Forecasting Macroeconomic Variables Using Diffusion Indexes in Short Samples with Structural Change

Anindya Banerjee

European University Institute

Massimiliano Marcellino

IEP-Bocconi University, IGIER and CEPR

Igor Masten

University of Ljubljana

Banque de France, 7 September 2007

Motivation

- Factor models useful for forecasting macro variables, large literature showing this, e.g., Stock and Watson (2002a, 2002b) and Forni et al. (2004) for the US, Marcellino, Stock and Watson (2003) for the EA, Artis, Banerjee and Marcellino (2005) for the UK, Schumacher (2006) for Germany, Bruneau, de Bandt, Flageollet and Michaux (2006) for France, Den Reijer (2006) for The Netherlands, Banerjee, Marcellino and Masten (2006) for the new EU members.

- Alternative methods for factor estimation, several comparative studies, see e.g. meta analysis in Eickmeier and Ziegler (2007).

- Fewer results for the large N small T case, even though factor models should be efficient also in this case, and even with $N>T$. Interesting applications include New EU member countries and the Euro area.

- Additional problem for the New EU member countries and the Euro area is parameter instability

Short overview of the paper

- Forecasting performance of diffusion index-based methods in short samples with structural change, based on:

  - Detailed simulation study: DGPs with different types of structural change, relative forecasting performance of factor models and traditional time series methods.

  - Empirical applications for the Euro area and Slovenia: relatively short samples of data and structural changes are likely.

- Main findings:
  - Coherence b/w the empirical and simulation results.
  - Relatively good performance of factor-based forecasts in short samples with structural change.

Structure of the talk

- Monte Carlo analysis
- The case of the euro area
- Some other related results on forecasting euro area inflation
- Conclusions

Monte Carlo Experiments

- **Purpose**: Understand the sensitivity of the performance of factor- and non-factor methods to:

  - *T* and *N*
  - various features likely to characterize the data in practice: degree of persistence of the factors and the presence of structural change
  - The data are generated by a dynamic factor model that allows for autoregressive factors, auto- and cross-correlation in idiosyncratic errors and time-varying parameters

DGP

- $x_{it} = \lambda_{it}^{'} f_t + e_{it}$
- $f_t = A_t f_{t-1} + u_t, \qquad A_t = \alpha_t I_r$
- $\alpha_t = d\left(\alpha_{t-1} + 1/T\, \eta_t\right) + (1-d)\alpha_1 I\left(T_B\right) + (1-d)\alpha_0,\ \ \alpha_0 = \overline{\alpha}$
- $I\left(T_B\right) = \begin{cases} \underline{0, \forall t \le T_B} \\ 1, \forall t > T_B \end{cases} \quad d = \begin{cases} 0, \text{breaking} & \alpha \\ 1, \text{time varying} & \alpha \end{cases}$
- $\lambda_{it} = \lambda_{it-1} + (c/T)\zeta_{it}$
- $(1 - aL)e_{it} = \left(1 + b^2\right)v_{it} + bv_{i+1,t} + bv_{i-1,t}$
- $y_t = \iota' f_{t-1} + \varepsilon_t$

- f_t and λ_t are $r \times 1$, r=1, ..., 5
- e_{it}, v_{it}, and ε_t are i.i.d. $N(0,1)$, while ζ_{it} and u_t are i.i.d. $N(0,I_r)$. u_t is independent of e_{it}, v_{it}, ε_t and ζ_{it}
- Factor persistence α:

o stable and fixed (d = 0 and T_B = T, $\alpha = \{0.3, 0.5, 0.7\}$)

o continuously time-varying persistence (d = 1, $\overline{\alpha} = \{0.3, 0.5, 0.7\}$)

o discrete break in persistence of factors (d = 0 and T_B = $T/2$, $\alpha_1 = 0.4$ when $\alpha_0 = 0.3$ and $\alpha_1 = -0.4$ when $\alpha_0 = 0.7$ -> persistence from 0.3 to 0.7 and viceversa)

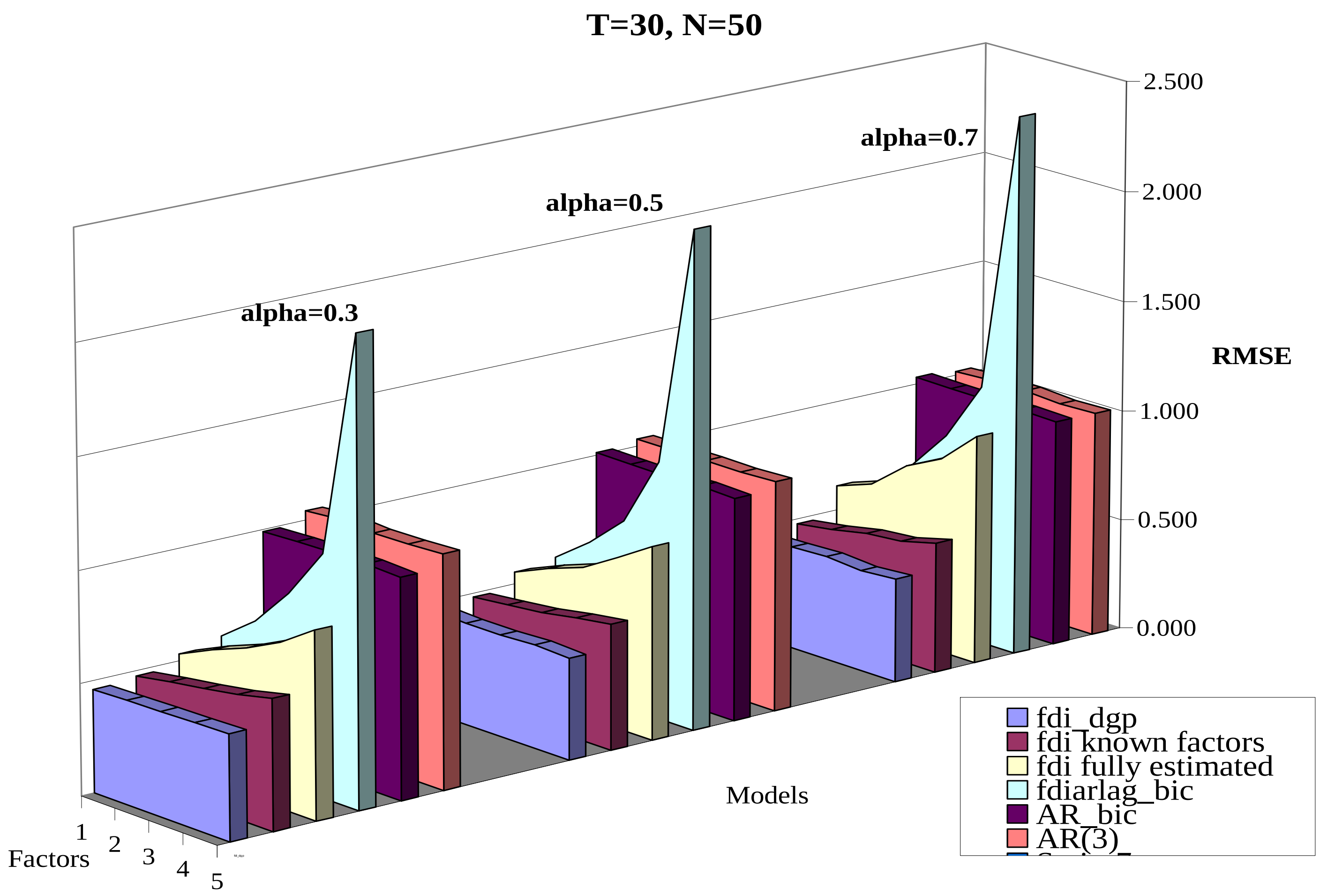
- Case of double variance of factors
- Time-varying factor loadings ($c = 5$)
- Cross-correlated idiosyncratic components ($a = 0.5,\ b = 1$)
- *T* and *N* combinations:
  - *T* = 30, *N* = 50 relevant for new EU members on quarterly frequency
  - *T* = 50, *N* = 50
  - *T* = 50, *N* = 100
  - *T* = 150, *N* = 50

- Models estimated on artificial data:

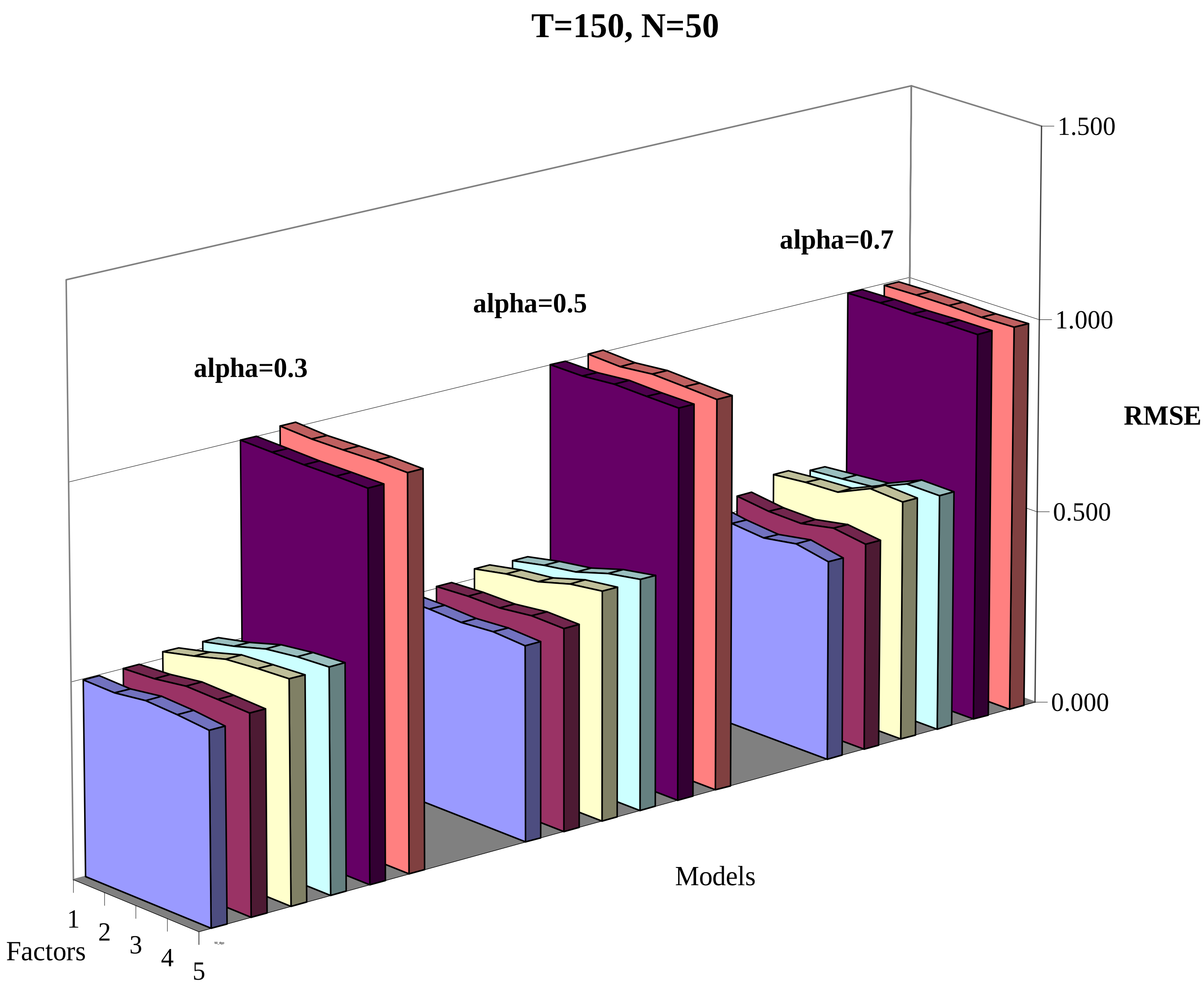
  - AR(1)-benchmark, AR(3) and AR with BIC selection

  - Factor models: (1) *fdi_dgp* (not estimated), (2) known factors, estimated coefficients, (3) fully estimated, but knowing the model's structure, and (4) lags of factors and *y* (*fdiarlag_bic*).

Figure 3: Time-varying lambda - *h* = 1



MSE relative to AR(1)


T=150, N=50
alpha=0.3
alpha=0.5
alpha=0.7
1.500
1.000
0.500
0.000
RMSE
Models
Factors
1
2
3
4
5

Summary of Monte Carlo results

(a) Continuous changes in factor persistence do not seem to matter, even in short samples.

(b) Discrete changes do matter but the impact on relative performance of factor methods leads either to improvement or deterioration, depending upon the value of the (starting) persistence parameter, the direction of the change and the magnitude of the *T* and *N* dimensions.

(c) Time varying factor loadings are important except when *T* and *N* are large (in line with SW 2002) – empirically relevant (Figure 3)

(d) Ranking of the impact of the different kinds of stability is (c) to (b) to (a)

(e) Factor models outperform AR models in the majority of cases, even in short samples subject to changes

(f) Relative performance of factor models deteriorates fast with number of factors in the DGP (especially when selection is BIC based)

(g) As expected, the variance of the idiosyncratic component of the target variable is important. (Figure 4)

(h) Similar results for $h=4$

Empirical example (Euro area)

- *Forecasting models (h=1):* $y_{t+h}^{h} = \mu + \alpha(L) y_t + \beta(L)' Z_t + \varepsilon_{t+h}^{h}$

- Construction of y_{t+h}^{h} depends on order of integration of y_t

- Forecasting models under comparison:

1) *Autoregressive forecast* (Z_t excluded)

2) *Autoregressive forecast with second differencing* - the variable of interest treated as I(2)

3) *Autoregressive forecast with intercept correction*

4) *VAR forecasts (*in the empirical analysis for the EA Z_t includes lags of IP growth, inflation, and a short-term interest rate)

5) *Factor-based forecasts.* Z_t contains the estimated factors from a dynamic factor model along the lines of Stock and Watson (2002b). *Factor models can have:*

- Fixed number of factors (up to 6)
- Lags of factors and AR terms – BIC selection
- Factors extracted either from balanced or unbalanced panel

6) Pooling of factor models also considered, separately for standard and intercept corrected forecasts.

- Forecast comparison: simulated out-of-sample MSE relative to the benchmark AR forecast with West (1996) standard errors

The data

- Euro area: 58 monthly series, period 1991:2 – 2005:10, collected from OECD Main Economic Indicators and Eurostat

o Sub-sample analysis around the introduction of the Euro:

o Sample: 1991:2 – 2005:10, forecast: 1997:1 – 2005:10

o Sample: 1991:2 – 1998:11; 1997:1 – 1998:12

o Sample: 1999:1 – 2005:10; 2003:11 – 2005:10

Figure 6: Recursive adjusted R^2, *h* = 1, Euro area

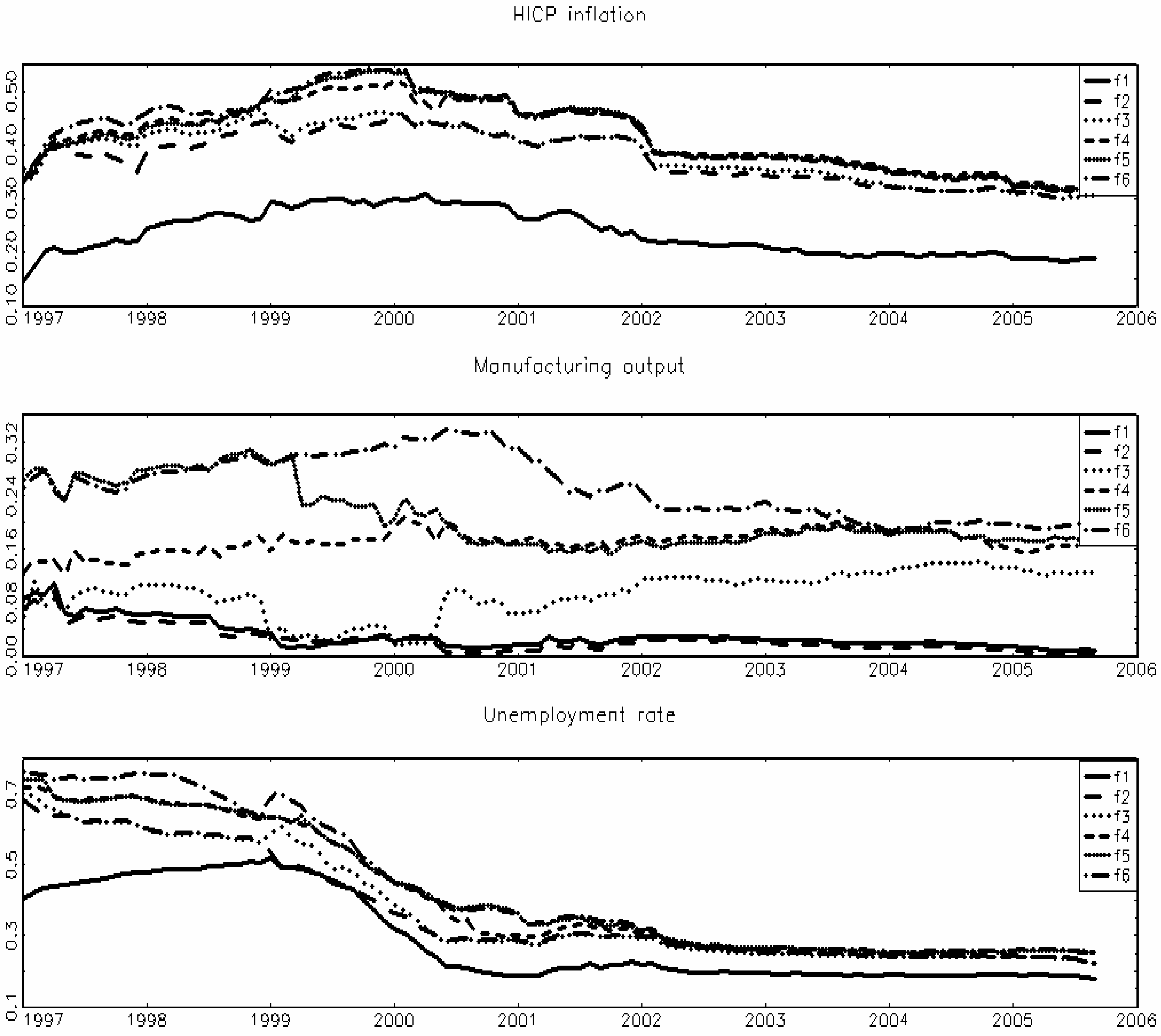


Figure 7: Euro-area inflation: Recursive Coefficients from fac_fdiarlag_bic Model (=fac_2)

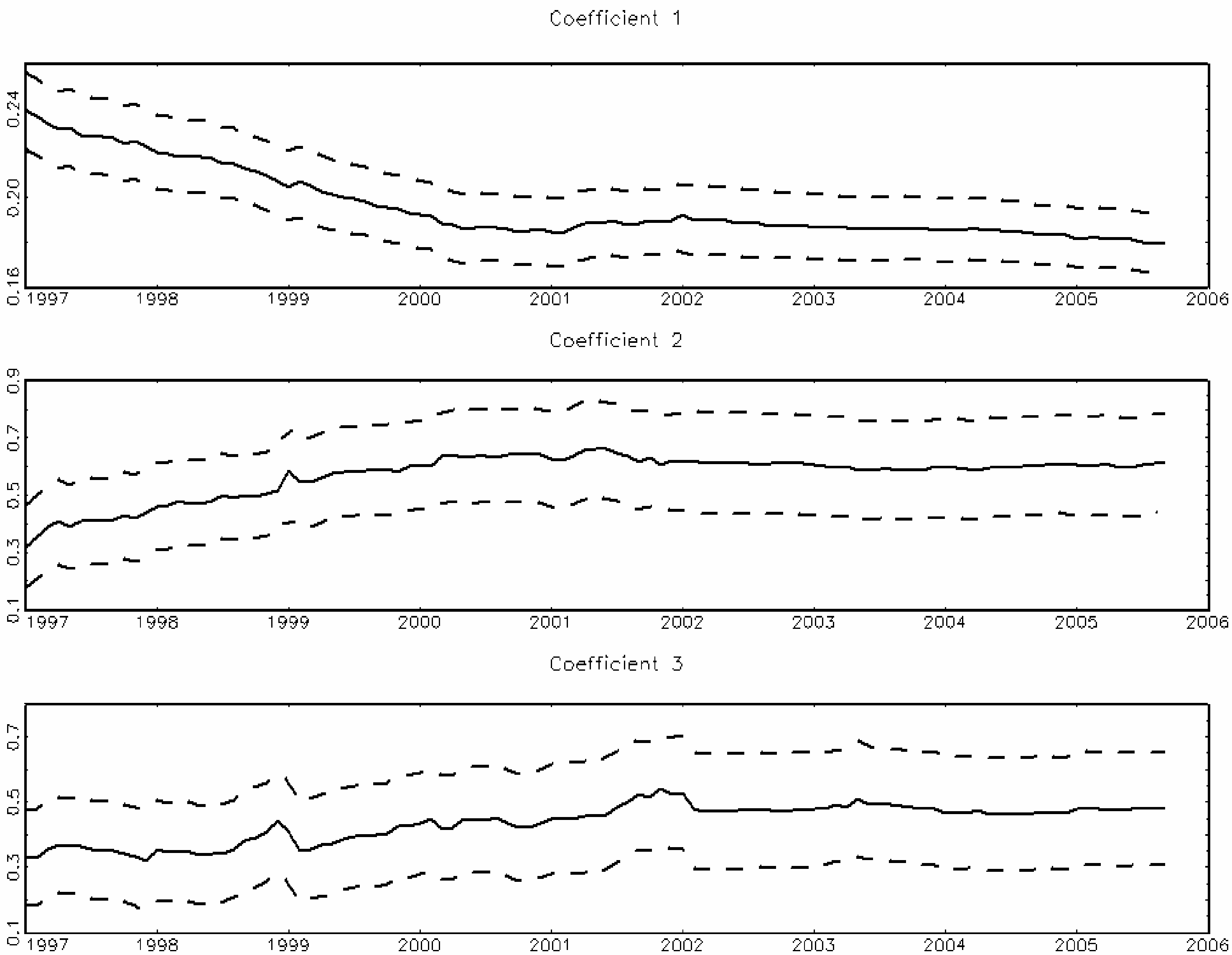
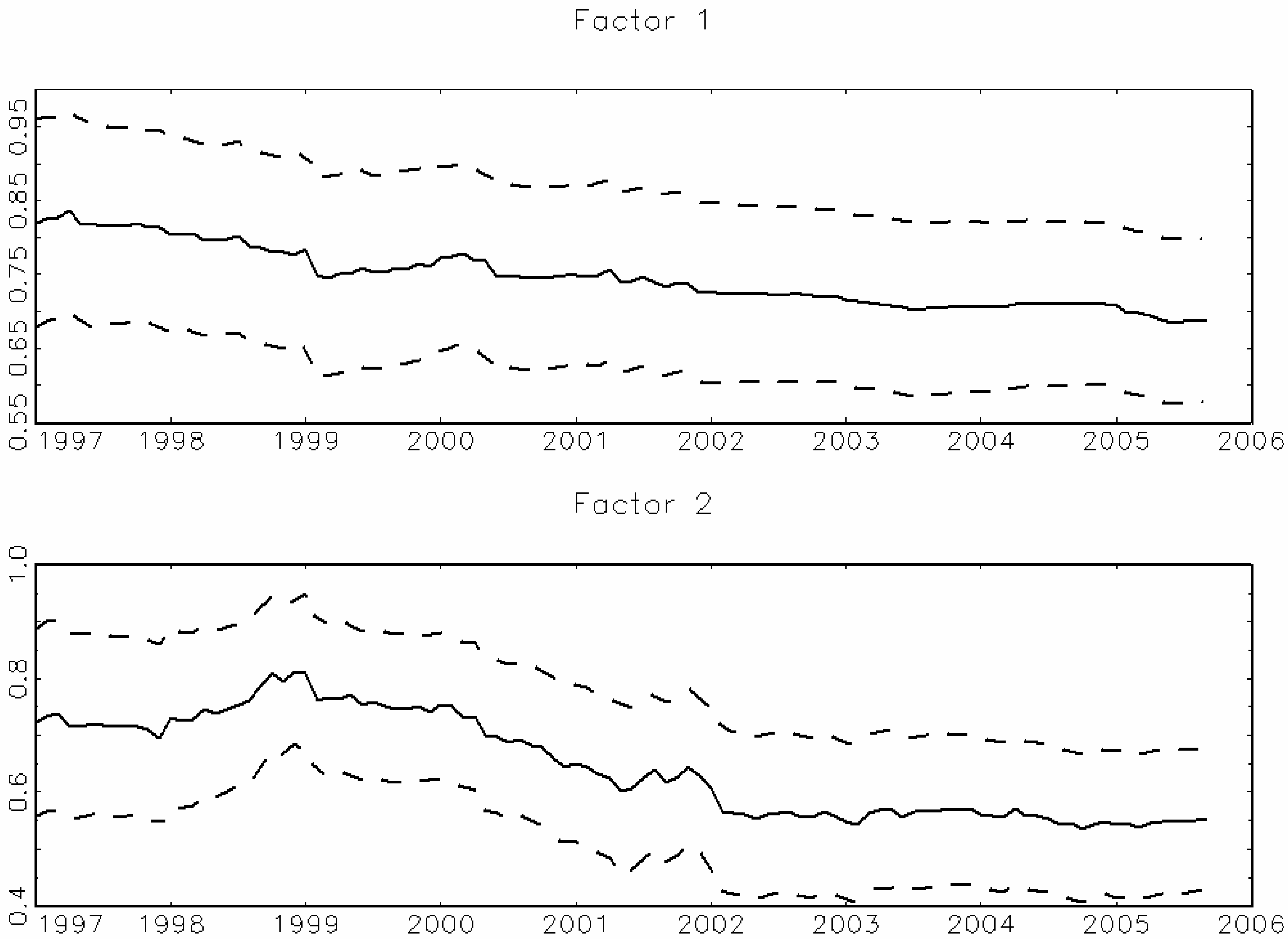


Figure 11: Recursive persistence of factors



	Inflation		
Forecast method	Est. 91-05 For. 97-05	Est. 91-98 For. 97-98	Est. 99-05 For. 04-05
ar_bic	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
ar_bic_i2	1.01 (0.05)	0.79 (0.14)	1.27 (0.33)
ar_bic_ic	2.10 (0.56)	1.85 (0.85)	2.54 (1.33)
varf	1.00 (0.06)	0.85 (0.12)	1.55 (0.65)
varfic	2.18 (0.60)	1.62 (0.58)	3.78 (3.37)
fac__fdiarlag_bic	0.99 (0.11)	0.63 (0.18)	1.01 (0.17)
fac__fdiar_bic	0.99 (0.11)	0.63 (0.18)	1.01 (0.17)
fbp__fdiarlag_bic	1.01 (0.12)	0.65 (0.17)	1.03 (0.18)
fbp__fdiar_bic	1.01 (0.12)	0.65 (0.17)	1.01 (0.17)
fac__fdiar_01	1.00 (0.06)	1.02 (0.14)	1.01 (0.17)
fac__fdiar_02	1.02 (0.10)	0.64 (0.18)	0.96 (0.18)
fac__fdiar_03	0.99 (0.09)	0.58 (0.18)	1.00 (0.19)
fac__fdiar_04	0.99 (0.12)	0.55 (0.17)	0.97 (0.18)
fac__fdiar_05	0.99 (0.12)	0.55 (0.17)	0.96 (0.17)
fac__fdiar_06	1.00 (0.12)	0.61 (0.18)	1.04 (0.17)
F_pooled	1.00 (0.09)	0.69 (0.17)	1.14 (0.22)
F_ic_pooled	1.10 (0.14)	0.62 (0.18)	1.30 (0.31)
RMSE for AR	0.097	0.095	0.075

Table 2: Fraction of variance of the panel explained by the factors

Factor	Marginal	Cumulative
1	0.14	0.14
2	0.09	0.23
3	0.07	0.30
4	0.06	0.36
5	0.05	0.41
6	0.04	0.45
7	0.04	0.49
8	0.04	0.52
9	0.03	0.56
10	0.03	0.59
11	0.03	0.61
12	0.03	0.64
N	57	

	Inflation – Bai and Ng (2005) preselection					
Forecast method	Est. 91-05 For. 97-05		Est. 91-98 For. 97-98		Est. 99-05 For. 04-05	
ar_bic	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)
ar_bic_i2	1.01	(0.05)	0.79	(0.14)	1.27	(0.33)
ar_bic_ic	2.10	(0.56)	1.85	(0.85)	2.54	(1.33)
fac__fdiarlag_bic	0.89	(0.09)	0.64	(0.15)	0.86	(0.19)
fac__fdiar_bic	0.89	(0.09)	0.64	(0.15)	0.87	(0.18)
fbp__fdiarlag_bic	0.92	(0.08)	0.66	(0.14)	0.86	(0.19)
fbp__fdiar_bic	0.92	(0.08)	0.66	(0.14)	0.87	(0.18)
fac__fdiar_01	0.89	(0.09)	0.64	(0.15)	0.87	(0.18)
fac__fdiar_02	0.89	(0.09)	0.64	(0.15)	0.95	(0.20)
f_pooled	0.96	(0.08)	0.72	(0.15)	1.00	(0.17)
f_ic_pooled	1.61	(0.33)	1.06	(0.30)	1.59	(0.51)
RMSE for AR	0.097		0.095		0.075	

A few additional related results

- Is the AR model a good forecasting benchmark?

Marcellino (2004, IJF). Data from Fagan, Henry and Mestre (2001), for 1970:1-1997:4, on consumer prices (HICP) and the gdp deflator (YED). The best forecasting models belong to the ARTV method (AR with RW parameters). However, linear AR models rank fourth or fifth and the differences are not large. Similar results for monthly HICP from Marcellino, Stock and Watson (2003). Similar results for the US (Marcellino (2006)), with vanishing gains from ARTV over the most recent period.

- What kind of models could handle instability in short samples?

- ARTV (tend to overperform STAR, NN and MS)

- Stock and Watson’s P/T model with Stochastic Volatility

- Koopman and Marcellino, generalizations of ARTV

- Boss, Koopman and Marcellino, stuctural time series models with Stochastic Volatility

- BVAR (De Mol, Giannone and Reichlin (2006)) and BRRR (Carriero, Kapetanios and Marcellino (2007))

- Does the loss function matter?

- MSE or MAE typically give same ranking

- Point forecast or path forecast can make a difference (Jorda and Marcellino (2007))

- Frequency of evaluation can make a difference. Banerjee, Marcellino and Masten (2005), Ceccheti, Chu and Steindel (2000) find a lot of instability in leading properties of inflation indicators.

Conclusions

- The paper deals with the forecasting performance of diffusion index-based methods in short samples with structural change.
- Monte Carlo experiments reveal that the most significant effects on the forecasting performance of factor models come from time-variation in factor loadings, especially for small T panels likely to be encountered in practice.

- Empirical examples showed clear evidence of instability particularly for the Euro area forecasts and factors that occurred in the time period contiguous to the inauguration of the Euro area and the introduction of the euro, giving considerably intuitive economic content to the finding of instability.
- These findings are then easily linked up with the performance of factor models by conducting sub-sample forecast comparisons, and bearing in mind our results from the simulation study.
- Overall, good forecasting performance of factor models also in small samples with breaks, though careful specification is required.