated on the basis of their MSFE
- evaluation period is Mar-01 through Jan-07

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- to asses the importance of data release, the forecasts are done three times a month, corresponding to different information sets:

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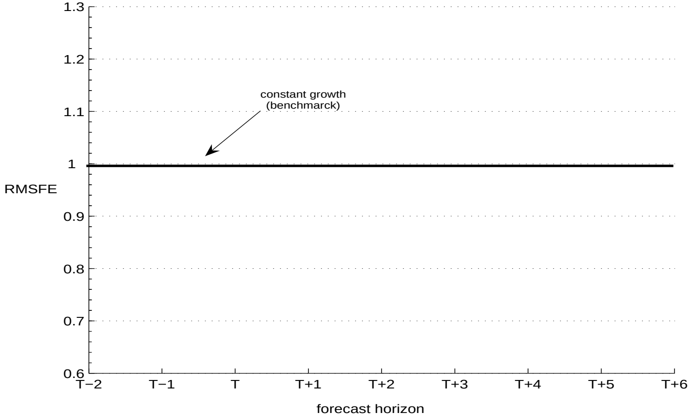

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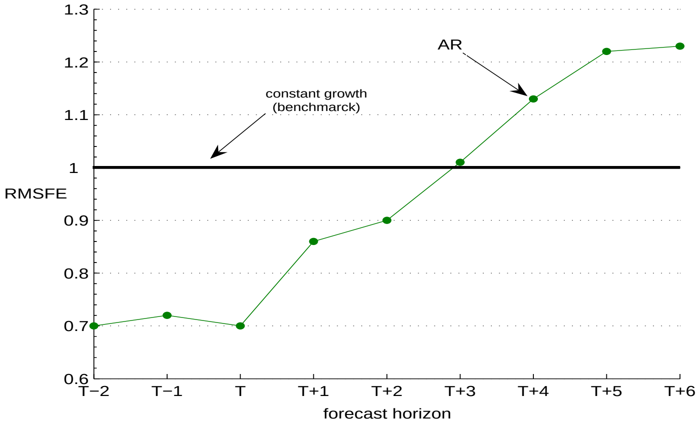

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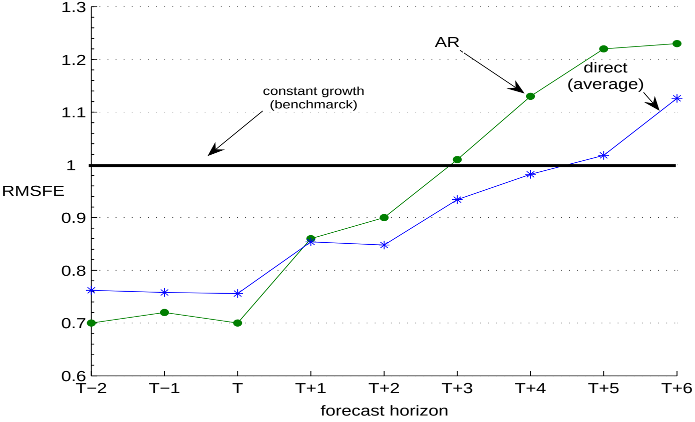

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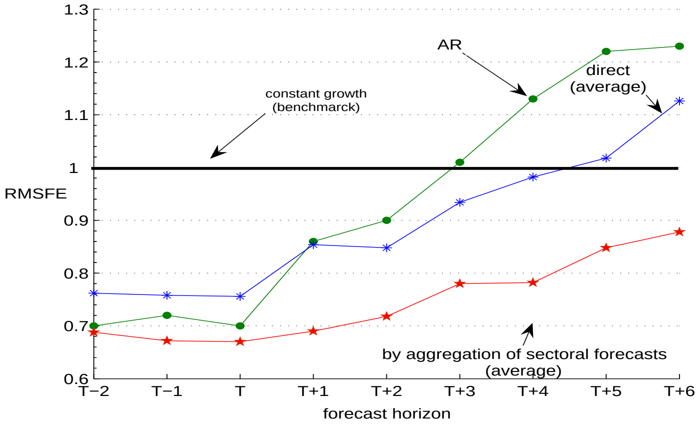

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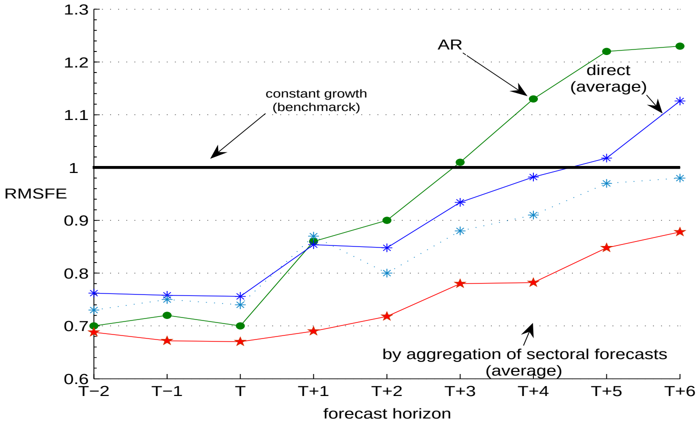

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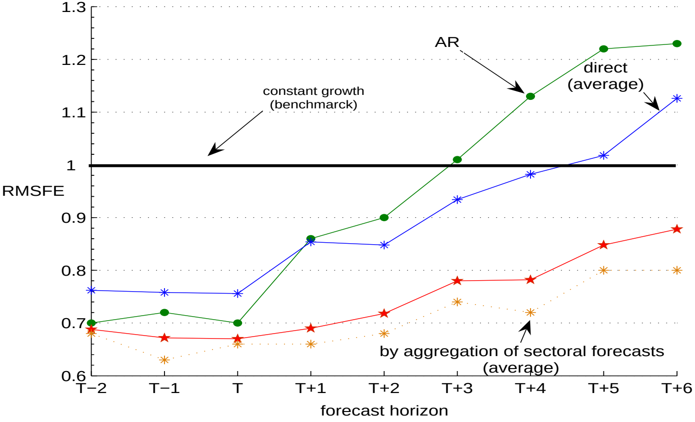
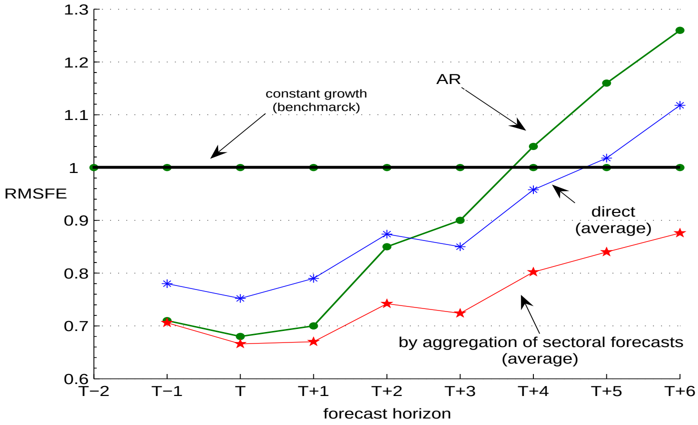


Forecasting in the middle of month T

Available data:

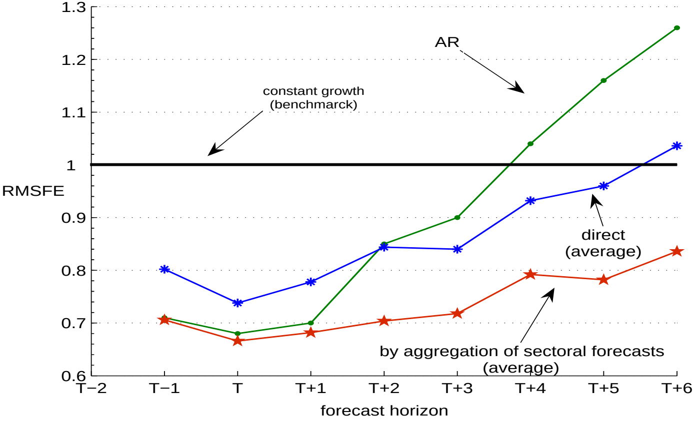
- Manufacture index till T-2 new!!!
- Survey data till T-1



Forecasting at the end of month T

Available data:

- Manufacture index till T-2
- Survey data till T new!!!



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- extend to a dynamic setting
- explore potentially more efficient algorithms for maximum likelihood estimation
- use real-time official data to forecast, and definite data for the evaluation, to reproduce a more realistic setting

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Monte Carlo results

The effects of erroneously modelling block-specific factors*.
$r = 1$, EML with $n^{\mathrm{b}} = 5$.

$TR_{(EML)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$T = 50$	0.95	0.98	0.98	0.99	0.99	0.99
$T = 100$	0.96	0.98	0.99	0.99	0.99	0.99
$T = 150$	0.96	0.98	0.99	0.99	0.99	0.99

$TR_{(EML)} / TR_{(PC)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$T = 50$	1.008	1.004	1.002	1.001	1.001	1.001
$T = 100$	1.010	1.004	1.002	1.002	1.001	1.001
$T = 150$	1.011	1.005	1.002	1.002	1.001	1.001

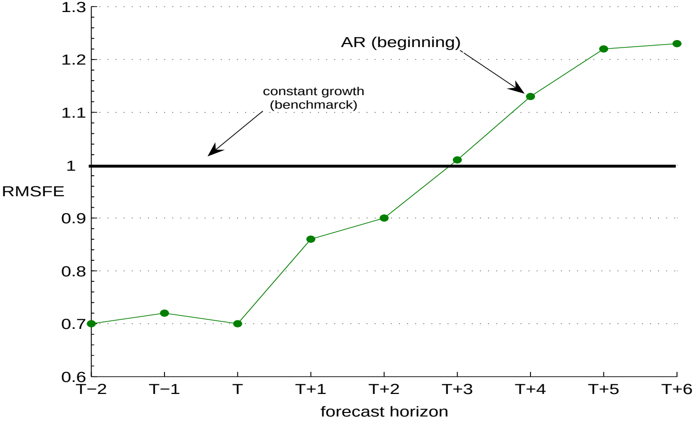
$TR_{(EML)} / TR_{(QML)}$

	$n = 20$	$n = 50$	$n = 100$	$n = 150$	$n = 200$	$n = 250$
$T = 50$	0.998	0.999	1.000	1.000	1.000	1.000
$T = 100$	0.999	1.000	1.000	1.000	1.000	1.000
$T = 150$	0.999	1.000	1.000	1.000	1.000	1.000

* Medians across 1000 repetitions

The effect of official data release

Only on AR forecast. In particular for 1 month ahead forecasts



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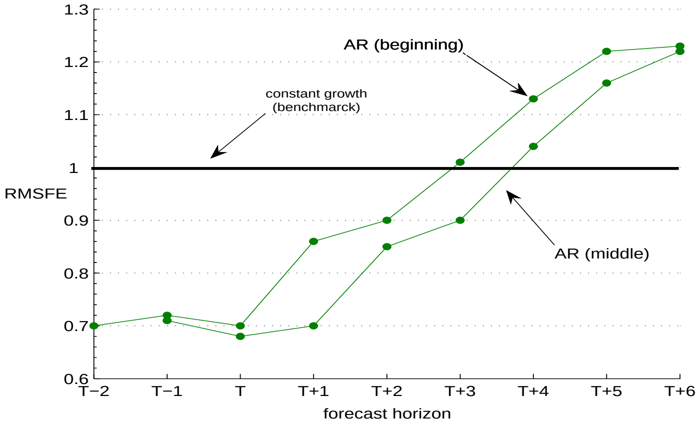
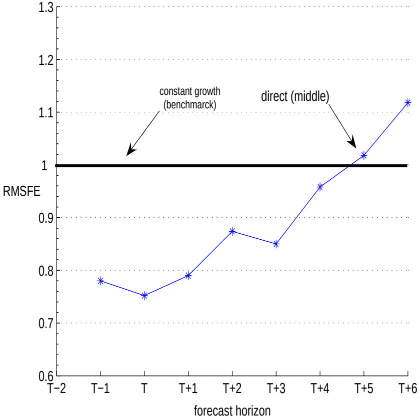
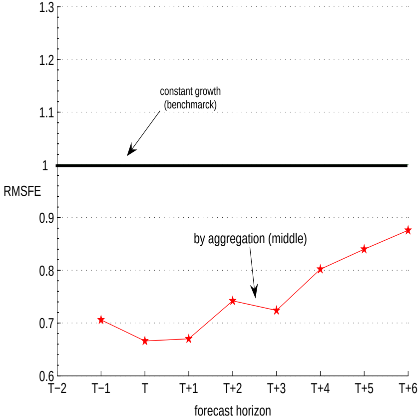


The effect of survey data release

Only little effects





The effect of survey data release

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