Real time forecasts of inflation: the role of financial variables

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Introduction

We present a mixed frequency model to forecast inflation in real time

- It can be easily estimated on a daily basis using all the information available up to that date
- it combines the information on long-run and short-run dynamics of inflation

Main findings:

- it has a stronger predictive power than standard monthly models
- it outperforms forecasts implied in HICP-future contracts

Motivations

Over the last few years there has been a growing importance in forecasting macro variables in real time:

- Monetary policy
  - the introduction of “explicit” inflation targets
  - “the need of a modern monetary policy based on market expectations” (Woodford 2003)
- Financial markets
  - anticipate Monetary Policy
  - new contracts require continuous forecasts

Outline of the presentation

- We present the two main ingredients of our approach:
  - modelling the long run component of inflation
  - daily financial variables
- Introduce mixed-frequency data models
- Present our models for the EA HICP
- Two exercises of forecast evaluation to compare our models with standard models and market expectations

Modelling long run component with factor models

- Large dimensional Factor Models have become increasingly popular in the construction of reliable coincident and leading indicators
- Developed by Forni et al. (2000, 2005) and Stock and Watson (2002), they can handle in a parsimonious way the information contained in a large data set ▸ Factor det
- They do this by extracting few 'common components' from the correlation structure of the data that explain most of the variability of the data

1. Examples of business index: EUROCOIN and Chicago Fed National Activity Index
2. Examples of core inflation: Kapetanios (2004) for UK and Cristadoro et al. (2008) for EA

Core Inflation

- We use a Core inflation index obtained from a Generalized Dynamic Factor model (Cristadoro et al. (2008))
- This measure of core inflation is an estimate of the unobserved component that drives the persistent or 'long run' movements in inflation
- By construction it is cleaned from the effects of transient and idiosyncratic shocks:
  - It is a smooth indicator
  - It provides timely signal of future (long-medium run) price changes

Real time forecasting with factor models

- Large scale factor models are not “ideal” to forecast in real time:
  - unbalanced end of sample
  - temporal aggregation bias
  - practical issues (download and data treatment)
- Flourishing of literature on these issues
  - New Eurocoin (Altissimo et al. (2006))
  - Factor - MIDAS dealing with the end of sample adjustment (Marcellino-Schumacher (2008))
  - Mixed frequency unobserved component models (Mittnik-Zadrozny (2005), Aruoba et al. (2007))

Role of financial variables

- An alternative solution is to look at variables that are highly correlated with inflation but that are sampled at higher frequency, such as commodity prices and financial variables
- Notable characteristics of these variables:
  - potentially forward looking
  - released in continuous time
  - not subject to revisions
- Use of financial variables to forecast inflation is not new. Stock and Watson (2001) present a good survey: evidence is not conclusive and results are model dependent. Using DFM Forni et. al. (2003) and Giannone et. al. (2006) found some evidence

Our approach

- What we propose is a simple mixed frequency model that incorporates the previous approaches:

1. exploit the rich information on low-medium frequencies of inflation that comes from a Dynamic Factor Model
2. combine in a mixed frequency model the monthly core inflation index with daily prices of commodities and financial assets

- $\Rightarrow$ This allows us to capture recent information on possible movements of inflation as well as its long run underlying dynamics

Mixed frequency data models:

- Allows us to have in the same models variables sampled at different frequencies, e.g. monthly and daily
- They are particularly useful when the relevant explanatory variables come at high frequency but the endogenous is sampled a lower frequency
- We follow the specification of Mixed Data Sampling regression models (MIDAS) introduced by Ghysels, Santa-Clara and Valkanov (2004, 2007)

A simple MIDAS model

- Let us assume the month t has M days, then a simple model for monthly inflation π_t is

$$\pi_t^m = \alpha z_{t-k}^m + \beta B\left(L^{\frac{1}{M}}; \boldsymbol{\theta}\right) x_t^d + \varepsilon_t$$
$$= \alpha z_{t-k}^m + \beta \sum_{k=1}^{M} b\left(k; \boldsymbol{\theta}\right) L^{\frac{k}{M}} x_t^d + \varepsilon_t$$
$$= \alpha z_{t-k}^m + \beta \left(b\left(1; \boldsymbol{\theta}\right) x_{t-\frac{1}{M}}^d + b\left(2; \boldsymbol{\theta}\right) x_{t-\frac{2}{M}}^d + \ldots\right) + \varepsilon_t$$

- z_{t-k}^m is a vector of MONTHLY lagged variables; x_t^d is the DAILY variable

$L^{\frac{k}{M}}$ is the "daily" lag operator:

$L^{\frac{1}{M}} x_t^d = x_{t-\frac{1}{M}}^d$ is the daily daily observation of month t

$L^{\frac{2}{M}} x_t^d = x_{t-\frac{2}{M}}^d$ is the penultimate daily observation of month t

How to construct daily forecasts

Let asssume we stand at the 15^{th} of sept. I want to forecast current inflation.

- Estimate the model using monthly data til august and daily til the 14^{th} of august

$$\pi_{aug} = \alpha z_{Jul} + \beta_1 x^d_{14aug} + \beta_2 x^d_{13aug} + \beta_3 x^d_{12aug} + \ldots$$

- Forecast using the estimated parameter values

$$\hat{\pi}_{sept} = \hat{\alpha} z_{aug} + \hat{\beta}_1 x^d_{14sept} + \hat{\beta}_2 x^d_{13sept} + \hat{\beta}_3 x^d_{12sept} + \ldots$$

- Common specification for $b(k,\theta)$ are

$$b(k,\theta) = \frac{f(k,\boldsymbol{\theta})}{\sum_{k=0}^{K} f(k,\boldsymbol{\theta})}$$

where

1. $f(k,\theta) = \exp\left(\theta_1 k + \theta_2 k^2\right) \Rightarrow$ Almon exponential pol.
2. $f(x,\theta) = \frac{\Gamma(\theta_1+\theta_2)}{\Gamma(\theta_1)\Gamma(\theta_1)} x^{\theta_1 - 1} (1-x)^{\theta_2 - 1} \Rightarrow$ Beta pol.

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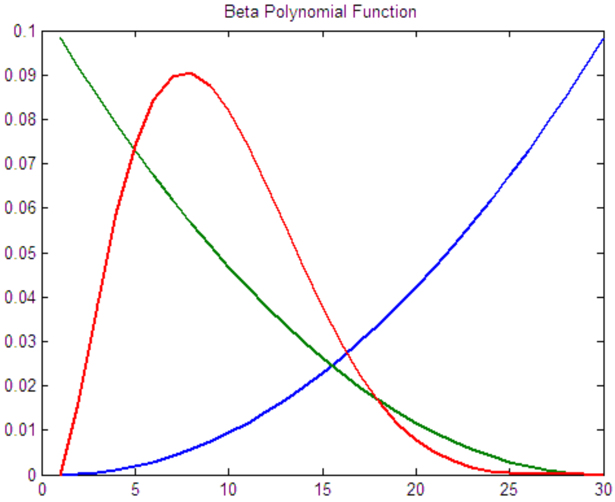


Empirical Applications:

1. We compare three mixed frequency models vs standard models
2. We compare them to inflation expectations extracted from HICP future contracts

- Dataset monthly/daily from May 1992 to September 2007
- Estimation: iterative, constrained, nonlinear maximum likelihood
- Recursive forecast scheme

Three models for euro area (year-on-year HICP) inflation

MONTHLY variables, common to all models: past inflation, lag of oil price and core inflation lagged five

Model 1: Captures shocks from both domestic and foreign prices:

- DAILY variables: the short term rate and changes in the interest rate spread and oil future prices

Model 2: Captures shocks coming from abroad:

- DAILY var: changes in the wheat price, oil futures and exchange rate

Model 3: Captures shocks only from interest rates:

- DAILY var: long term interest rate and changes in the interest rate spread and in the short term rate

Real time forecasts of monthly inflation

- First exercise we compute RMSFE of M1, M2 and M3 and compare them with those some benchmark models:
- AR and ARMA models chosen according to Schwarz criterion
- Two VARs including the same monthly variables as our models:
- this would tell us about the importance of daily variables
- We use 10 years as burning periods and generate recursive forecasts from May 2002 til Sept. 2007

Comparison with standard monthly models: RMSFE

sample 2002:5-2007:9	months ahead	
Our models	0	1
Model 1	0.158	0.226
Model 2	**0.148**	**0.208**
Model 3	0.163	0.216
Univariate models		
RW	0.185	0.261
AR(1)	**0.181**	0.250
ARMA(2,1)	0.184	**0.248**
Multivariate models		
MV 2	**0.169**	**0.234**
MV 3	0.173	0.244

Note: MV 2: VAR with inflation, core inflation and oil price

MV 3: VAR with inflation, core inflation, oil price and interest rate

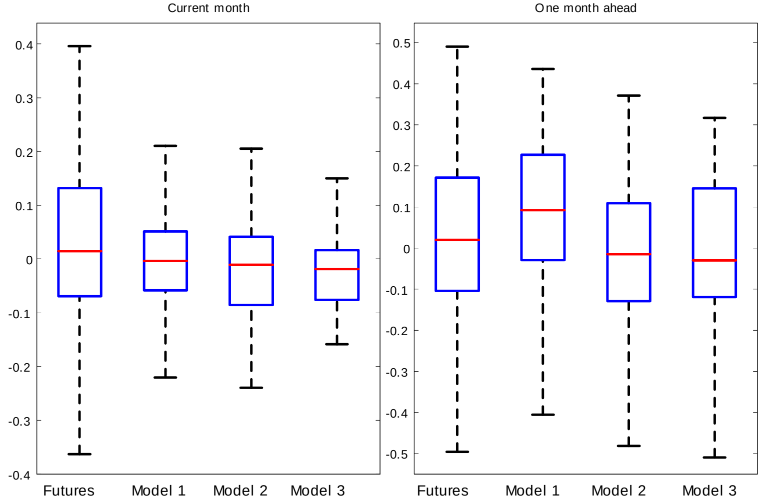
Application 1: results

- All the mixed frequency models outperform standard models
- In particular they produce better forecast than VARs showing that daily variables do improve forecasts
- The improvement compared to standard models is similar in t and $t+1$
- Among the mixed frequency models MODEL 2 seem to produce the best forecasts

Model forecasts vs market expectations

- We compare our models' forecasts with the current and one-month ahead expected inflation rate implied in quotes of EA HICP future daily contracts (CME) from October 2005 to September 2007
- Why future contract underlying inflation rate:
  - They are useful tool to extract market inflation expectations
  - Wolfers and Gurkaynak (2006) predictive power of future contracts is better than that of survey data
  - they also are better suited than the break-even inflation rate (negligible liquidity risk premium)

Comparison with daily futures (2005:10 2007:9)



Comparison with daily futures: DM test

	current month		one month ahead	
	squares	abs	squares	abs
Model 1	0.012	0.044	0.006	0.015
	(2.883)	(3.754)	(0.763)	(0.889)
Model 2	0.010	0.037	0.004	0.028
	(2.277)	(3.061)	(0.434)	(1.748)
Model 3	0.008	0.035	0.010	0.032
	(1.618)	(2.786)	(0.943)	(1.909)

Note: Diebold Mariano test on the difference between derivative and model prediction errors.

In parentheses, Newey West adjusted t-stat

Forecast encompassing test : combination weights

	current month			one month ahead		
	M1_b	M2_b	M3_b	M1_b	M2_b	M3_b
Coefficients:						
cost	-0.136	-0.188	-0.228	0.044	0.176	0.036
	(-1.366)	(-2.113)	(-2.262)	(0.296)	(1.277)	(0.241)
deriv	0.297	0.351	0.414	0.389	0.388	0.384
	(3.083)	(3.670)	(4.017)	(4.835)	(4.650)	(4.590)
midas	0.769	0.634	0.691	0.609	0.517	0.588
	(9.749)	(8.893)	(7.821)	(6.356)	(6.442)	(5.997)
Test a diagnostics:						
Wald F statistic	38.23	30.78	23.76	22.27	21.97	21.15
P value, %	0	0	0	0	0	0
Test b diagnostics:						
Wald F statistic	3.37	5.74	6.23	15.86	12.33	7.65
P value, %	1.8	0.0	0.2	0	0	0

Note: (1) test a: the null hypotesis is that economic derivatives forecasts encompass MIDAS (b0=b2=0; b1=1)
(2) test b: the null hypotesis is that MIDAS forecasts encompass the economic derivatives (b0=b1=0; b2=1)
(3) in brackets: heteroskedasticity and autocorrelation consistent (Newey West) standard error of the coefficients.

Forecast combination

RMSFE	current month		one month ahead	
	single	combined	single	combined
Model 1	0.123	0.117	0.219	0.191
Model 2	0.132	0.123	0.224	0.195
Model 3	0.140	0.128	0.211	0.189
Futures	0.166		0.233	

Note: Forecast combination with OLS estimated weights

Conclusion

- We presented an approach that:
- can be estimated and run daily to produce up-to-date forecasts
- combines the information on long-run and short-run movements of inflation
- performs quite well compared to standard models
- some room for improvement with market expectations

END OF PRESENTATION

How do they work?

- Let us assume a large number of time series $y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})$
- Dynamic Factor Models extract a few common factors $\chi_{h,t}$, $h = 1, ...q$ such that

$$y_{i,t} = \sum_{h=1}^{q} b_{i,h}(L)\chi_{h,t} + \xi_{i,t}$$

where $\xi_{i,t}$ is an idiosyncratic shock
- These common factors are chosen in order to explain most of the variability of the data at low and medium frequency
- The common factors can be seen as the prediction of the "common" long-run dynamics of the data