EuroMInd-$\mathcal{D}$: A Density Estimate of Monthly Gross Domestic Product for the Euro Area

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Introduction

What is EuroMInd-$\mathcal{D}$?

EuroMInd-$\mathcal{D}$ is a density estimate of monthly GDP constructed according to a bottom–up approach:

- Step 1: Density estimates for seven GDP components by output (value added) type and four GDP components by expenditure type are obtained
- Step 2: Respective component densities from step 1 are combined to obtain GDP estimate by output and expenditure type
- Step 3: Both GDP estimates from step 2 are combined to the final density estimate of GDP

Breakdown of GDP at market prices by output and expenditure type:

- From the output side GDP is decomposed as follows:

Label	*Value added of branch*	
A–B	Agriculture, hunting, forestry and fishing	+
C–D–E	Industry, incl. Energy	+
F	Construction	+
G–H–I	Trade, transport and communication services	+
J–K	Financial services and business activities	+
L–P	Other services	=
	Total Gross Value Added	+
TIS	Taxes less subsidies on products	=
	GDP at market prices	

- The breakdown of total GDP from the expenditure side is the following:

Label	*Component*	
FCE	Final consumption expenditure	+
GCF	Gross capital formation	+
EXP	Exports of goods and services	-
IMP	Imports of goods and services	=
	GDP at market prices	

Methodology:

- Step 1:
  - Medium-size dynamic factor model handling mixed frequencies of observation and ragged–edged data structures
  - Bootstrap algorithm: for simulating from the distribution of the maximum likelihood estimators of the model parameters, and conditional simulation filters, for simulating from the predictive distribution of GDP $\Rightarrow$ estimates reflect both **filtering and parameter uncertainty**
- Step 2: Aggregation of individual component densities expressed in chain–linked measures that guarantees cross–sectional additivity (annual overlap)
- Step 3: Density combination using different weighting schemes

Evaluation:

Real–time density forecasts evaluated with different tests based on the probability integral transform and by applying scoring rules

Dynamic factor model for the complete data

Let $\mathbf{y}_t = [y_{1t}, \dots, y_{it}, \dots, y_{Nt}]'$, $t = 1, \dots n$, denote an $N \times 1$ vector of $I(1)$ time series. The elements of the vector $\mathbf{y}_t$ include a set of monthly coincident indicators and the relevant GDP component.

$$\Delta \mathbf{y}_t = \mathbf{m} + \boldsymbol{\theta}(L)\boldsymbol{\chi}_t + \boldsymbol{\chi}_t^*.$$

- $\mathbf{m}$ is an $N \times 1$ vector of drifts, $\mathrm{E}(\Delta \mathbf{y}_t) = \mathbf{m}$
- $\boldsymbol{\chi}_t$ is a vector of $K < N$ stationary common factors. For $K = 1$, there is a single index, with AR specification

$$(1 - \phi_1 L - \dots - \phi_p L^p)\chi_t = \eta_t, \quad \eta_t \sim \mathrm{NID}(0, \sigma^2_\eta)$$

- $\boldsymbol{\theta}(L) = \boldsymbol{\theta}_0 + \boldsymbol{\theta}_1 L + \dots + \boldsymbol{\theta}_J L^J$, $\boldsymbol{\theta}_j$ is an $N \times K$ matrix of loadings
- $\boldsymbol{\chi}_t^*$ is the idiosyncratic component,

$$\mathbf{D}(L)\boldsymbol{\chi}_t^* = \boldsymbol{\eta}_t^*, \quad \boldsymbol{\eta}_t^* \sim \mathrm{NID}(\mathbf{0}, \boldsymbol{\Sigma}_{\eta^*}),$$

$$\mathbf{D}(L) = \mathrm{diag}\left[d_1(L), d_2(L), \dots, d_N(L)\right],$$

  with $d_i(L) = 1 - d_{i1}L - \dots - d_{ip_i}L^{p_i}$ and $\boldsymbol{\Sigma}_{\eta^*} = \mathrm{diag}(\sigma_1^2, \dots, \sigma_N^2)$.
- η_t and $\boldsymbol{\eta}_t^*$ are mutually uncorrelated at all leads and lags.

For filtering and signal extraction under temporal aggregation, it is preferable to set up the model in terms of the level of the variables.

- define the single index $\mu_t = \mu_{t-1} + \chi_t, \mu_0 = 0$,
- define the idiosyncratic component $\boldsymbol{\mu}_t^*$, such that $\boldsymbol{\mu}_t^* = \mathbf{m} + \boldsymbol{\mu}_{t-1}^* + \boldsymbol{\chi}_t^*$, with $\boldsymbol{\mu}_0^* = \mathbf{0}$

The model can be extended to account for the presence of regression effects, common to the N time series equations, leading to the following specification (which assumes $J = 1$):

$$
\begin{array}{lcll}
\mathbf{y}_t & = & \boldsymbol{\theta}_0\mu_t + \boldsymbol{\theta}_1\mu_{t-1} + \boldsymbol{\mu}_t^* + \mathbf{B}\mathbf{x}_t, & t = 1, ..., n, \\
\phi(L)\Delta\mu_t & = & \eta_t, & \eta_t \sim \text{NID}(0, \sigma_\eta^2), \\
\mathbf{D}(L)\Delta\boldsymbol{\mu}_t^* & = & \boldsymbol{\delta} + \boldsymbol{\eta}_t^*, & \boldsymbol{\eta}_t^* \sim \text{NID}(\mathbf{0}, \boldsymbol{\Sigma}_{\eta^*}),
\end{array}
\quad (1)
$$

- $\mathbf{x}_t$ is a $k \times 1$ vector of explanatory variables
- $\mathbf{B}$ is an $N \times k$ matrix of coefficients.
- $\boldsymbol{\delta} = \mathbf{D}(1)^{-1}\mathbf{m}$.
- We further assume that $\sigma_\eta^2 = 1$ as an identification restriction.

State space representation and temporal aggregation

- The monthly model for the complete data in (1) can be represented in state space form (SSF).
- The SSF is modified to take into consideration the observational constraints arising as a result of temporal aggregation (mixed frequency data).

Partition the vector $\mathbf{y}_t$ as $\mathbf{y}_t = [\mathbf{y}_{1t}', \mathbf{y}_{2t}']'$

- $\mathbf{y}_{1t}$ collects N_1 monthly indicators
- $\mathbf{y}_{2t}$ collects N_2 flow variables subject to temporal aggregation, so that we observe

$$\mathbf{y}_{2,3\tau} + \mathbf{y}_{2,3\tau-1} + \mathbf{y}_{2,3\tau-2}, \qquad \tau = 1, 2, \ldots, [n/3], \tag{2}$$

with τ denoting quarters and $[\cdot]$ being integer division.

Our treatment of temporal aggregation draws on Harvey 1989, who introduced the so–called cumulator variable, $\mathbf{y}_{2t}^{c}$, constructed as follows:

$$\mathbf{y}_{2,t}^{c} = \rho_t \mathbf{y}_{2,t-1}^{c} + \mathbf{y}_{2t}, \tag{3}$$

where

$$\rho_t = \begin{cases} 0, & \text{if } t = 3(\tau - 1) + 1, \\ 1, & \text{otherwise.} \end{cases}$$

The vector $\mathbf{y}_{2t}^{c}$ used to create new augmented state and observation vectors. Its values are unobserved for the first and second month of each quarter.

Estimation and signal extraction

- The model is estimated by maximum likelihood, using the prediction error decomposition, performed by the Kalman filter
- Sequential processing is used as an efficient algorithm for multivariate time series with missing values and ragged-edge structure. The univariate time series are processed in a sequence that reflects their publication schedule.

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Density estimation (nowcasting and forecasting)

Let y_t denote a generic monthly GDP component; the aim is drawing samples $y_{t+l}^{(r)}, t = 1, \dots, n$, $r = 1, \dots, R$, and $l \geq 0$, from the conditional distribution $f(y_{t+l}|\mathbf{Y}_s^{\dagger})$.

If $\boldsymbol{\psi}$ denotes the vector containing the hyperparameters of the model, we let $\tilde{\boldsymbol{\psi}}$ denote its maximum likelihood estimator (MLE). Assume that $\tilde{\boldsymbol{\psi}}$ has a distribution represented by a density function $f(\tilde{\boldsymbol{\psi}}_s)$. The required density is obtained as

$$f(y_{t+l}|\mathbf{Y}_s^{\dagger}) = \int f(y_{t+l}|\tilde{\boldsymbol{\psi}}, \mathbf{Y}_s^{\dagger}) f(\tilde{\boldsymbol{\psi}}) \mathrm{d}\tilde{\boldsymbol{\psi}}. \tag{4}$$

Bootstrap and conditional simulation

We can draw samples $y_{t+l}^{(r)}, r = 1, \ldots, R$, from (4) by the method of composition, using the following algorithm:

1. Obtain a bootstrap sample $\tilde{\psi}^{(r)} \sim f(\tilde{\psi})$. The paper documents a bootstrap algorithm that obtains simulated series from the innovations form of the univariate representation of the multivariate state space form, conditional on the MLE $\tilde{\psi}$.
2. Obtain an independent sample $y_{t+l}^{(r)} \sim f(y_{t+l}|\tilde{\psi}^{(r)}, \mathbf{Y}_s^{\dagger})$, by the simulation smoother. Conditional on the parameter vector $\tilde{\psi}^{(r)}$, we draw samples from the conditional distribution of the states, and hence of the monthly GDP component, given the past (filtered distribution), the current information (real–time distribution), and all the available information (smoothed distribution).

Pooling the density estimates of the GDP components

- The methods outlined in the previous section yield estimates for the monthly GDP components in chain–linked volumes, with the year 2000 as the reference year.
- As it is well known, chain–linked volume measures are not consistent in aggregation, e.g. the sum of the value added of the six sectors plus taxes less subsidies would not deliver GDP at market prices, unless they are first expressed at the average prices of the previous years.
- To obtain our density estimates of monthly GDP at market prices and chained volumes from the output and expenditure approaches, labelled EuroMInd-$\mathcal{D}_o$ and EuroMInd-$\mathcal{D}_e$, we need to pool the GDP components density draws, according to a multistep procedure proposed by Frale et al (2011), that enforces the so–called annual overlap method.

The procedure consists essentially of three main steps:

1. *Dechaining*, aiming at expressing the draws at the average prices of the previous years.
2. *Aggregation*, which computes total GDP for the output and expenditure approaches, expressed at the average prices of the previous year, according to the two identities:

$$\begin{aligned}\text{GDP at market prices} &= \textstyle\sum_i \text{Value added of branch } i + \text{TIS}, \\ & \quad i = \text{A–B, C–D–E, F, G–H–I, J–K, L–P} \\ \text{GDP at market prices} &= \text{FCE} + \text{GCF} + \text{EXP} - \text{IMP}\end{aligned}$$

3. *Chain linking*, aiming at expressing GDP at chain–linked volumes with reference year 2000.

Hence, the EuroMInd-$\mathcal{D}_o$ and EuroMInd-$\mathcal{D}_e$ density estimates arise as a linear opinion pool with known fixed aggregation weights of the conditional densities of the GDP components at the prices of the previous years (step 1 converted the density at chained volumes into densities at the prices of the previous years), that is then converted at chain–linked volumes.

The data

- A total of 36 time series is used to estimate EuroMInd-$\mathcal{D}$.
- The sample period starts in January 1995 and ends in June 2014 for most of the monthly indicators.
- The GDP quarterly components are available up to the first quarter of 2014; for the second quarter, only the flash estimate of total GDP is available.
- The series concerning the GDP components are released with 65 days of delay with respect to the end of each quarter.
- Among the monthly indicators, the financial aggregates are compiled by the ECB with a publication delay of around 30 days from the closing of the reference month. The data for the Industry sector and retail (such as the Industrial Production Index and Car registrations) are released about 45 days after the end of the reference month. Other indicators, such as those for construction (index of production and building permits), the series for the agricultural sector and the labour market (employment and hours worked) have a publication delay of about 70 days.

Time series	Frequency	Delay
A–B: Agriculture, hunting and fishing		
Production of milk	m	60
Bovine meat production in tons	m	60
Value added (chain–linked volumes) AB	q	65
C–D–E: Industry, incl. energy		
Index of Industrial Production Germany	m	45
Index of Industrial Production France	m	45
Index of Industrial Production Italy	m	45
Index of Industrial Production Spain	m	45
Volume of work done (hours worked)	m	60
Value added (chain–linked volumes) CDE	q	65
F: Construction		
Monthly production index	m	70
Building permits	m	70
Volume of work done (hours worked)	m	70
Value added (chain–linked volumes) F	q	65
G–H–I: Trade, transport and communication services		
Monthly production index for consumption goods	m	45
Index of deflated turnover	m	35
Car registrations	m	15
Value added (chain–linked volumes) GHI	q	65
J–K: Financial services and business activities		
Monetary aggregate M3 (deflated)	m	27
Loans of MFI (deflated)	m	27
Value added (chain–linked volumes) JK	q	65
L–P: Other services		
Debt securities issued by central government (deflated)	m	27
Value added (chain–linked volumes) LP	q	65

Time series	Frequency	Delay
TIS: Taxes less subsidies on products		
Index of Industrial Production for the euro area	m	45
Index of deflated turnover, retail sector	m	35
Taxes less subsidies (chain–linked volumes)	q	65
FCE: Final consumption expenditure		
Monthly production index for consumption goods	m	45
Index of deflated turnover, retail sector	m	35
Car registrations	m	15
Final consumption expenditure (chain–linked volumes)	q	65
GCF: Gross capital formation		
Monthly production index (CDE) euro area	m	45
Monthly production index for capital goods	m	45
Building permits	m	70
Gross capital formation (chain–linked volumes)	q	65
EXP: Exports of goods and services		
Monthly Export volume index	m	42
Monthly production index for intermediate goods	m	45
Exports of goods and services (chain–linked volumes)	q	65
IMP: Imports of goods and services		
Monthly Import volume index	m	42
Monthly production index for intermediate goods	m	45
Imports of goods and services (chain–linked volumes)	q	65

The EuroMInd-$\mathcal{D}$ historical density Estimates

- We illustrate the monthly GDP density estimates conditional on the complete dataset available at the time of writing (mid July 2014). Our density estimates are based on $M = 5,000$ draws from the conditional distribution of total GDP, obtained from pooling the draws of the components.
- The EuroMInd indicator by Frale et al. (2011) combines the two point estimates of monthly GDP obtained from the output and the expenditure approaches using weights that are proportional to the average estimation error variance. The weights used for EuroMind could be adopted to combine the density forecasts as well, so that EuroMInd-$\mathcal{D} = 0.75 \times$ EuroMInd-$\mathcal{D}_o$ + $0.25 \times$ EuroMInd-$\mathcal{D}_e$.

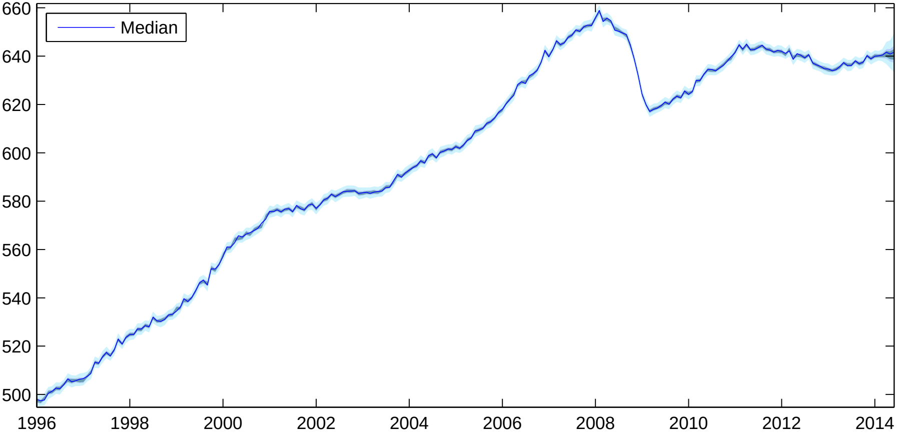


Figure : EuroMInd-$\mathcal{D}$. Shaded regions correspond to 50%, 70% and 95% probability bands, respectively.

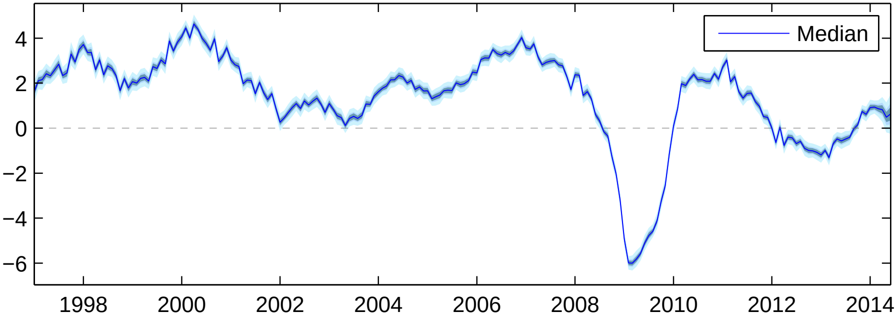
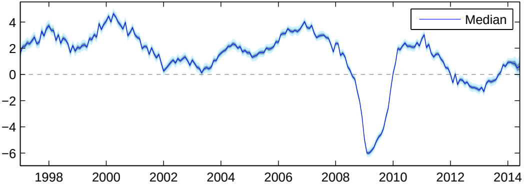
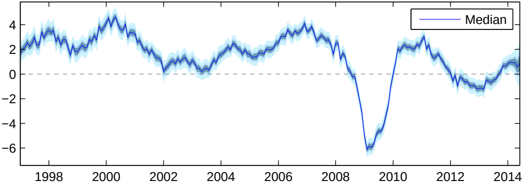


Figure : EuroMInd-$\mathcal{D}$ in growth rates. Shaded regions correspond to 50%, 70% and 95% probability bands, respectively



(a) Output approach



(b) Expenditure approach

Figure : EuroMInd-$\mathcal{D}$ in growth rates. Shaded regions correspond to 50%, 70% and 95% probability bands, respectively.

Evaluation and combination: a pseudo real–time experiment

We assess the accuracy of the density estimates by comparing them to the quarterly GDP observations by a pseudo real-time exercise.

- We divide the whole sample into the training sample from 1995.Q1 to 2000.Q4 and the evaluation sample from 2001.Q1 to 2014.Q1.
- We focus on three GDP density estimates for quarter τ, that we make available respectively 3, 2, and 1 months in advance with respect to the published GDP figure.
- The GDP figure becomes available 65 days after the closing of the reference quarter τ, i.e. at time (in months) $3\tau + 2.5$

- Our estimates are computed respectively after the closing of quarter $\tau - 1$ at times $3(\tau - 1) + 1.5, 3(\tau - 1) + 2.5$ and $3(\tau - 1) + 3.5$. In providing density forecasts for quarter τ, we thus distinguish between three information sets.
- The first density estimate is conditional on the information until $3(\tau - 1)$ and the monthly indicators available in $3(\tau - 1) + 1.5$.
- The second information set additionally includes the monthly indicators in $3(\tau - 1) + 2.5$ and GDP for quarter $\tau - 1$.
- The last density forecasts is conditioned on the third information up to and including period $3(\tau - 1) + 3.5$.
- Depending on a particular information set, forecast samples are first obtained for every month of the considered quarter τ and are subsequently aggregated to quarterly density forecasts.
- Density forecasts for every GDP component are based on $M = 1,000$ draws from the respective conditional distribution.

Figure : EuroMInd-$\mathcal{D}_o$ (output approach): information set 1

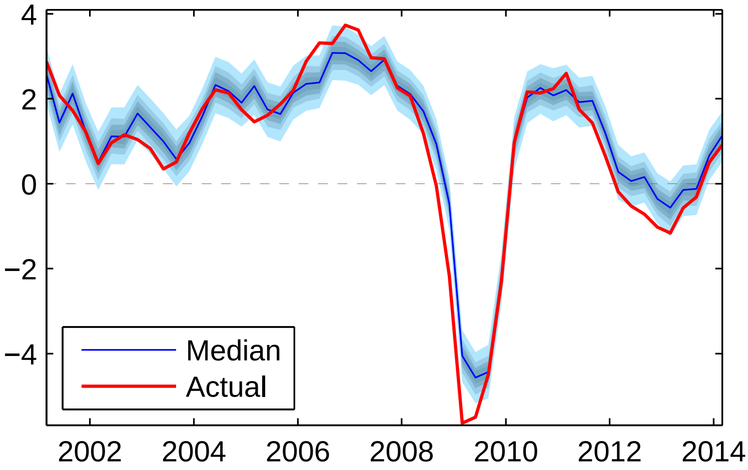


Figure : EuroMInd-$\mathcal{D}_o$ (output approach): information set 2

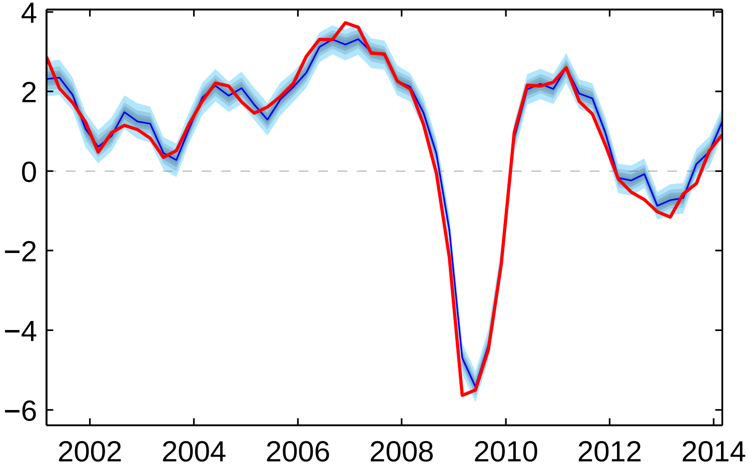


Figure : EuroMInd-$\mathcal{D}_o$ (output approach): information set 3

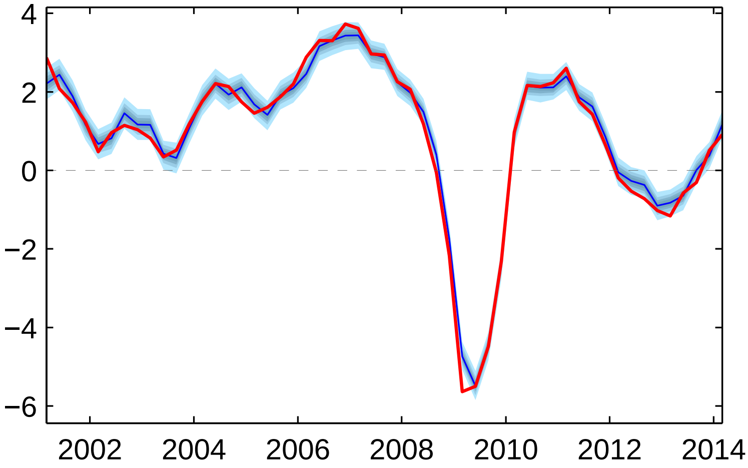


Figure : EuroMInd-$\mathcal{D}_e$ (expenditure approach): information set 1

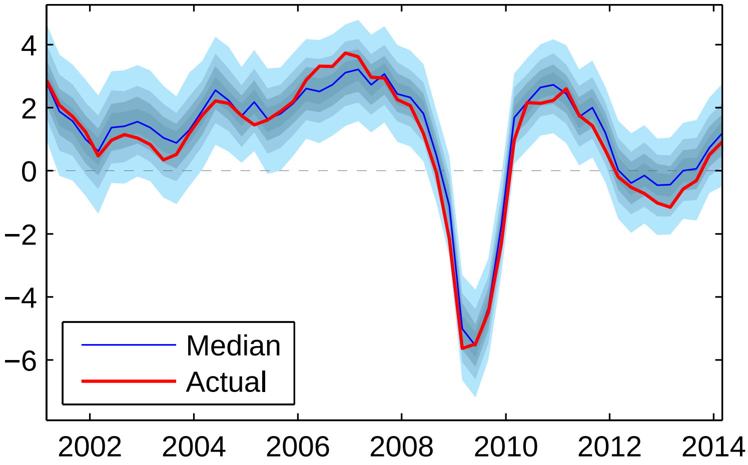


Figure : EuroMInd-$\mathcal{D}_e$ (expenditure approach): information set 2

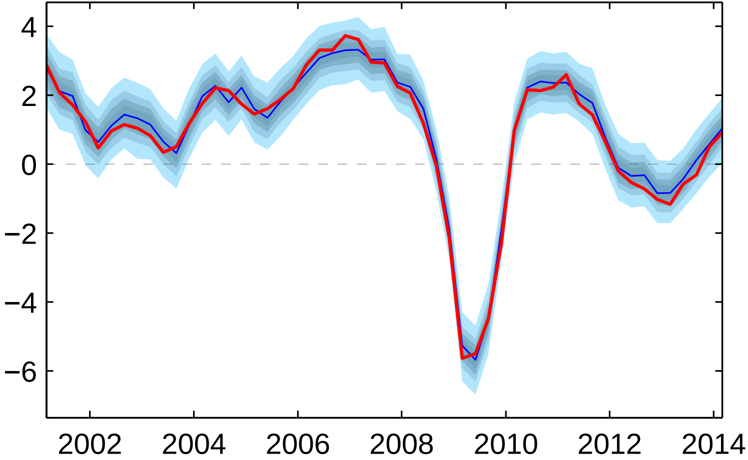
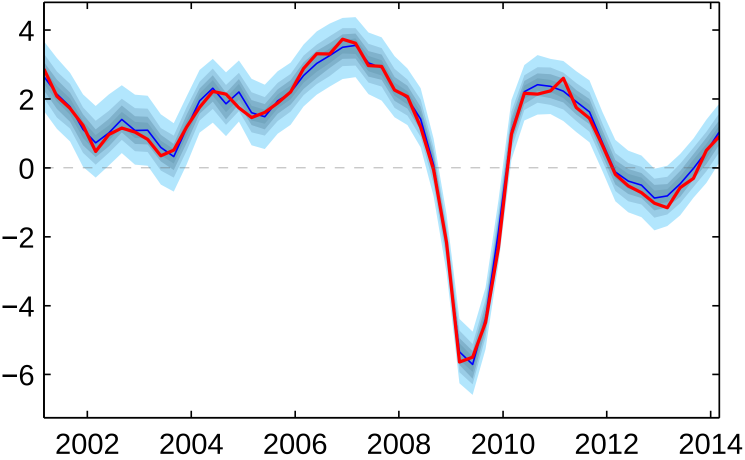


Figure : EuroMInd-$\mathcal{D}_e$ (expenditure approach): information set 3



Density combination

We combine the predictive densities arising from the output and the expenditure approaches using a linear opinion pool.

$$c_\tau(u) = w_{o,\tau}\, f_\tau(u|I_{o,\kappa}) + w_{e,\tau}\, f_\tau(u|I_{e,\kappa}),$$

$c_\tau(u)$: pooled forecast density at quarter τ,
$I_{i,\kappa}, i = o, e,$: information set available at time point κ for forecasting quarter τ.
We use recursive weights:

$$w_{i,\tau} = \frac{s_{i,\tau}}{\sum_{i\in\ o,e} s_{i,\tau}}, \quad i = o, e$$

- based on the log score, $s_{i,\tau} = \exp\left[\sum_{\underline{\tau}}^{\tau} \mathrm{LogS}_\tau(y_\tau|I_{i,\kappa})\right]$.
- based on the continuous ranked prob. score (CRPS), $s_{i,\tau} = \left[\sum_{\underline{\tau}}^{\tau} \mathrm{CRPS}_\tau(y_\tau|I_{i,\kappa})\right]$.
- Additionally, we consider two non–recursive weighing schemes ($w_{i,\tau} = w_i$): equal weights ($w_i = 1/2$) and weights based on the MSE ($s_i = 1/\mathrm{MSE}_i$) .

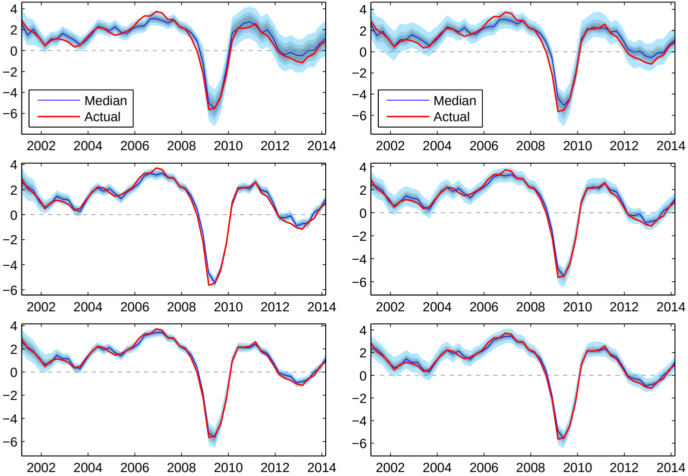


Figure : Combined real–time quarterly density forecasts of the Euro area annual GDP growth rates 2001.Q1 – 2014.Q1. Left panels: log score, information set 1, 2, 3. Right panels: CRPS: information set 1, 2, 3

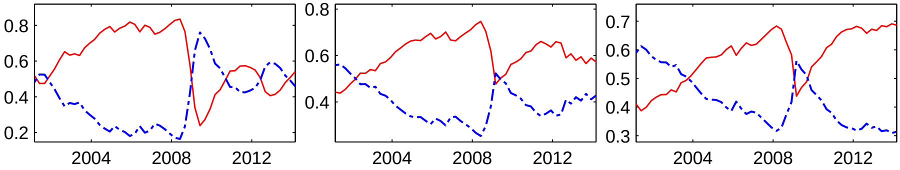


Figure : Recursive CRPS weights: information set 1, 2, 3, respectively (columns); solid line: output approach, dash–dot line: expenditure approach

Table : Evaluation real–time density forecasts of quarterly GDP and its components

Component	Information set	Tests on PITs KS	CvM	AD	χ^2	Q(4)	Tests on transformed PITs BS	Berkowitz
A–B	1	1.012	0.307	1.365	8.132	15.109*	0.107	15.163*
	2	1.147	0.395	1.902	10.849	3.934	1.197	1.330
	3	1.086	0.371	1.791	9.642	4.122	1.145	1.272
C–D–E	1	0.983	0.317	1.379	8.132	9.283	0.156	9.023*
	2	0.807	0.221	0.999	3.906	3.420	0.449	2.671
	3	1.026	0.420	2.032	19.000*	9.967*	0.819	6.986
F	1	1.257	0.363	1.873	14.170*	19.338*	0.243	15.099*
	2	1.054	0.248	1.495	7.528	16.805*	0.566	17.728*
	3	0.774	0.187	0.948	5.415	4.926	0.071	2.232
G–H–I	1	1.330	0.276	1.727	13.566	19.172*	0.920	29.494*
	2	0.716	0.163	0.810	7.226	6.898	0.176	4.341
	3	0.662	0.153	0.682	3.302	3.726	0.391	4.972
J–K	1	0.997	0.273	1.374	7.226	26.705*	0.018	25.838*
	2	0.657	0.167	0.716	6.321	5.209	0.008	1.620
	3	0.691	0.172	0.712	5.415	4.604	0.007	1.512
L–P	1	0.890	0.259	1.076	4.811	5.512	0.047	8.547*
	2	0.522	0.122	0.358	4.208	6.255	0.151	6.348
	3	0.618	0.131	0.453	2.396	6.491	0.264	6.859
TIS	1	1.326	0.596*	2.886*	15.981*	8.412	0.001	15.456*
	2	1.063	0.342	1.422	10.849	17.535*	0.046	16.886*
	3	0.873	0.265	1.104	7.226	19.538*	0.041	17.431*
GDP: output a.	1	1.411*	0.731*	6.009*	22.924*	43.768*	4.165	92.475*
	2	1.091	0.400	2.524*	9.943	12.763*	0.033	17.429*
	3	0.897	0.299	1.853	11.151	8.102	3.628	15.272*

Table : PIT tests for evaluation real–time density forecasts of quarterly GDP and its components

Component	Information set	Tests on PITs KS	CvM	AD	χ^2	Q(4)	Tests on transformed PITs BS	Berkowitz
FCE	1	2.202*	1.919*	9.430*	18.698*	44.753*	0.030	35.184*
	2	2.241*	1.421*	6.067*	18.698*	15.641*	0.035	11.502*
	3	2.181*	1.413*	6.067*	16.887*	13.051*	0.016	11.597*
GCF	1	1.160	0.396	1.986	10.849	8.545	0.032	12.599*
	2	1.226	0.384	1.380	8.736	15.093*	0.014	15.088*
	3	1.225	0.336	1.123	10.245*	14.786*	0.009	15.102*
IMP	1	1.177	0.453	2.063	4.811	17.669*	0.057	13.611*
	2	1.097	0.331	1.345	5.415	3.039	0.044	3.074
	3	1.030	0.253	0.966	7.528	4.131	0.137	3.485
EXP	1	0.553	0.106	0.266	2.698	32.707*	0.206	15.669*
	2	0.880	0.185	0.764	5.415	6.675	0.034	3.282
	3	0.719	0.161	0.598	11.453	10.139*	0.006	8.763
GDP: exp. approach	1	2.390*	1.602*	7.986*	50.094*	42.405*	0.020	82.544*
	2	1.943*	1.485*	7.641*	50.698*	16.428*	0.044	61.766*
	3	2.061*	1.668*	8.486*	61.566*	8.881	0.009	69.108*
GDP: combined (log score)	1	1.645*	0.650*	2.633*	18.094*	31.999*	0.098	27.385*
	2	0.971	0.407	2.458	9.943	16.145*	0.020	15.590*
	3	1.116	0.303	1.437	7.528	10.085*	0.014	10.457*
GDP: combined (CRPS)	1	1.410*	0.733*	5.466*	20.811*	46.246*	1.020	73.607*
	2	0.967	0.400	2.504*	8.736	15.148*	0.063	17.383*
	3	1.117	0.306	1.675	6.925	10.204*	0.594	9.059*

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2. Model specification and inference
   - The single index dynamic factor model for the complete data
   - State space form and temporal aggregation
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3. Density estimation, bootstrapping and conditional simulation
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Conclusions

- The paper has presented EuroMInd-$\mathcal{D}$, a density estimate of monthly GDP in chain-linked volumes based on the pooling of the density estimates for 11 GDP components.
- The density predictions and nowcasts appear to be well calibrated, when they are conditional on an information set that includes at least the release of the quarterly national accounts for the previous quarter.
- The sharpness of the probabilistic estimates renders EuroMInd-$\mathcal{D}$ a useful tool for the assessment of macroeconomic conditions in the euro area.
- While the current paper concentrated on the evaluation of its predictive accuracy, we think that EuroMInd-$\mathcal{D}$ can serve well the purpose of characterising the business cycle via the probabilistic detection of turning points and the decomposition of output into trends and cycles.

- The density estimates reflect parameter and filtering uncertainty. They do not incorporate model uncertainty, as the specification of the model is taken as given and capitalises upon the indicator selection and specification search (number of factors and their lags, autoregressive orders) performed in Frale et al. (2011).
- Further research should be directed towards the incorporation of business survey variables, often referred to as soft indicators, in the information set. Our preliminary experimentation, based on the two factors specification considered in Frale et al. (2011), led to reject their inclusion on the grounds of the lack of sharpness and overdispersion of the density estimates, due to the contribution of parameter uncertainty.

Thank you for your attention!