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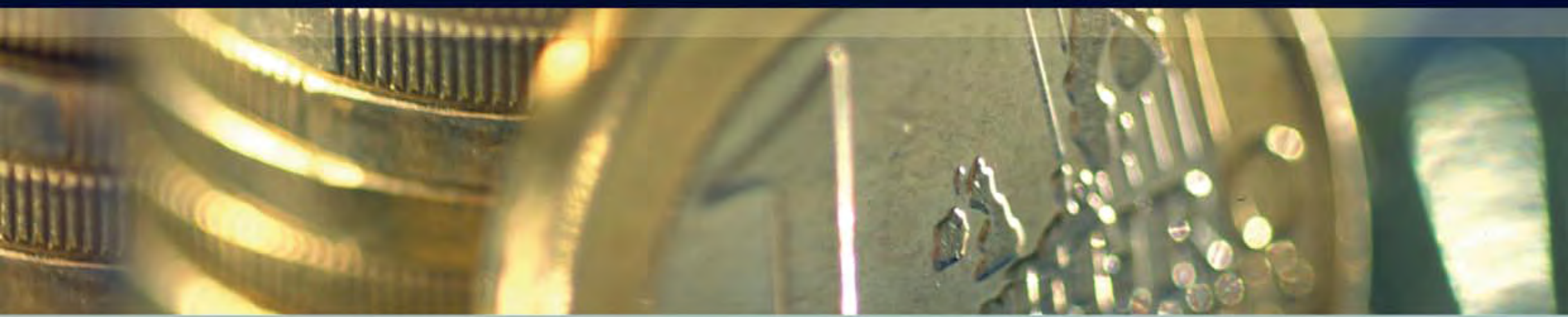

Does capacity utilisation help estimating the TFP cycle?

Christophe Planas, Werner Roeger and Alessandro Rossi

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Does capacity utilization help estimating the TFP cycle? *

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Abstract

In the production function approach, accurate output gap assessment requires a careful evaluation of the TFP cycle. In this paper we propose a bivariate model that links TFP to capacity utilization and we show that this model improves the TFP trend-cycle decomposition upon univariate and Hodrick-Prescott filtering. In particular, we show that estimates of the TFP cycle that load information about capacity utilization are less revised than univariate and HP estimates, both with 2009 and real-time TFP data vintages. We obtain this evidence for twelve pre-enlargement EU countries.

KEYWORDS: Cobb-Douglas production function, Hodrick-Prescott filter, output gap, revisions.

*The views expressed in this paper are those of the authors and should not be attributed to the European Commission.

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Contents

1 Introduction

Output gap is the key variable of the cyclical adjustment of EU Member States budget balance (see European Commission, 2005). Following a 2002 ECOFIN decision, the European Commission (EC) measures output gap through a Cobb-Douglas production function (see Denis et al., 2002) that relates the gap to the cyclical components of labour and of total factor productivity (TFP). While the labour cycle is estimated using unemployment and wage inflation in a Phillips curve relationship (see Denis et al., 2006), so far the EC procedure extracts the TFP cycle with the Hodrick-Prescott filter (HP; Hodrick and Prescott, 1997).

Output gap measures have been criticized for their real time performance; for Europe, see for example Runstler (2002), Planas and Rossi (2004), and Marcellino and Musso (2008) who exploit a comprehensive real time data set for comparing several methodologies as well as the various approaches adopted by international organisations. Although overlooked in these studies, a most striking feature is that all methods failed to identify a positive output gap in early 2000, towards the end of the IT boom. Output gaps for this period have been substantially revised upward when information about the 2002 economic downturn became available. Extending series with forecasts before HP-detrending could not alleviate the problem, mainly because of the forecasts imprecision close to turning points. One possible strategy is to use economic indicators which go along with the business cycle but are not revised. Capacity utilisation (CU) measures have been previously suggested in the literature (see e.g. Ruenstler, 2002, Proietti, Musso and Wastermann, 2007, and European Commission, 2008, pp.94-105), but so far no model-based justification have been given. Here we introduce CU within the production function framework by explicitly allowing for variations in the use of the capital stock. A strong correlation between CU and the cyclical component of TFP naturally arises. As an alternative to HP detrending, we thus propose a model that links the cyclical component of TFP to CU. We show that CU series do bring a gain in precision to the TFP trend-cycle decomposition, and that they help overcoming the 2000 output gap underestimation problem.

In Section 2 we discuss the link between TFP and CU in the Cobb-Douglas production function framework. The bivariate system that we obtain has similarities with Kuttner's (1994) model for measuring potential output. For model estimation we resort to Bayesian analysis. The Bayesian framework is convenient for imposing a strong prior about the inertia of the productivity potential growth. It has also the advantage of eliminating the pile-up effect, i.e. the occurence of 0-coefficient estimates for the unobserved shocks variances (see Stock and Watson, 1988) that yields deterministic components. In real-time, obtaining a trend that is sometimes deterministic and sometimes stochastic is unacceptable because the decomposition results excessively instable over time.

To verify the relevance of CU to TFP cycle estimation, we compare the bivariate estimates to those returned by a univariate decomposition and by the HP filter. The comparison is made in terms of revisions in TFP cycle estimates recorded over the years 2000-2009 that cover two important boom bust episodes for which large revisions are expected. If CU contains valuable information for TFP decomposition, its use should limit the revisions in preliminary estimates. Details about the empirical methodology are given in Section 3.

Section 4 reports results for each Member States. In order to give some actual relevance to our investigation, we consider both 2009 data and real-time TFP vintages. For CU, two types of series are used that mainly differ about the coverage of the service sector. The exercise is carried out for twelve pre-enlargement countries, namely BE, DK, DE, EL, ES, FR, IE, IT, LU, NL, PT, and UK. The other three pre-enlargement countries AT, FI, and SW are left out for missing CU data. Overall we find that CU has informative content for TFP trend-cycle decomposition in the twelve countries considered, and for both 2009 and real-time TFP vintages. The results are summarized in Section 5.

2 A model for capacity utilization and TFP

According to the Cobb-Douglas production function, output Y is obtained from the combination of capital stock K and labour L, both employed at the available total factor productivity TFP:

$$Y = TFP\ K^{1-\alpha}\ L^{\alpha}$$

The constant α represents the labour share of income. Because capital K cumulates past investment at some depreciation rate, output gap only depends on labour gap and on the TFP cycle, say C. These short-term fluctuations C are related to variations in the capacity utilization of capital and labour inputs that we denote CU_K and CU_L, respectively. TFP also contains persistent efficiency improvements P, so $TFP = P \times C$.

Writing the production function as:

$$Y = P\ (CU_K \times K)^{1-\alpha}\ (CU_L \times L)^{\alpha}$$

suggests that the link between TFP gap and capacity utilization is such that:

$$C = CU_K^{1-\alpha}\ CU_L^{\alpha}$$

No capacity utilization measure however discriminates between the different factors. Only aggregate capacity utilization series are available. They are usually built from surveys, so by construction we expect CU and CU_K to be significantly correlated. Given that average hours worked per employee already contains some cyclical movements, the link with labour utilization should be somewhat looser. But if there are fluctuations in the degree of labour hoarding that are not captured by hours, a correlation between labour and capital utilization should nevertheless be present. We thus assume:

$$cu_L = \gamma cu_K + \epsilon \qquad 0 < \gamma < 1$$

where small letters denote logarithms and ϵ is a random shock which can be itself autocorrelated in case of movements in cu_L that are not exactly synchronised with cu_K. Hence TFP is related to capacity utilization through:

$$\text{tfp} = p + (1 - \alpha + \alpha\gamma)cu + \alpha\epsilon$$

This link can be exploited for estimating the TFP trend in a bivariate model such as:

$$\begin{aligned} \text{tfp}_t &= p_t + c_t \\ cu_t &= \mu_{cu} + \beta c_t + e_{cut} \qquad \beta = (1 - \alpha + \alpha\gamma)^{-1} \end{aligned} \tag{2.1}$$

where the sub-index $t = 1, \cdots, T$ introduces time. The cyclical component c_t is a stationary factor that is common to both TFP and CU series. Given standard values for the output elasticity of labour α and plausible values for γ, the loading coefficient β should be greater than one. The dynamic behaviour of the unobserved components p_t and c_t remains to specify. We consider:

$$\begin{aligned} \Delta p_t &= \mu_{t-1} \\ \mu_t &= w(1-\rho) + \rho\ \mu_{t-1} + a_{\mu t} && V(a_{\mu t}) = V_\mu \\ c_t &= 2A\cos(2\pi/\tau)\ c_{t-1} - A^2\ c_{t-2} + a_{ct} && V(a_{ct}) = V_c \end{aligned} \tag{2.2}$$

where $a_{\mu t}$ and a_{ct} are white noises. Equation (2.2) describes the TFP long-term path through a damped trend model with a coefficient w that catches the series average growth rate. The cyclical movements are reproduced using an AR(2) model with complex roots that are parameterized in terms of amplitude A and periodicity τ. For the stochastic term e_{cut}, we will consider either:

$$e_{cut} = a_{cut} \qquad \text{or} \qquad e_{cut} = \delta \; e_{cut-1} + a_{cut} \qquad V(a_{cut}) = V_{CU} \tag{2.3}$$

where a_{cut} is a white noise. The insertion of the autoregressive lag will depend on the statistical properties of the CU series. The bivariate system (2.1)-(2.3) is similar to the Phillips-curve augmented unobserved component model proposed by Kuttner (1994) for estimating potential output and output gap in the US.

3 Methodology for empirical validation

Model (2.1)-(2.3) describes a possible link between the cyclical movements of TFP and CU series. If such a link exists, making use of CU information should yield a gain in accuracy in TFP cycle estimates. We check this conjecture for twelve pre-enlargement EU Member States. Three estimation methods are considered: HP filtering, the univariate trend plus cycle model (2.2) and the bivariate system (2.1)-(2.3). The estimators are compared in terms of revisions recorded in TFP cycle latest estimates, both with 2009 data sets and with real-time data vintages.

The data are annual series for BE, DK, DE, EL, ES, FR, IE, IT, LU, NL, PT, and UK, all taken from AMECO database. The other three pre-enlargement countries AT, FI, and SW are left out for data unavailability. The TFP time span covers 1965-2009 with ten vintages available over the period 2000-2009. To capture cyclical fluctuations in capacity utilization, we use two different indicators: the Capacity Utilization Indicator (CUI) which is available for manufacturing only, and the EC Business Survey indicator (BS) that is for both manufacturing and services. CUI has the advantage that it is available since 1985 for most countries and since 1987 for few ones. Also BS is available for all countries but surveys for services only start in the years 1995-1998, at the exception of FR for which the starting date is 1988. The missing years before 1995 have been completed by merging with CUI after proper re-scaling, so BS and CUI are identical until the actual start of BS for services. A third CU measure called the Purchasing Managers Indicator (PMI) exists for some countries only. Because exhaustive country coverage is essential for any practical application, PMI have been excluded from this exercise. For information, Table A2 in Appendix gives the cross-correlations between CUI, BS, and PMI when available.

The exercise is performed using Bayesian techniques. Maximum likelihood estimation is of course feasible and less computationally intensive, but in recursive analysis occasional occurrences of 0-coefficient estimate for the unobserved component shock variances cause some instability in the trend-cycle decomposition. In the Bayesian framework, this pattern can be excluded by specifying an informative prior. Another advantage of the Bayesian approach is that the information brought by macroeconomic knowledge can be inserted into the analysis. In our context, we have a strong prior about the inertia of the potential growth of productivity. Our model implies a β-coefficient in (2.1) that is greater than one. And we also have some knowledge about the periodicity and amplitude of the business cycle.

All computations are made using Program Bayesian GAP downloadable at *eemc.jrc.ec .europa.eu*. Details about the procedures implemented can be read in Planas, Rossi and Fiorentini (2008). For the parameters in (2.1)-(2.3), we consider the following priors:

- Cycle amplitude A Beta-distributed with mean 0.4 and standard deviation 0.2;
- Cycle periodicity τ Beta-distributed with mean of 8 and standard deviation 3.5;
- Average growth w normally distributed with mean 0.015 and standard deviation 0.005; for ES, mean at 0.003 and standard deviation 0.002. The average growth w is always constrained to be positive.
- ρ normally distributed with mean 0.8 and standard deviation 0.3 restricted to the stationary $(0, 1)$ region;
- β given V_{CU} normally distributed with mean of 1.4 and standard deviation $0.3 \times V_{CU}$;
- for BE, FR, NL and UK, δ given V_{CU} normally distributed with mean 0.5 and standard deviation $0.5V_{CU}$ with a restriction to the stationary region $(0, 1)$;
- Inverted-gamma (IG) prior distributions are used for all variance parameters. As a tuning by country has been necessary, we report in Table A1 of the Appendix the hyper-parameters of the prior distribution of V_c, V_μ, and V_{CU} for each country.

The estimators are compared in terms of revisions in TFP cycle estimates. Let x^t denote the set of observations available at time t, i.e. $x^t = (x_1, \cdots, x_t)$. For univariate analysis, x_t represents TFP_t while in bivariate x_t contains both TFP_t and CU_t. The cycle estimates for period t based on observations until period $t+k$ is obtained as the expectation of c_t given observations x^{t+k}: i.e. $\hat{c}_{t|t+k} = E(c_t|x^{t+k})$. Hence the cycle estimates for a given point in time depend on the information available. A revision can be defined as the correction of preliminary estimates due to incoming observations. For instance, the difference $\hat{c}_{t|t+1}$ minus $\hat{c}_{t|t}$ measures the revision in the concurrent estimate $\hat{c}_{t|t}$ due to the availability of one further observation. For each country, we show the path taken by cycle estimates for the years 2000 to 2008 when observations are ending in 2000, 2001, $\cdots$, until 2009.

Revisions in real-time TFP gap estimates come from two different sources: forecast errors and parameter update - the signal extraction error or statistical uncertainty, and the use of real-time data sets that are corrected every year, i.e. data vintages. In order to shed light on the relative contribution of these two sources of revisions, we report results obtained first using the 2009 data vintage and then using real-time data sets. We summarize these revisions by computing their variances. For instance, averaging the squared values of the revisions obtained with one more observation from $t = 2001$ to $t = 2009$ approximates the variance of the first revision in concurrent estimates, i.e:

$$V(\hat{c}_{t|t+1} - \hat{c}_{t|t}) \simeq (1/9) \sum_{t=2000}^{2008} (\hat{c}_{t|t+1} - \hat{c}_{t|t})^2$$

The same computations can be done for evaluating empirically the variance of the second revision in concurrent estimates, i.e. $V(\hat{c}_{t|t+2} - \hat{c}_{t|t+1})$. As revisions are independent, we can cumulate them to obtain the variance of the revisions with k more observations, $V(\hat{c}_{t|t+k} - \hat{c}_{t|t})$. We obtain the variance of revisions when one more observation is available, when two more observations are available, and so on. For each country we report $\sqrt{V(\hat{c}_{t|t+k} - \hat{c}_{t|t})}$ for $k = 1$ to 4. This 1 to 4-period-ahead revision variance can be used to build a confidence interval around concurrent estimates for the estimates that will be obtained with k-more observations like for instance $c_{t|t} + / - 2\sqrt{Var(revision)}$. More details can be found in Planas and Rossi (2004). The theoretical analysis of revisions has been developed by Pierce (1980).

The model parameters are re-estimated every time the data set is updated. Notice that when the data previously observed are not updated, revisions on the trend and on the cycle sum to zero so they are equivalent in absolute value. This equivalence however breaks down when past data are revised. Because most TFP vintages show level shifts, real-time trend estimates do not converge over the different vintages. Here we focus on the behaviour of revisions in the cycle estimates obtained with 2009 series and with real-time vintages.

For each country, we report:

1. Fig.1: the TFP 2000-2009 vintages plus CU series;
2. Fig.2: the cycle and the trend growth estimated with the 2009 vintage;
3. Fig.3: for the 2009 data vintage, the prior and posterior distributions for a selection of parameters.
4. Table 1: the bivariate model fitted using the 2009 TFP vintage and the two CU series;
5. Fig.4: paths followed by the 2000-2008 cycle estimates over the years 2000-2009 with vintage 2009;
6. Fig.5: revisions standard deviation with up to 4 years of additional data, vintage 2009;
7. Fig.6: paths followed by the 2000-2008 cycle estimates over the years 2000-2009 with real-time vintages;
8. Fig.7: revisions standard deviation with up to 4 years of additional data, real-time vintages.

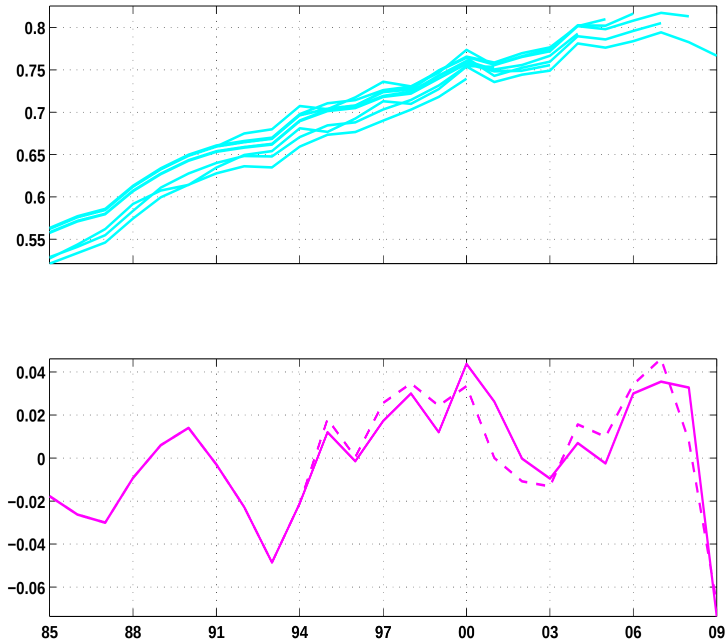
For all figures, HP is in **black**, the univariate model is in **red**, the bivariate one with CUI series is in **blue**, and the bivariate one with BS series is in **green**. A detailed explanation of the figures is given for the BE case in pages 10-15.

For HP, the filter is run on series extended with four forecasts. The forecasting models are I(1) for DK, IE, PT, BE, EL, IT, LU, UK; ARIMA(1,1,0) for DE; and ARIMA(0,1,1) for ES, FR, and NL. A constant drift is always included. The inverse signal to noise ratio is set equal to 100. Holding this ratio constant for all vintages gives a slight advantage to HP.

4 Country results

4.1 Belgium

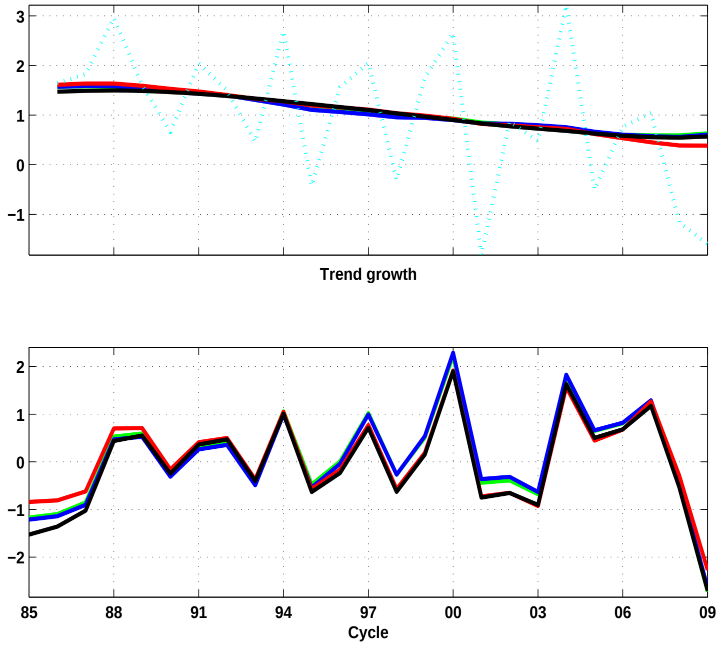
Figure 1
TFP vintages plus CU series



The upper plot shows the different vintages of the TFP series: the 2000 vintage ends in 2000, the 2001 one in 2001 and so on. Time labels are visible on the lower plot. Two capacity utilization series are displayed: the continuous line represents the capacity utilization indicator CUI and the dotted line is the EC business survey indicator BS. Both series are displayed after a mean removal. The CUI and BS series are used alternatively.

Figure 2 below shows the posterior mean of the TFP trend growth for the years 1985-2009 together with the TFP series growth in dots and the series cycle. The HP estimate is in **black**, the univariate one is in **red**, the bivariate one with CUI series is in **blue**, and the bivariate estimate with BS series is in **green**.

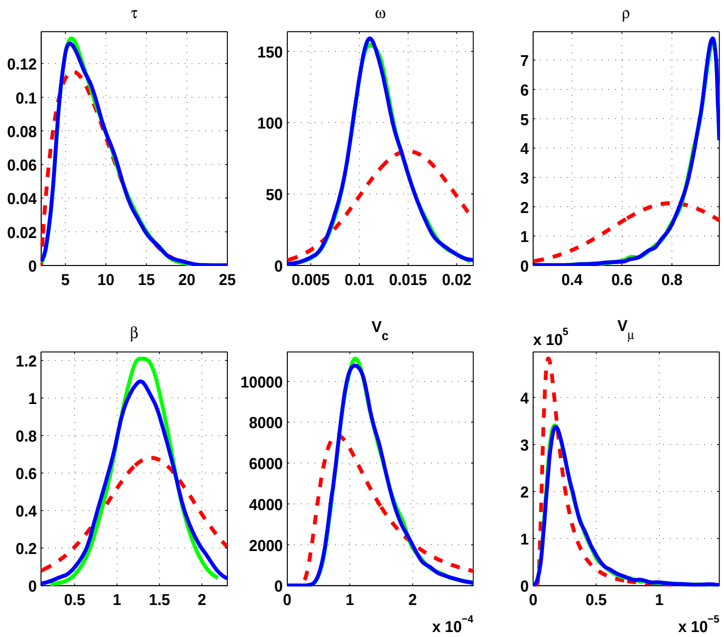
Figure 2 BE Vintage 2009
Trend growth and cycle ($\times 100$)



As can be seen, the trend growth is quite smooth. The cycle estimates obtained with the three estimation methods differ mostly in the second sample half: loading CU information increases the TFP gap for the years 1997-2009.

For the 2009 vintage, Figure 3 below shows the prior distribution (−−) together with the posterior distributions obtained with CUI series (in **blue**) and with the BS series (in **green**) for a selection of parameters.

Figure 3 BE Vintage 2009
Prior and posterior distributions



As can be seen, the data contain information about all parameters but V_μ. In particular, the β coefficient that relates the TFP cycle to capacity utilization is sharply estimated, with mode value above one as expected. The prior on V_μ has strongly imposed the view that the TFP growth should evolve quite slowly, so the posterior could not depart from this hypothesis.

Table 1 below summarizes the parameter posterior distributions obtained with the 2009 vintage in terms of modes and standard deviations. As can be seen, the posterior modes are stable with respect to the use of CUI or BS series.

Table 1 BE Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \quad (1 - 2Acos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}/(1-\delta L)$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	δ	β	V_{CU}
CUI										
	0.011	0.96	1.8×10^{-6}	0.33	5.56	10.8×10^{-5}	-0.001	0.4	1.28	40.5×10^{-5}
	(0.003)	(0.09)		(0.13)	(3.3)		(0.01)	(0.23)	(0.37)	
BS										
	0.011	0.97	1.7×10^{-6}	0.34	5.75	10.8×10^{-5}	-0.001	0.55	1.28	32.7×10^{-5}
	(0.003)	(0.09)		(0.13)	(3.26)		(0.01)	(0.2)	(0.33)	

Figures 4 and 6 in the next pages show the behavior of the cycle estimate for the periods 2000, 2002, ..., 2008 obtained assuming that the data are ending in 2000, ..., until 2009. Vintage 2009 means that past TFP data are assumed to not be updated. Figure 6 is like Figure 4 but using real-time data. The x-axis displayed in the graph bottom line refers to the last point of the dataset used. The first estimates displayed is always the concurrent one, i.e. $\hat{c}_{t|t}$. For instance, in Figure 4 the first small plot in the upper right corner shows the path taken by the estimate of the cycle for the year 2000 using datasets ending successively in 2000, in 2001, and so on until 2009: i.e. $\hat{c}_{2000|2000+k}$ for $k = 0, 1, \cdots, 8$.

Figure 4 BE Vintage 2009
Paths followed by the 2000-2008 cycle estimates

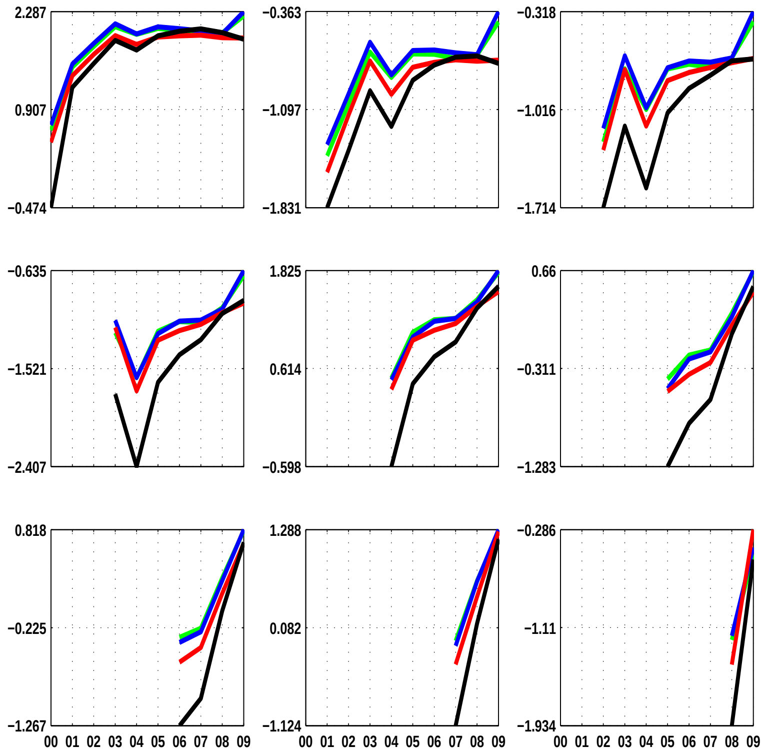
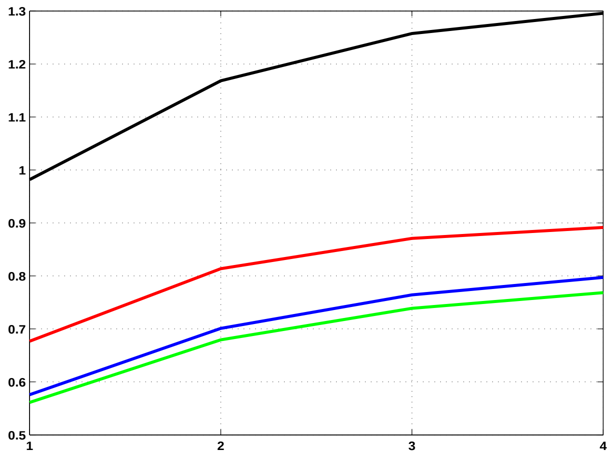


Figure 5 BE Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 BE Real-time vintages
Paths followed by the 2000-2008 cycle estimates

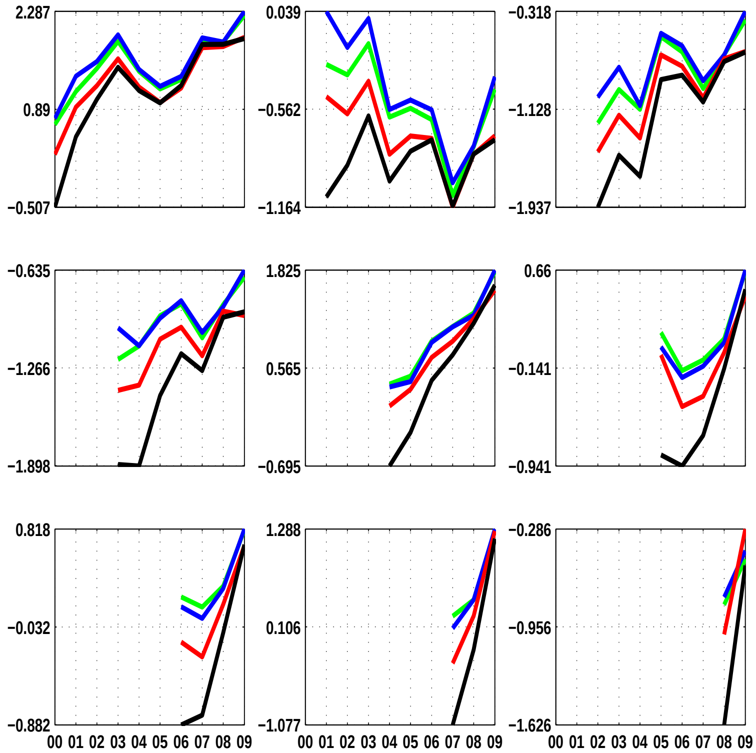
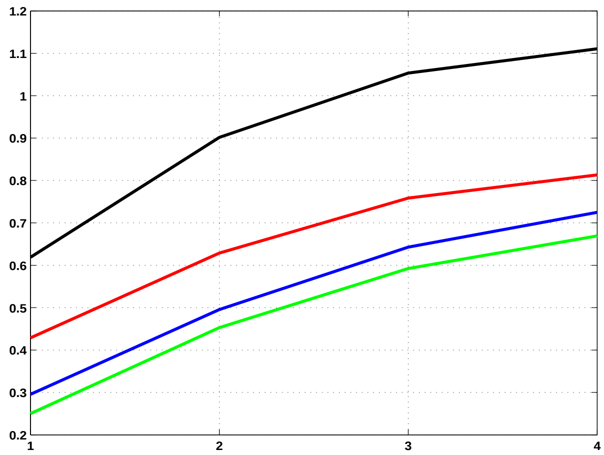


Figure 7 BE Real-time vintages
Revisions standard deviation $(\times 100)$



Figures 5 and 7 show the average squared first-four revisions due to the the incoming of new observations from 2001 to 2009. These averages estimate the variance of the revisions with k more observations, $V(\hat{c}_{t|t+k} - \hat{c}_{t|t})$ - see Section 3. The lower the revision variance, the more reliable are the TFP cycle estimates. As can be seen, the estimates that load CU data are performing better both in real-time and with the 2009 vintage.

Summary for BE:

- **TFP data** The TFP series level shifts downward after 2000 for all post-2000 vintages.
  CU data The two series are quite similar.
  Link TFP-CU The β-coefficient is significantly different from 0 and above than 1 as expected.
  Revisions The bivariate model yields less revisions than univariate and HP decompositions both with 2009 data and real-time vintages, with both CUI and BS series.
  CUI vs. BS The BS series yields slightly less revisions than CUI.

As Figure 4 and 6 show, the HP filter fails to capture the cyclical nature of the strong TFP growth at the end of the 90s and indicates a negative TFP gap in 2000. The bivariate estimates give a positive TFP gap because of cyclical indicators pointing to above average capacity utilisation in 2000. The revisions are not confined to the year 2000 but the HP filter is revised heavily in the direction of the bivariate estimates in subsequent years. A similar phenomenom seems to be taking place for the years 2007-2008 where the HP preliminary estimates are heavily revised upward.

For the other countries, Figures 1-7 and Table 1 are reported together with a short comment and the summary.

4.2 Germany

Figure 1
TFP vintages plus CU series

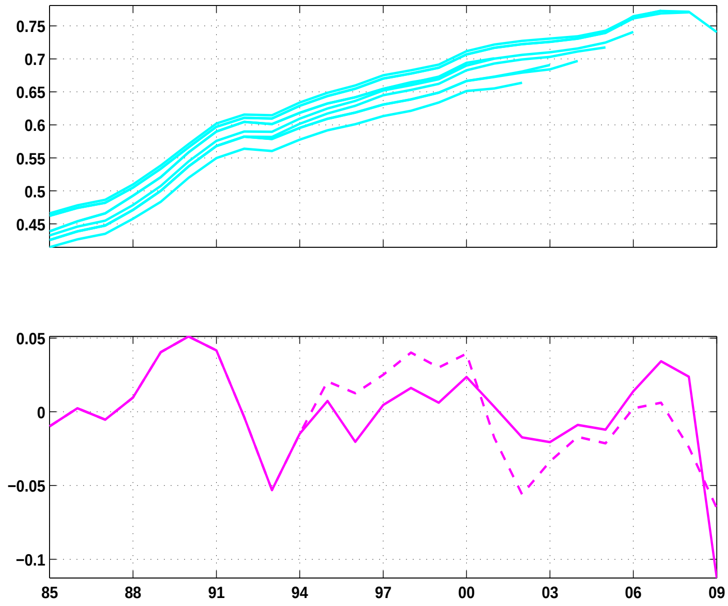


Figure 2 DE Vintage 2009 $(\times 100)$
Trend growth and cycle

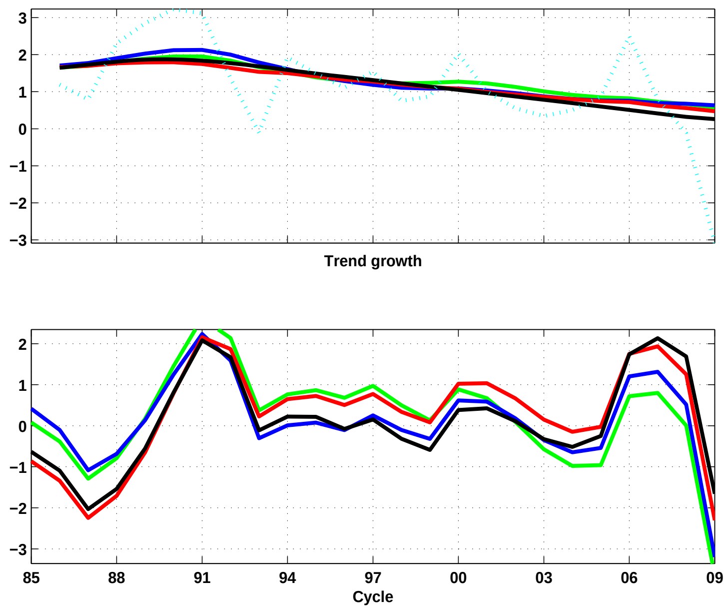


Figure 3 DE Vintage 2009
Prior and posterior distributions

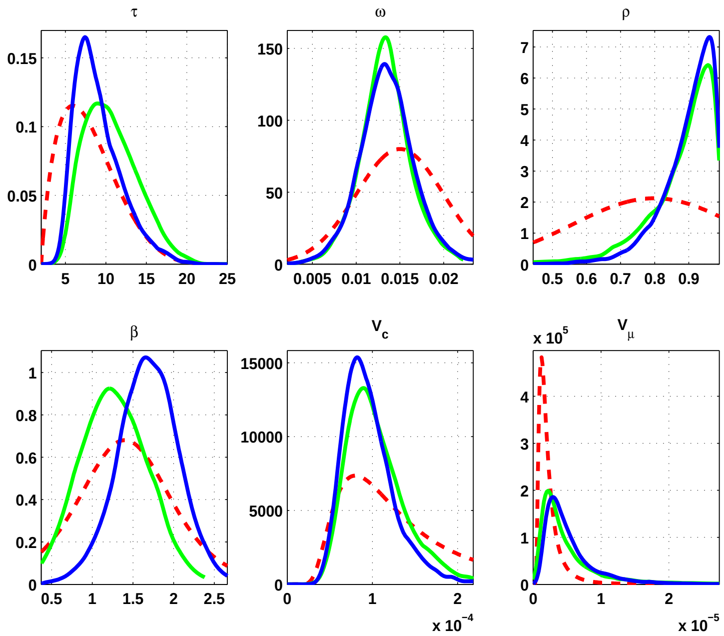


Table 1 DE Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.013	0.96	2.9×10^{-6}	0.62	7.41	8.2×10^{-5}	-0.001	1.66	63.1×10^{-5}
	(0.003)	(0.08)		(0.14)	(2.87)		(0.01)	(0.38)	
BS									
	0.013	0.96	2.3×10^{-6}	0.65	8.97	8.9×10^{-5}	-0.003	1.21	74.9×10^{-5}
	(0.003)	(0.1)		(0.14)	(3.25)		(0.01)	(0.42)	

Figure 4 DE Vintage 2009
Paths followed by the 2000-2008 cycle estimates

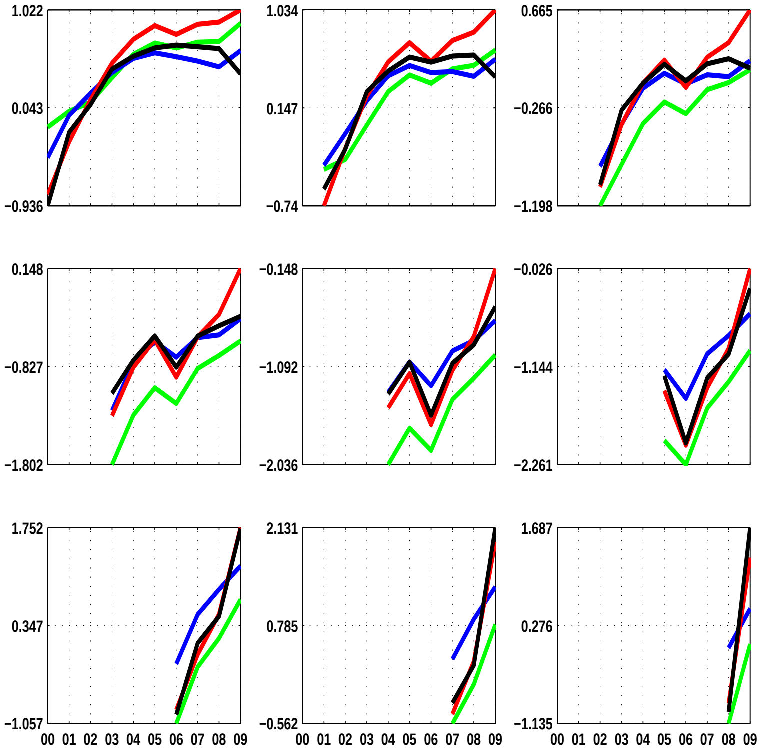


Figure 5 DE Vintage 2009
Revisions standard deviation $(\times 100)$

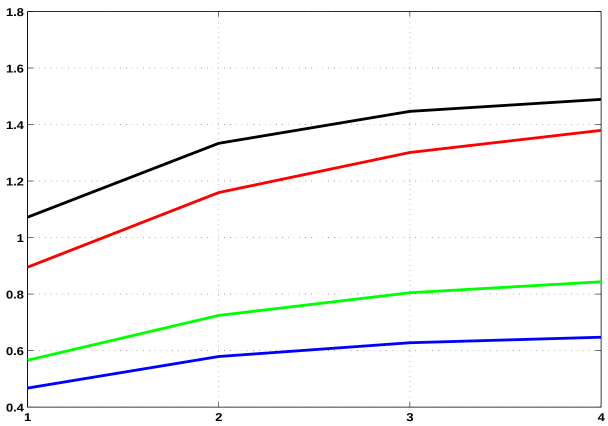


Figure 6 DE Real-time vintages
Paths followed by the 2000-2008 cycle estimates

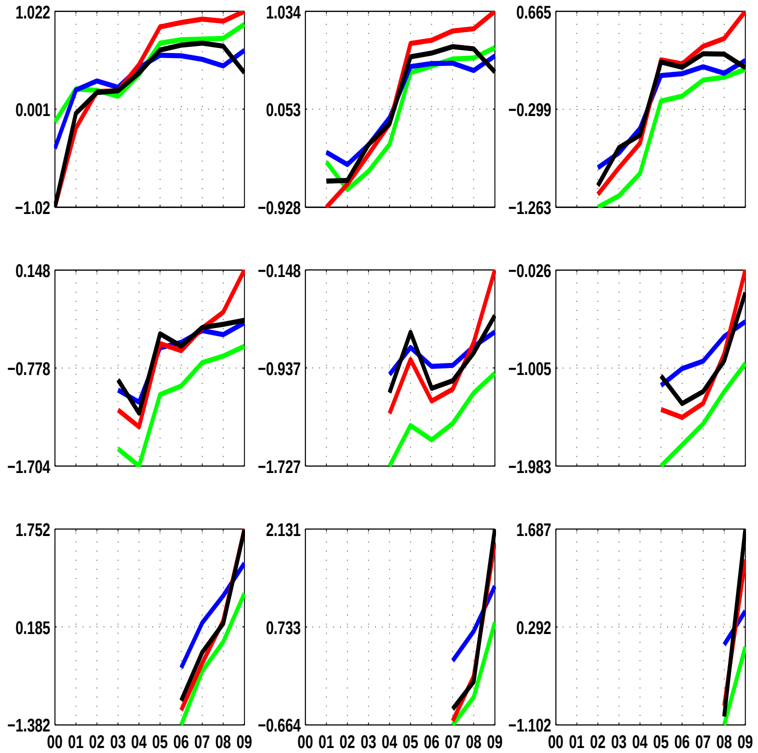
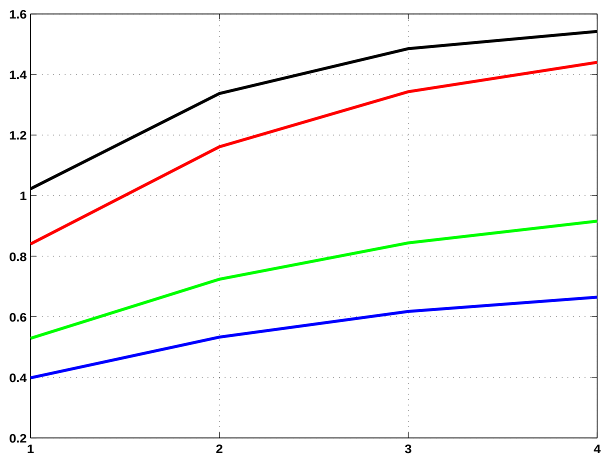


Figure 7 DE Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for DE:

- **TFP data** The TFP vintages are systematically shifted upward.

  CU data The CUI and BS series are similar. The largest difference occurs in 2008, CUI standing at one-percentage point higher than BS. Both series have a dip in 2009.

  Link TFP-CU The β-coefficient is significantly different from 0, with posterior mode above one as expected. It takes larger values with the CUI series.

  Revisions The bivariate model yields less revisions than univariate and HP decompositions both with 2009 data and real-time vintages, and with both CUI and BS series.

  CUI vs. BS The posterior distributions of model parameters seem robust to the use of CUI vs. BS. Less TFP gap revisions are obtained with the CUI series.

The cyclical information for the year 2000, indicating above average capacity utilisation, avoids a strong negative TFP gap for 2000 in the bivariate case. In contrast, the HP filter fails to capture the cyclical nature of high TFP growth resulting in a strongly negative TFP gap. In 2001-2006, the bivariate estimates did not outperform HP in terms of revisions. In 2007-2008, HP goes through large positive revisions with a sign switch. The bivariate estimates that use CUI are the most stable for these years.

4.3 Denmark

Figure 1
TFP vintages plus CU series

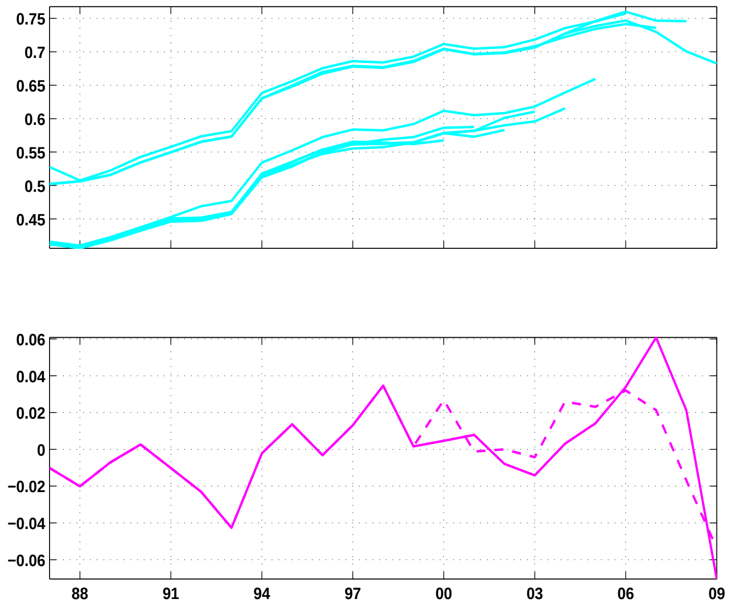


Figure 2 DK Vintage 2009
Trend growth and cycle $(\times 100)$

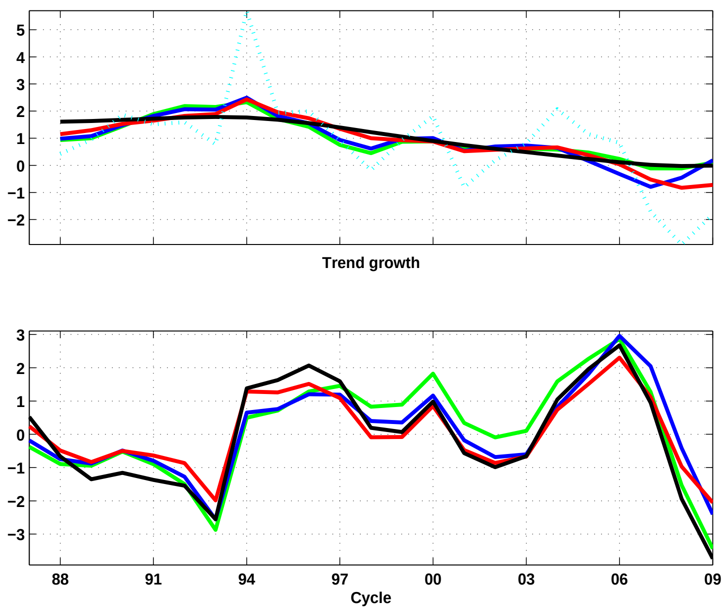


Figure 3 DK Vintage 2009
Prior and posterior distributions, 2009 vintage

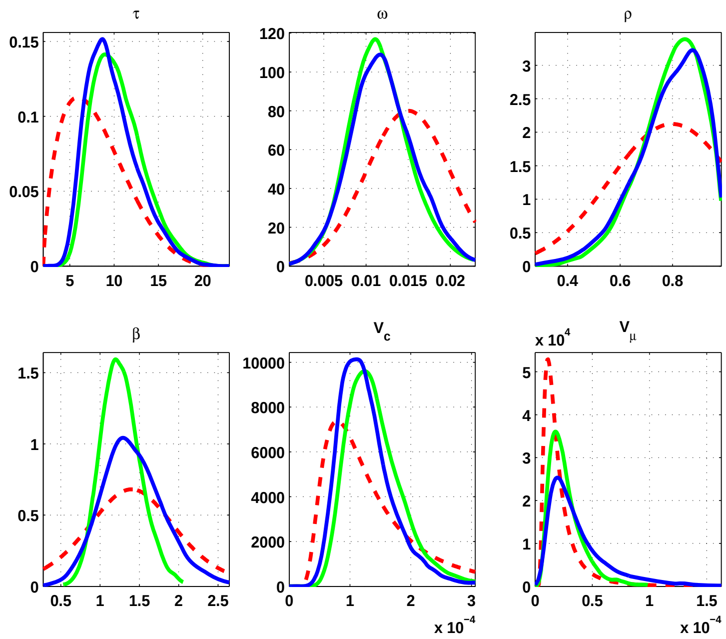


Table 1 DK Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \quad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}/(1-\delta L)$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	δ	β	V_{CU}
CUI										
	0.012	0.88	19.3×10^{-6}	0.53	8.71	11.1×10^{-5}	0	0	1.29	23.6×10^{-5}
	(0.004)	(0.13)		(0.13)	(2.84)		(0.01)	(0)	(0.4)	
BS										
	0.011	0.85	18×10^{-6}	0.56	8.98	12.4×10^{-5}	-0.001	0	1.19	9.5×10^{-5}
	(0.004)	(0.12)		(0.12)	(2.81)		(0.01)	(0)	(0.26)	

Figure 4 DK Vintage 2009
Paths followed by the 2000-2008 cycle estimates

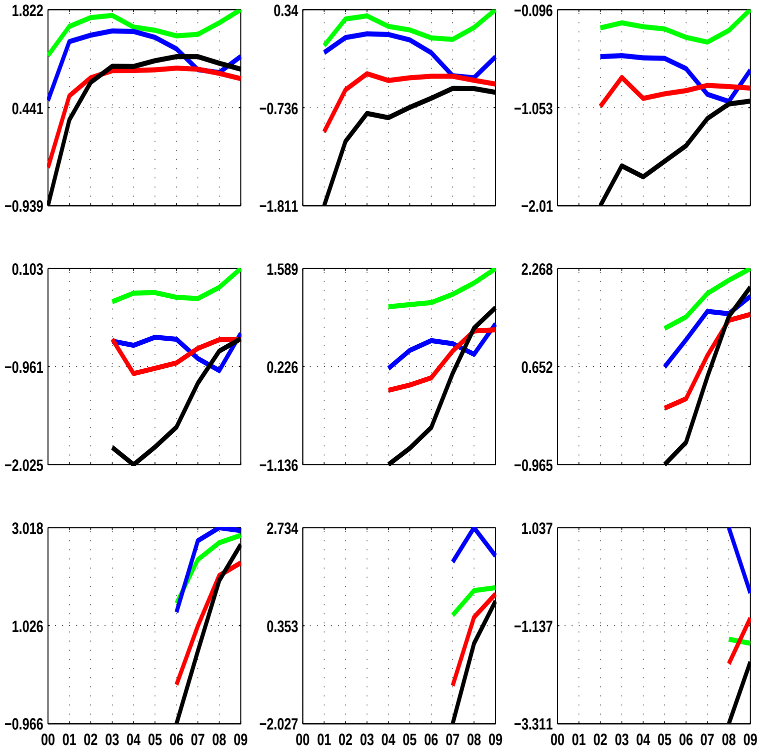
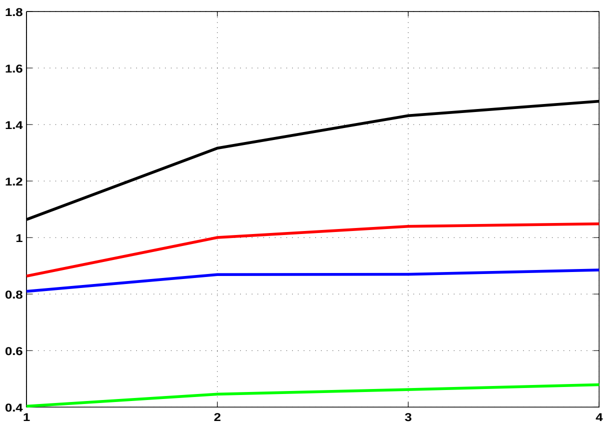


Figure 5 DK Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 DK Real-time vintages
Paths followed by the 2000-2008 cycle estimates

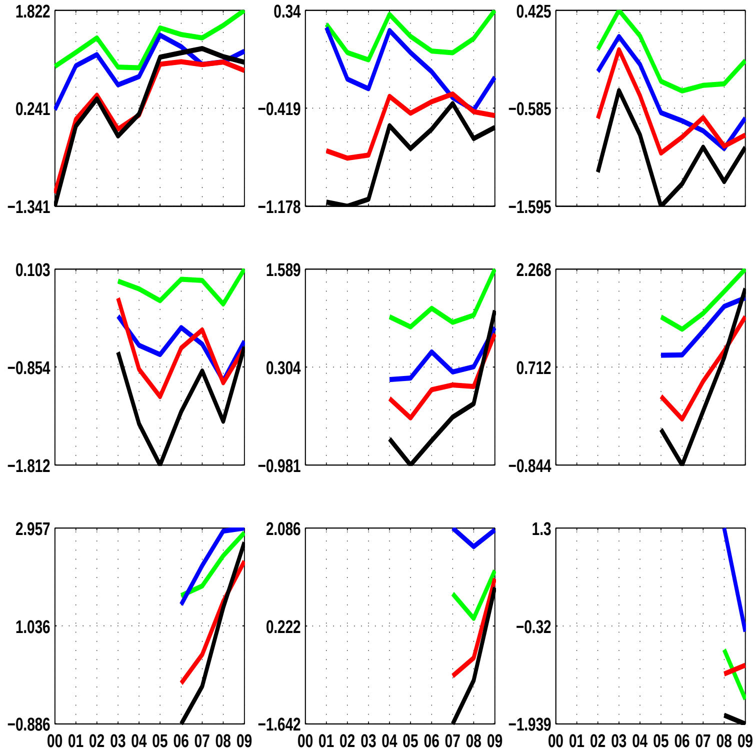
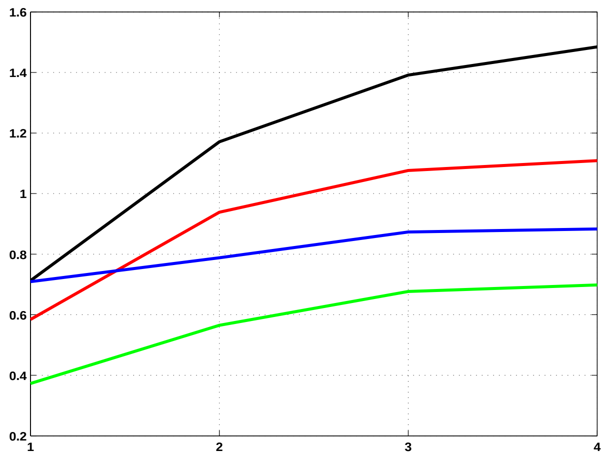


Figure 7 DK Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for DK:

- **TFP data** There is large level shift in the TFP vintages available after 2005.
  CU data There is a large positive outlier in the CUI series in the year 2007. Both series record a large dip in 2009.
  Link TFP-CU The β-coefficient is significantly different from 0. The posterior mode is above one as expected and slightly larger with CUI than with BS.
  Revisions The bivariate model yields less revisions than univariate and HP decompositions both with the 2009 data and the real-time vintages, with both CUI and BS series.
  CUI vs. BS Less revisions are obtained with the BS series.

In 2000, the HP estimate miss the information about capacity utilization above average and returns a negative cycle. In contrast, the bivariate measures point to a positive gap, with agreement with the CU series. The HP preliminary estimate undergoes mostly positive revisions that bring it close to the bivariate estimates. Again the HP estimates for the years 2006-2007 are heavily revised.

4.4 Greece

Figure 1
TFP vintages plus CU

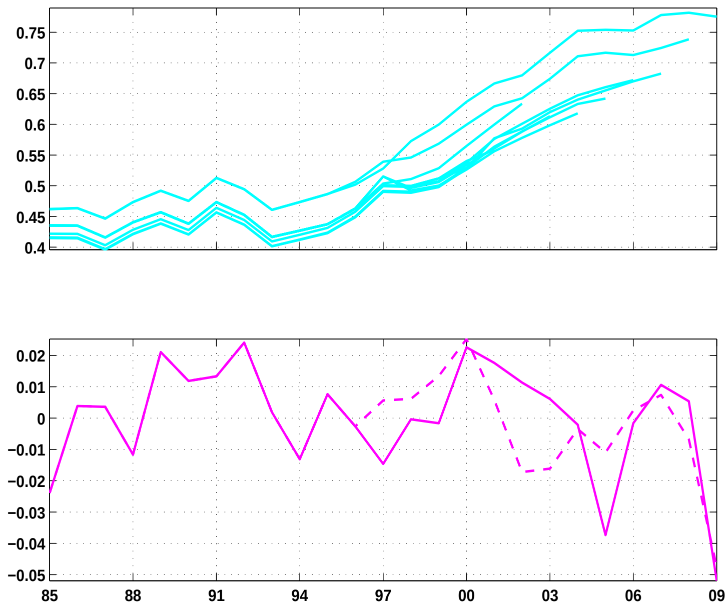


Figure 2 EL Vintage 2009
Trend growth and cycle $(\times 100)$

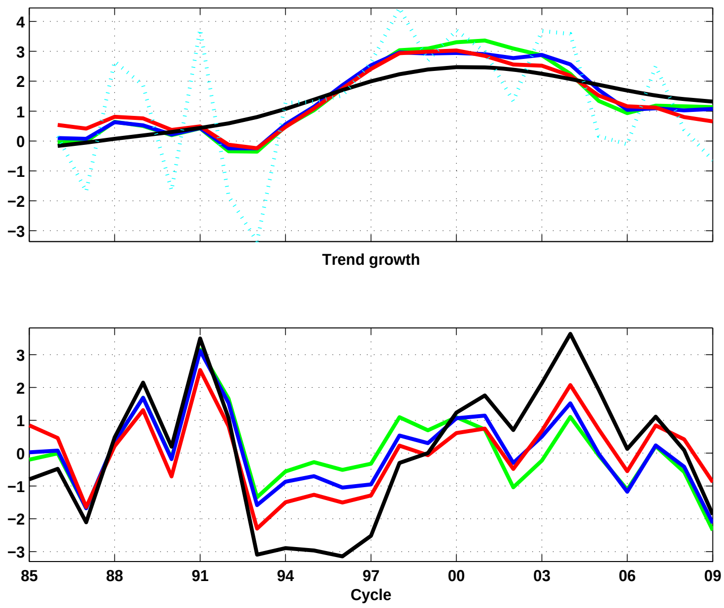


Figure 3 EL Vintage 2009
Prior and posterior distributions, 2009 vintage

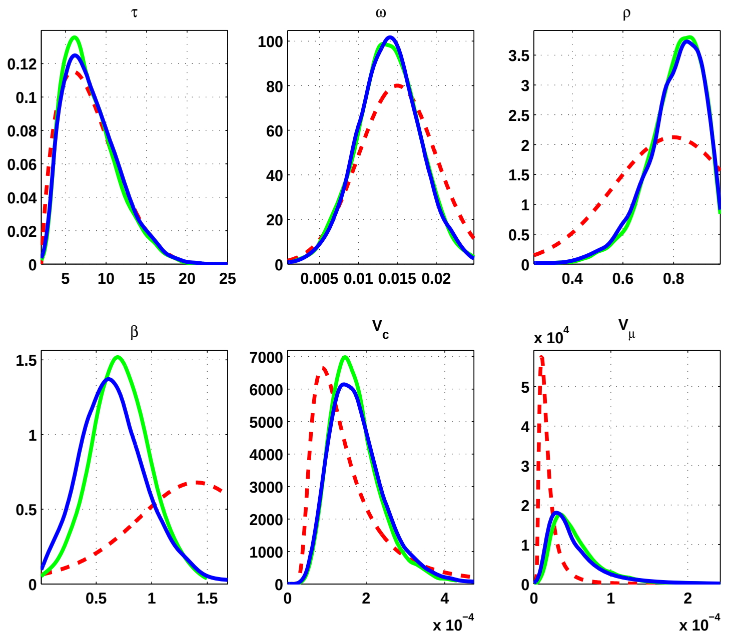


Table 1 EL Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2Acos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.014	0.85	$28.9{\times}10^{-6}$	0.38	6.15	$14.4{\times}10^{-5}$	0	0.61	$23.1{\times}10^{-5}$
	(0.004)	(0.11)		(0.13)	(3.33)		(0)	(0.31)	
BS									
	0.013	0.86	$34.3{\times}10^{-6}$	0.38	6.16	$14.7{\times}10^{-5}$	0	0.69	$16.7{\times}10^{-5}$
	(0.004)	(0.11)		(0.13)	(3.23)		(0)	(0.27)	

Figure 4 EL Vintage 2009
Paths followed by the 2000-2008 cycle estimates

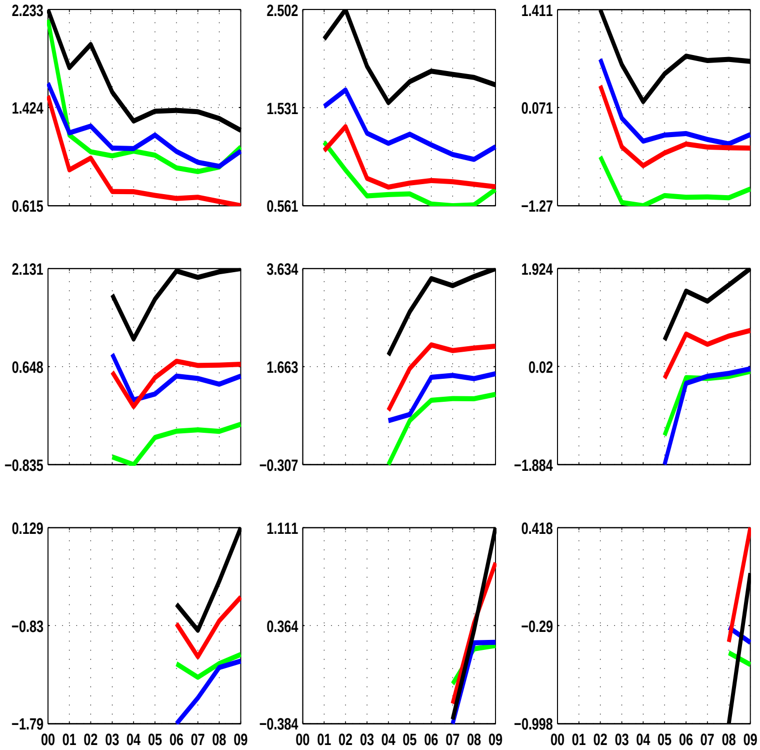
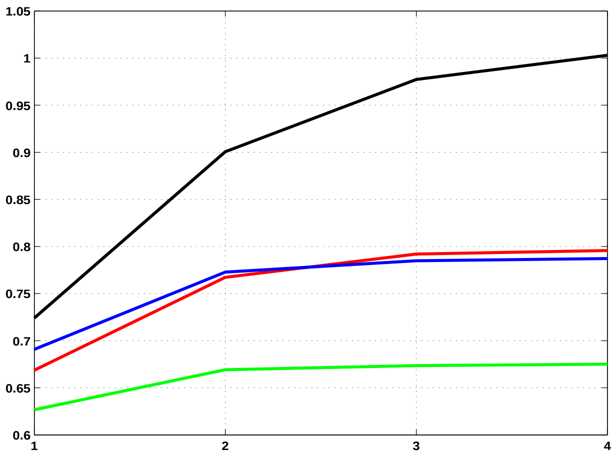


Figure 5 EL Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 EL Real-time vintages
Paths followed by the 2000-2008 cycle estimates

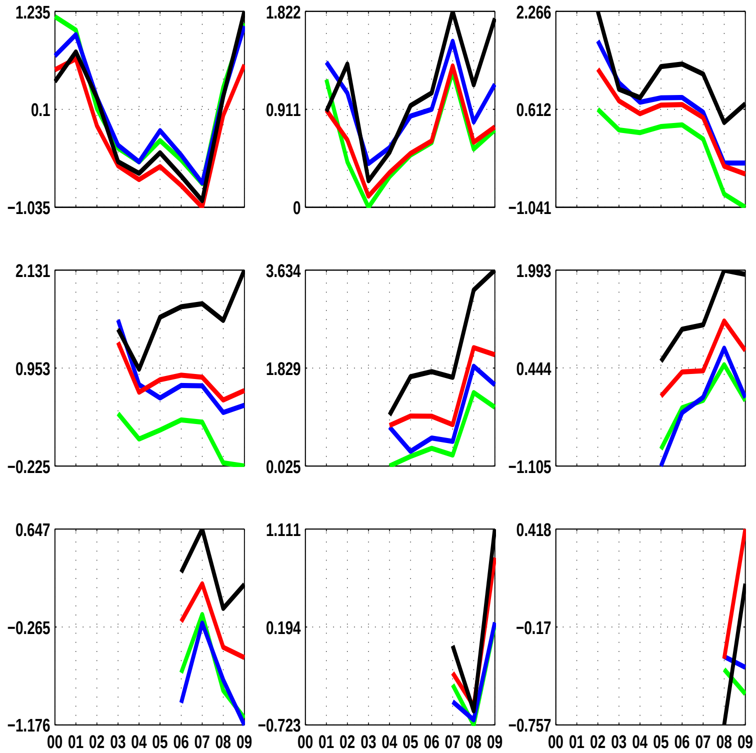
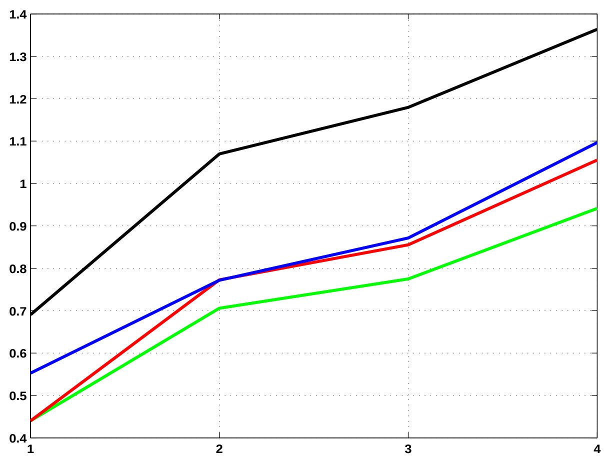


Figure 7 EL Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for EL:

- **TFP data** The 2008 vintage has a large positive level shift. The 2009 vintage is close to the 2008 series but has a greater growth during 1997-2000.
  CU data Both CU series show a large dip in 2009. There is another dip in the CUI data for 2005.
  Link TFP-CU The link is slightly more pronounced with the BS series. With both CUI and BS series the β-posterior mode is below one.
  Revisions The bivariate estimates that uses the BS series dominates with both the 2009 data and the real-time vintages.
  CUI vs. BS: less revisions are obtained with the BS series.

For the year 2000 all methods have a similar revision history. For the recent boom bust cycle, especially for the years 2007-2008 the HP TFP gap is more heavily revised.

4.5 Spain

Figure 1
TFP vintages plus CU series

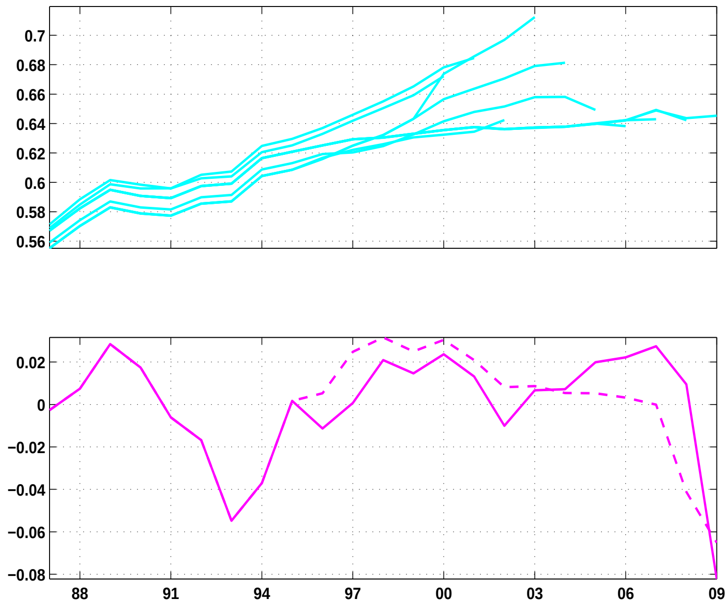


Figure 2 ES Vintage 2009
Trend growth and cycle $(\times 100)$

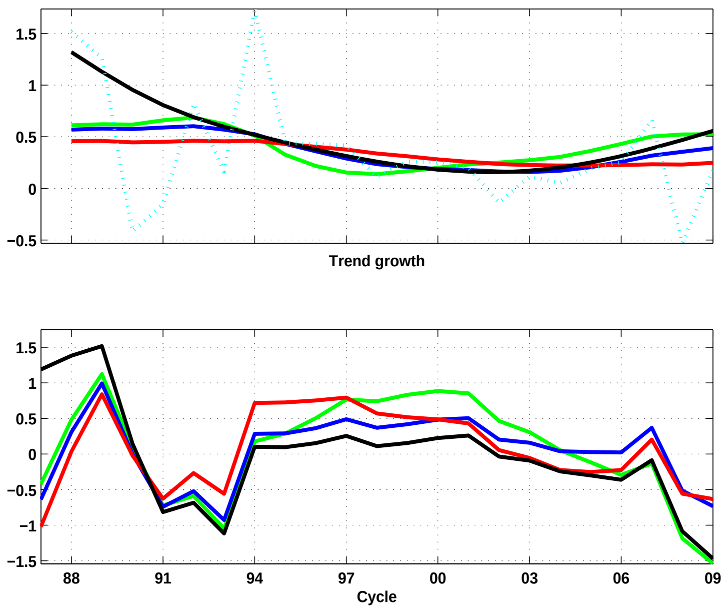


Figure 3 ES Vintage 2009
Prior and posterior distributions, 2009 vintage

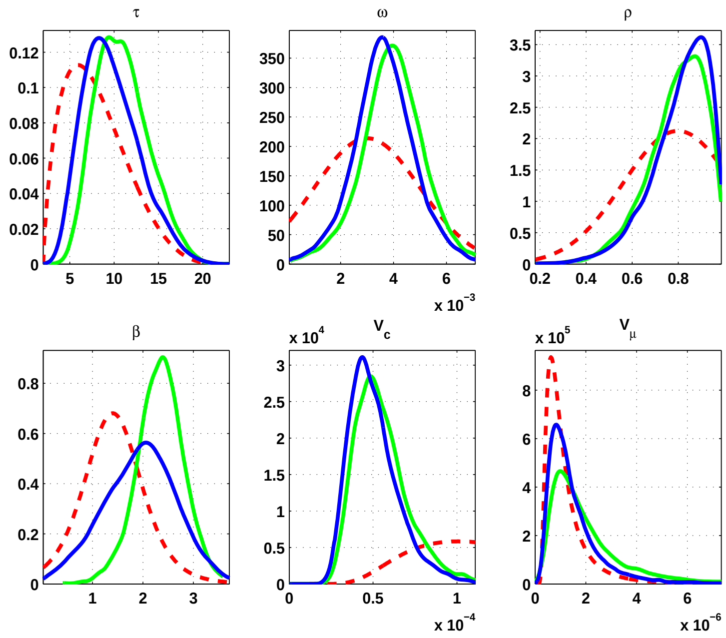


Table 1 ES Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.004	0.9	0.8×10^{-6}	0.45	8.29	4.4×10^{-5}	0	2.06	41.6×10^{-5}
	(0.001)	(0.13)		(0.14)	(3.14)		(0.01)	(0.72)	
BS									
	0.004	0.87	1×10^{-6}	0.52	9.43	4.9×10^{-5}	-0.001	2.4	21.9×10^{-5}
	(0.001)	(0.13)		(0.13)	(2.94)		(0.01)	(0.47)	

Figure 4 ES Vintage 2009
Paths followed by the 2000-2008 cycle estimates

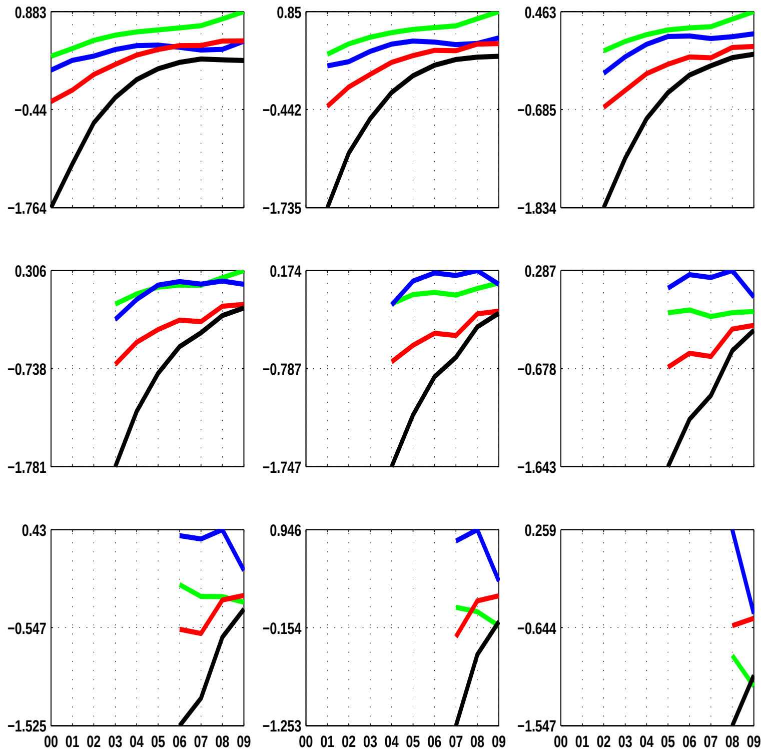


Figure 5 ES Vintage 2009
Revisions standard deviation $(\times 100)$

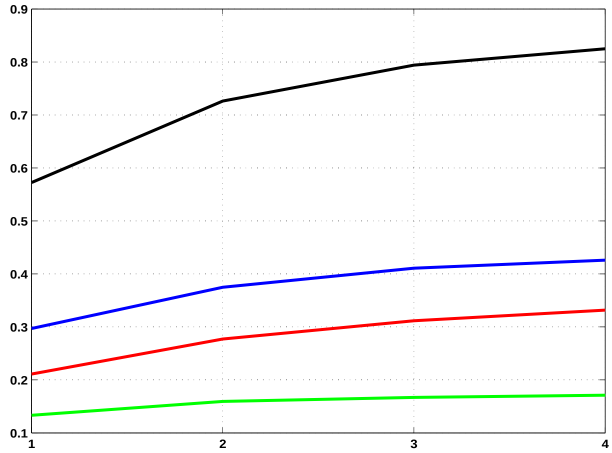


Figure 6 ES Real-time vintages
Paths followed by the 2000-2008 cycle estimates

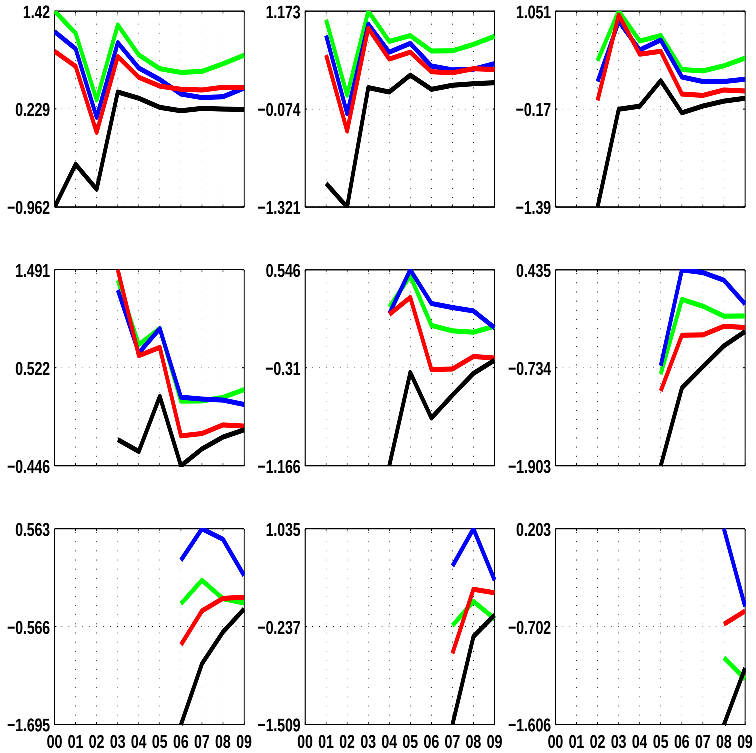
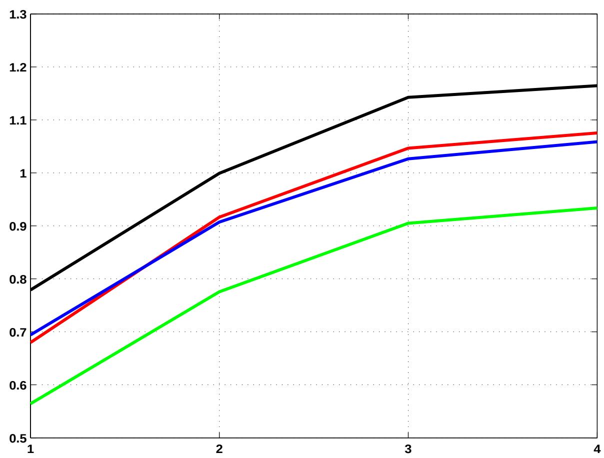


Figure 7 ES Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for ES:

- **TFP data** The post-1995 series growth seems to have almost-always been revised downward.
  CU data Both CU series show a large dip in 2009.
  Link TFP-CU The β-coefficient is significantly different from 0. It takes larger values when BS is used instead of CUI, and the posterior distribution is more concentrated around the mode.
  Revisions The bivariate model with BS data yields the less revisions with both 2009 data and real-time vintages.
  CUI vs. BS Less revisions are obtained with the BS series.

There is the well known tendency for the HP gap to be revised upward over time, i.e. the HP trend seems to be excessively optimistic in real time. With an initial HP estimate for 2000 at -0.3, subsquently revised positively towards the bivariate estimates, the 2000 phenomenom appears also for ES. The bivariate estimates that use the BS series are remarkably robust in the years 2006-2009. Again, HP is heavily revised in these years.

4.6 France

Figure 1
TFP vintages plus CU series

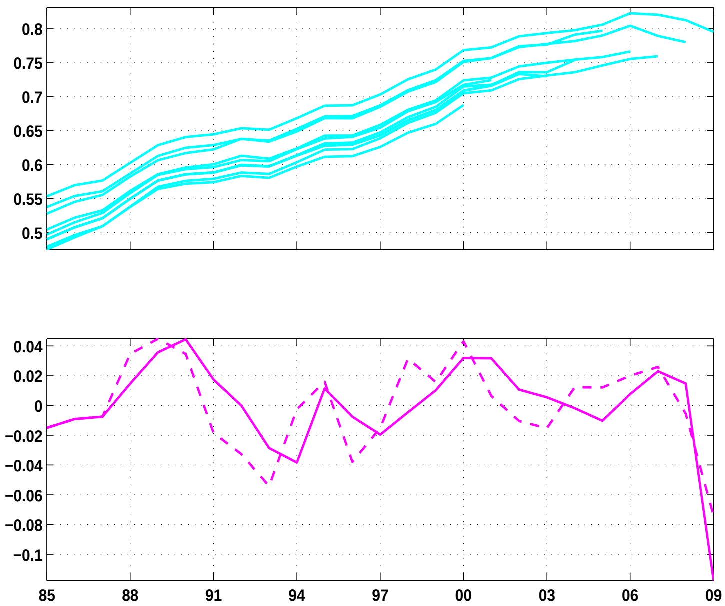


Figure 2 FR Vintage 2009 ($\times 100$)
Trend growth and cycle

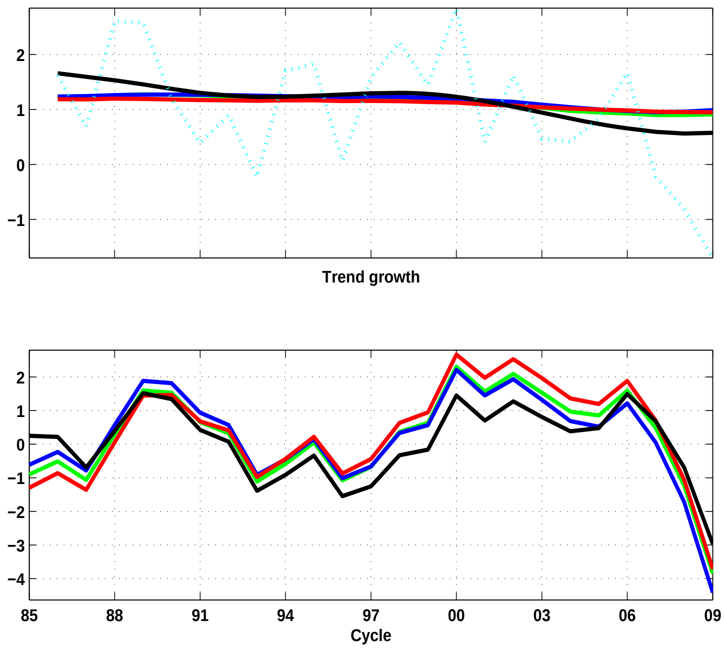


Figure 3 FR Vintage 2009
Prior and posterior distributions, 2009 vintage

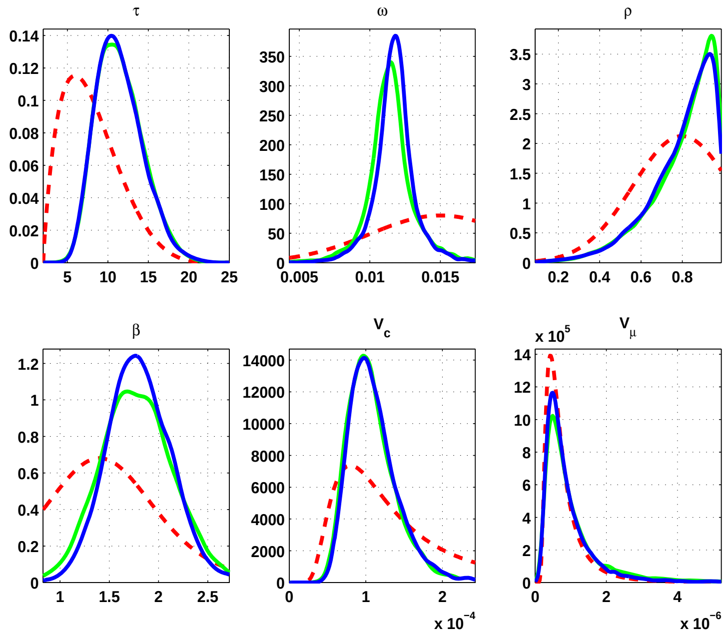


Table 1 FR Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \quad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}/(1-\delta L)$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	δ	β	V_{CU}
CUI										
	0.012	0.93	0.5×10^{-6}	0.58	10.47	9.8×10^{-5}	-0.003	0.2	1.77	29.5×10^{-5}
	(0.002)	(0.16)		(0.12)	(2.85)		(0.01)	(0.28)	(0.32)	
BS										
	0.011	0.94	0.5×10^{-6}	0.6	10.5	9.7×10^{-5}	-0.004	0.59	1.68	31.3×10^{-5}
	(0.002)	(0.16)		(0.12)	(2.86)		(0.01)	(0.18)	(0.37)	

Figure 4 FR Vintage 2009
Paths followed by the 2000-2008 cycle estimates

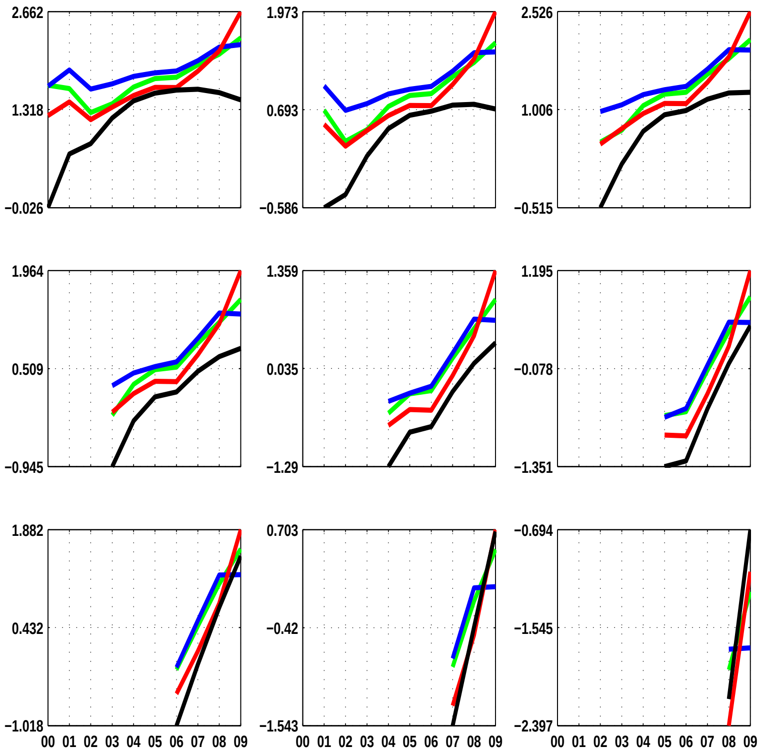
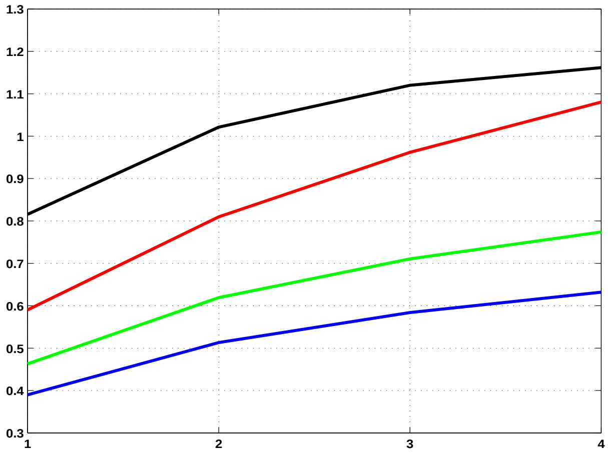


Figure 5 FR Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 FR Real-time vintages
Paths followed by the 2000-2008 cycle estimates

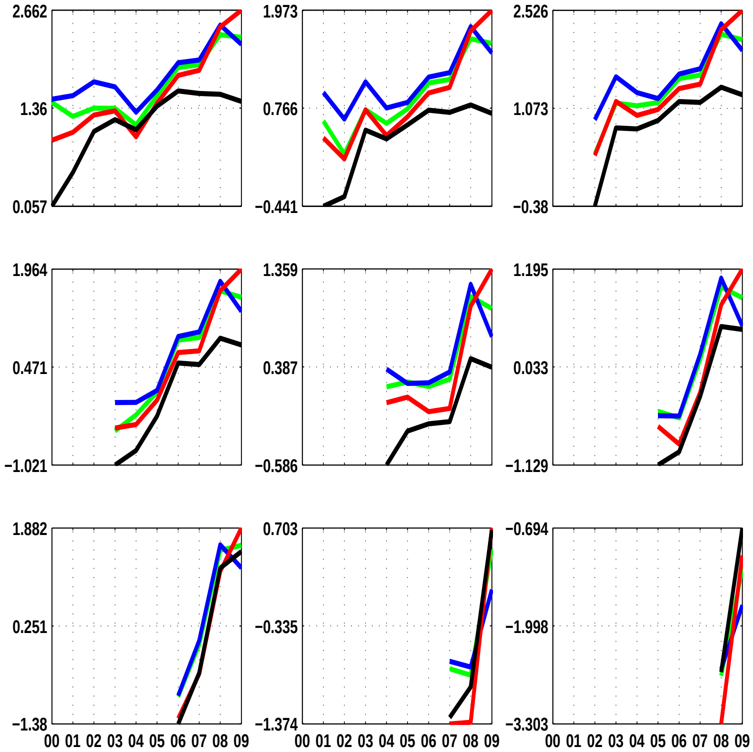
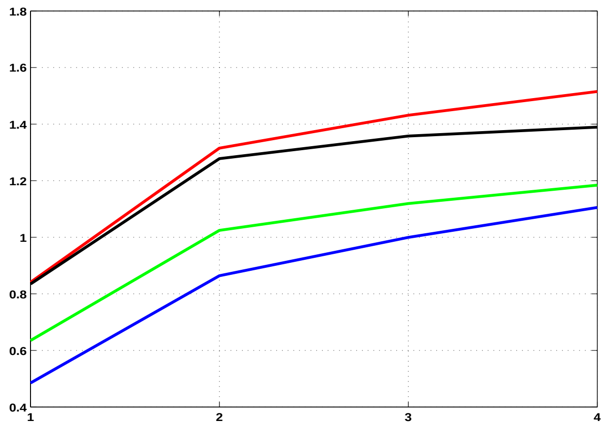


Figure 7 FR Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for FR:

- **TFP data** There is a noticeable level-shift in the 2008 and 2009 vintages.
  CU data CUI and BS have similar variability, the BS series is leading one period in the first sample half. Both have a large dip in 2009.
  Link TFP-CU The β-coefficient is significantly different from 0. The β-posterior distributions obtained with BS and with CU series are quite similar.
  Revisions Bivariate decompositions are performing better than HP for both 2009 and real-time datasets.
  CUI vs. BS: CUI yields less revisions.

For 2000, the HP TFP gap must be revised up strongly while the bivariate model correctly indicates a positive gap that is consistent with the cyclical indicators. We observe strong upward TFP gap revisions until 2004. The HP estimate show large instability in 2007-2008. The 2000 phenomenom that hits the HP estimates seems to take place again in 2009 in the opposite direction, the 2009 HP trend in Figure 2 being excessively pessimistic. On the contrary, estimates that exploit the CU information assign the last TFP decline to the gap so the 2009 potential growth has more inertia.

4.7 Ireland

Figure 1
TFP vintages plus CU series

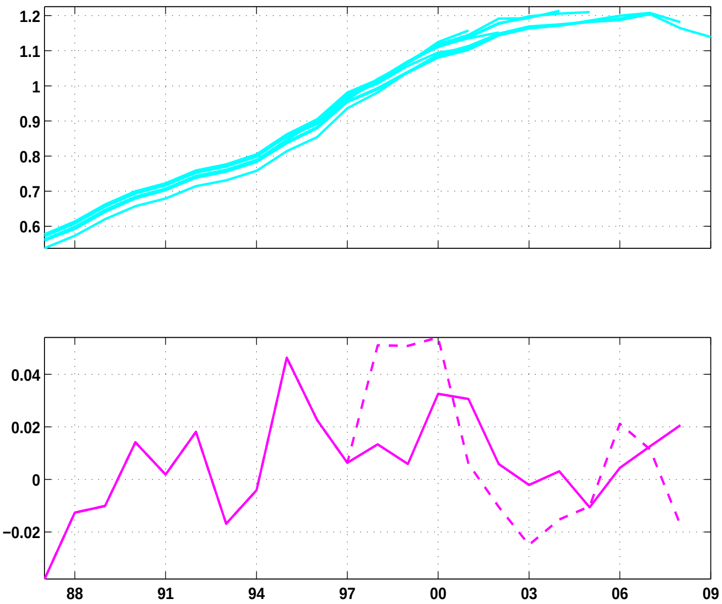


Figure 2 IE Vintage 2009
Trend growth and cycle

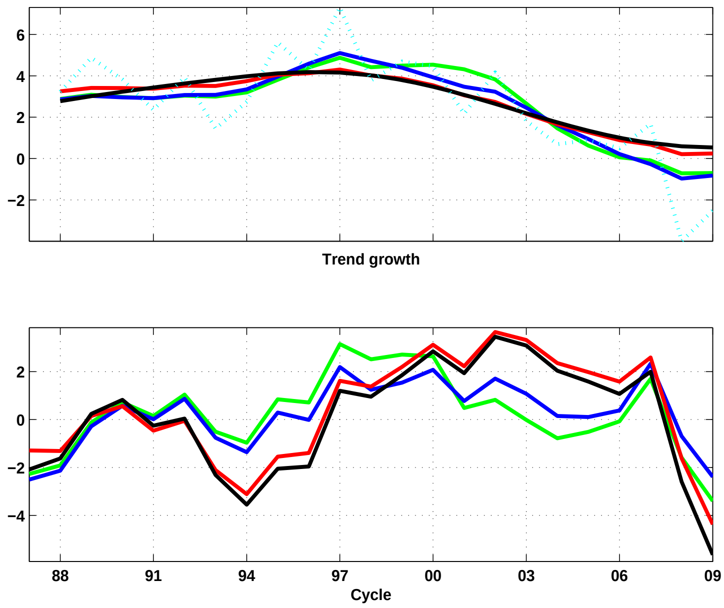


Figure 5
Prior and posterior distributions, 2009 vintage

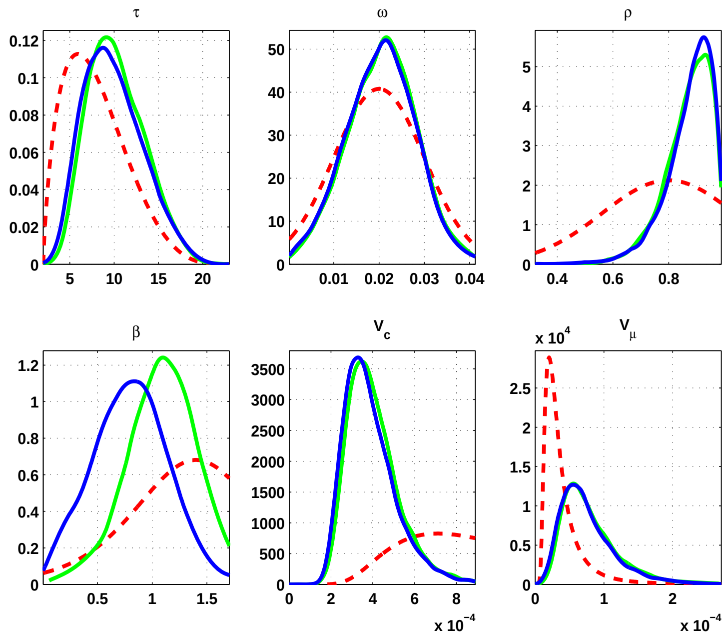


Table 1 IE Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.021	0.93	55.5×10^{-6}	0.43	8.75	32.9×10^{-5}	0.004	0.84	40.1×10^{-5}
	(0.008)	(0.09)		(0.15)	(3.31)		(0.01)	(0.35)	
BS									
	0.022	0.93	55.7×10^{-6}	0.48	9.09	34.7×10^{-5}	0.003	1.1	44.2×10^{-5}
	(0.008)	(0.08)		(0.14)	(3.16)		(0.01)	(0.33)	

Figure 4 IE Vintage 2009
Paths followed by the 2000-2008 cycle estimates

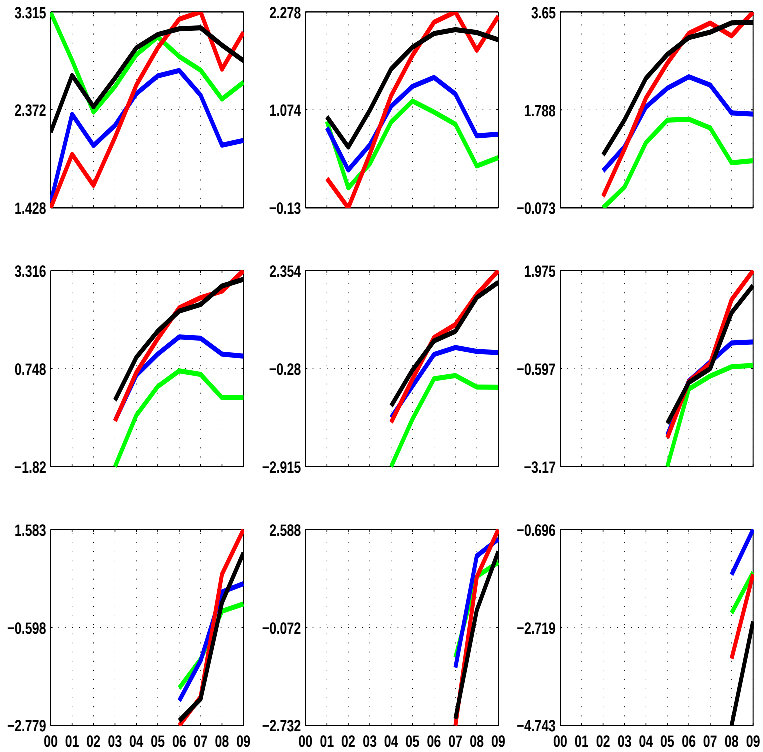
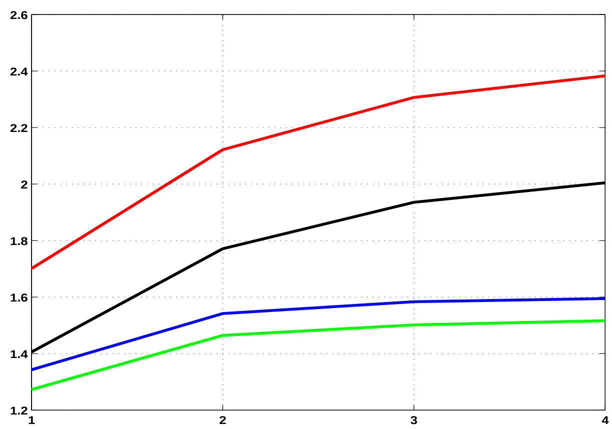


Figure 5 IE Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 IE Real-time vintages
Paths followed by the 2000-2008 cycle estimates

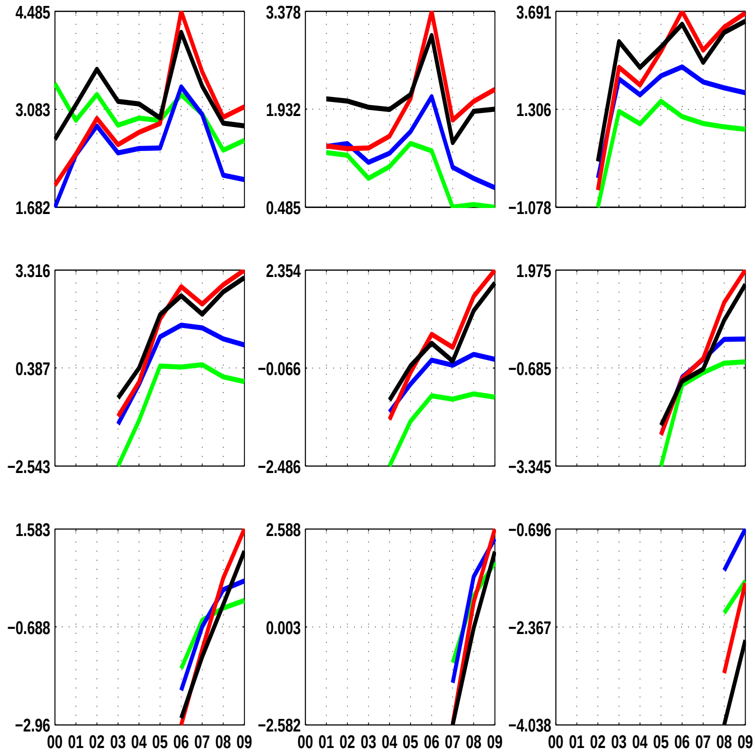
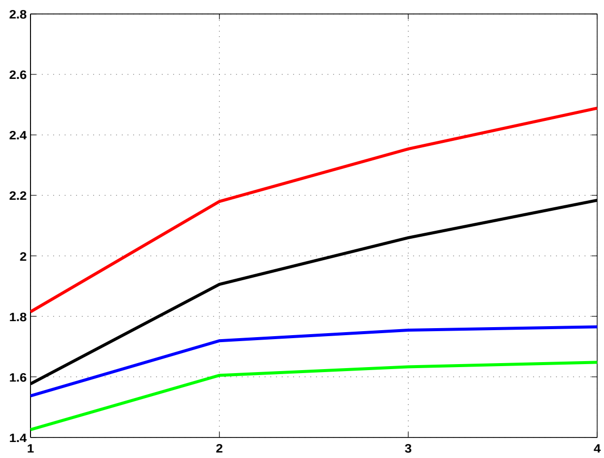


Figure 7 IE Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for IE:

- **TFP data** Vintages are stable enough.
  CU data The BS series seems slightly more variable than the CUI series. BS and CUI have opposite growth directions over 2006-2008. There is no CU data for 2009.
  Link TFP-CU The β-coefficient is significantly different from 0. It takes larger values when BS is used instead of CUI.
  Revisions The bivariate approach is best performing with both 2009 and real-time datasets.
  CUI vs. BS BS yields less revisions.

The HP filter generates a relatively smooth trend that has problems to capture the abrupt change in the trend growth rate, in particular the increase in TFP growth towards the end of the 90s and the subsequent decline. This can clearly be seen for the 2000 gap estimate: in this year, the smoothness assumption makes it difficult to the HP filter to properly account for the increase in trend TFP growth so the HP filter suggests a large positive output gap. As time passes, trend growth is slowly adjusted upwards for 2000 and the 2009 estimate for the year 2000 approaches, though it does not reach it, the bivariate. This last remains remarkably stable across the 2005-2009 vintages.

4.8 Italy

Figure 1
TFP vintages plus CU series

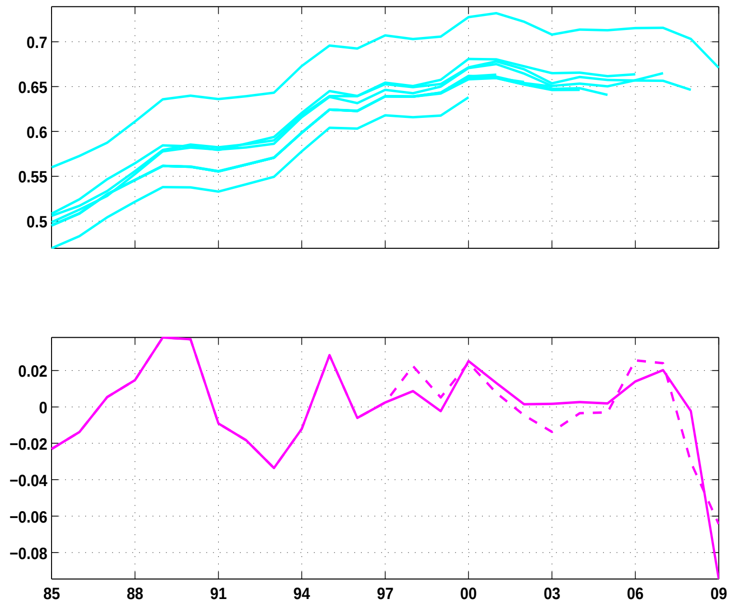


Figure 2 IT Vintage 2009
Trend growth and cycle ($\times 100$)

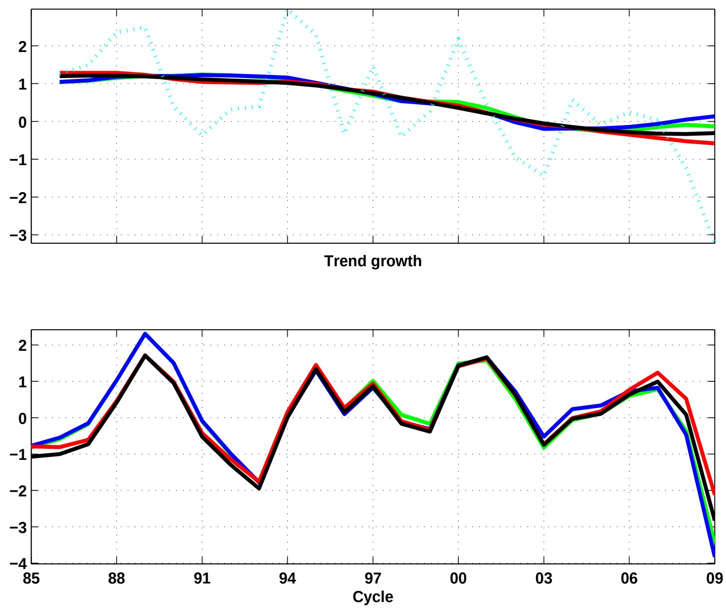


Figure 3 IT Vintage 2009
Prior and posterior distributions, 2009 vintage

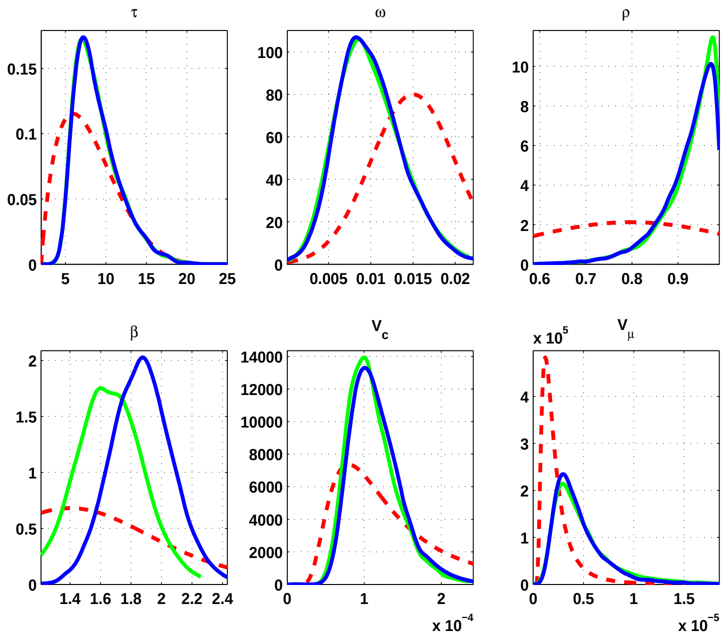


Table 1 IT Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.008	0.97	3×10^{-6}	0.57	7.2	10.1×10^{-5}	-0.001	1.88	9.6×10^{-5}
	(0.004)	(0.06)		(0.14)	(2.76)		(0.01)	(0.2)	
BS									
	0.009	0.98	2.9×10^{-6}	0.55	7.09	10×10^{-5}	0	1.6	12.9×10^{-5}
	(0.004)	(0.06)		(0.14)	(2.77)		(0.01)	(0.23)	

Figure 4 IT Vintage 2009
Paths followed by the 2000-2008 cycle estimates

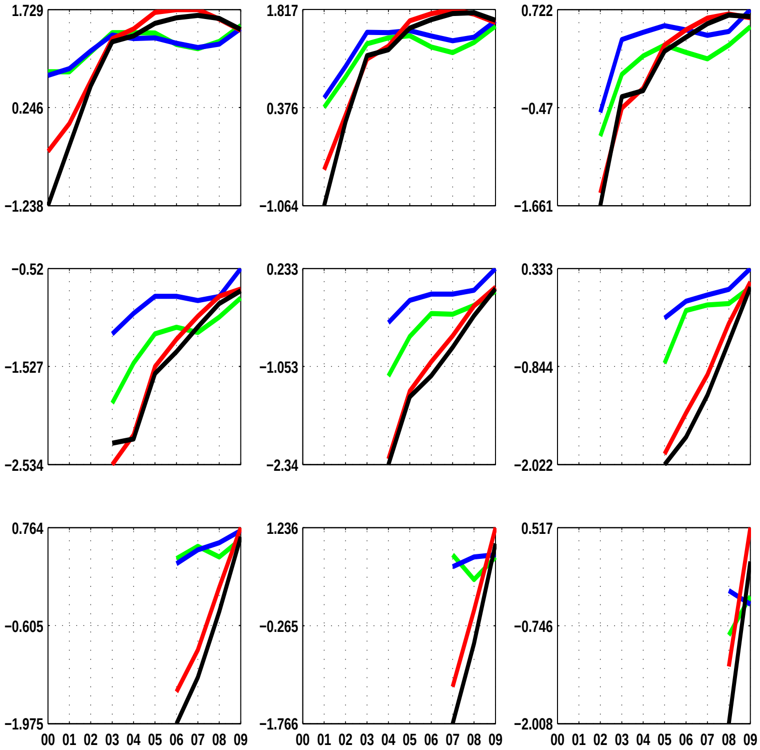
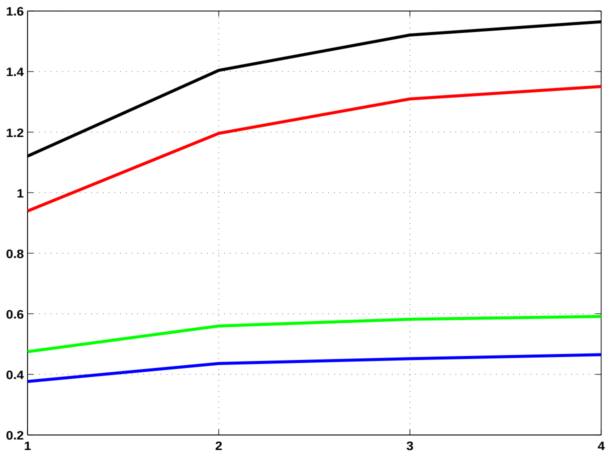


Figure 5 IT Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 IT Real-time vintages
Paths followed by the 2000-2008 cycle estimates

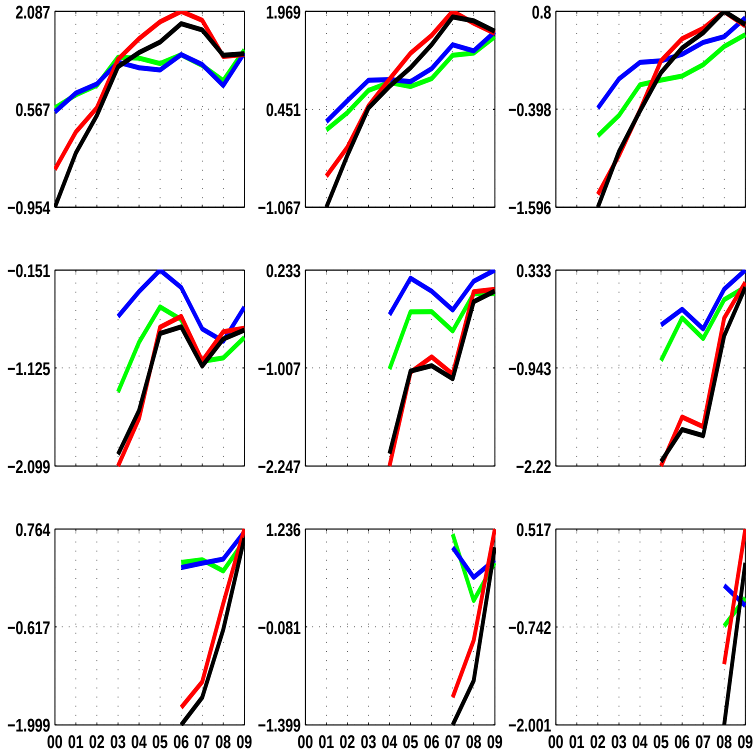
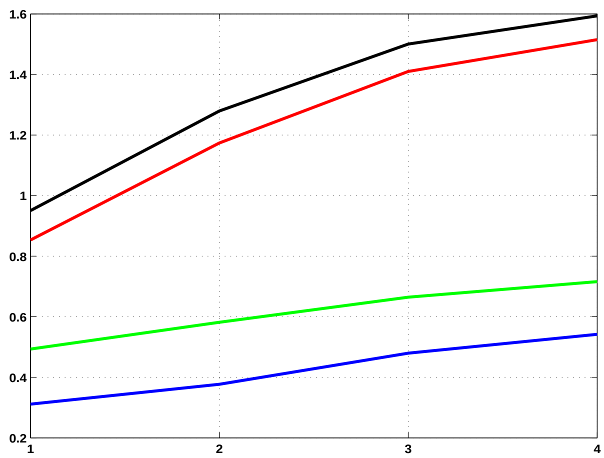


Figure 7 IT Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

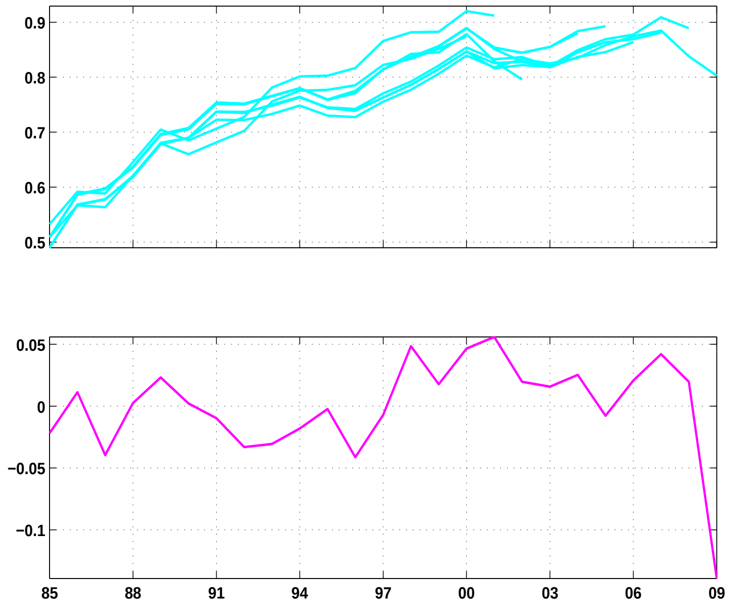
Summary for IT:

- **TFP data** The 2000-vintage has a low level and the 2009 one shows a positive level shift.
  CU data The two series are similar. Both end on a large dip in 2009.
  Link TFP-CU: the β-coefficient is far away from 0. It takes slightly larger values with CUI.
  Revisions: the bivariate model yields less revisions than univariate and HP decompositions both with the 2009 data and the real-time vintages, with both CUI and BS series.
  CUI vs. BS: less revisions are obtained with the CUI series.

The HP TFP gap estimate fails to capture the cyclical boom in 2000 and in 2006-2007. Also, revisions are slow to occur and affect all points between 2000 and 2007. There are substantially less revisions when the information on capacity utilisation is used, particularly for the years which exhibit peaks in capacity utilisation. Large revisions are recorded with HP for the gap in the years 2007-2008.

4.9 Luxembourg

Figure 1
TFP vintage plus CU series



The EC business surveys series are not available for LU.

Figure 2 LU Vintage 2009
Trend growth and cycle $(\times 100)$

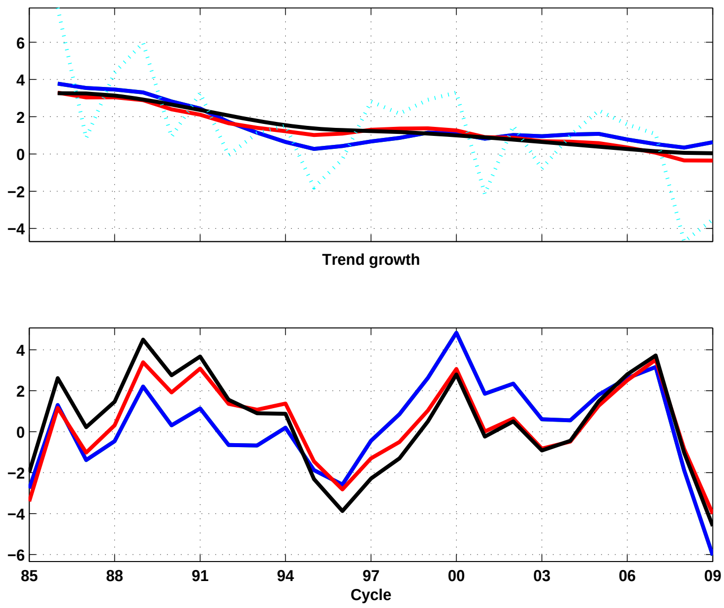


Figure 3 LU Vintage 2009
Prior and posterior distributions, 2009 vintage

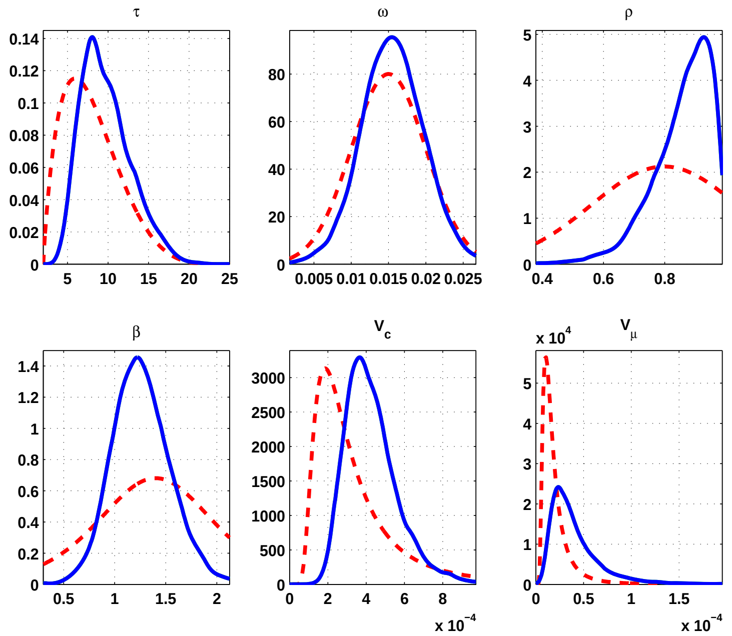


Table 1 LU Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2A\cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.015	0.93	23.2×10^{-6}	0.48	8.08	36.8×10^{-5}	-0.003	1.22	56.1×10^{-5}
	(0.004)	(0.1)		(0.13)	(3.05)		(0.01)	(0.29)	

Figure 4 LU Vintage 2009
Paths followed by the 2000-2008 cycle estimates

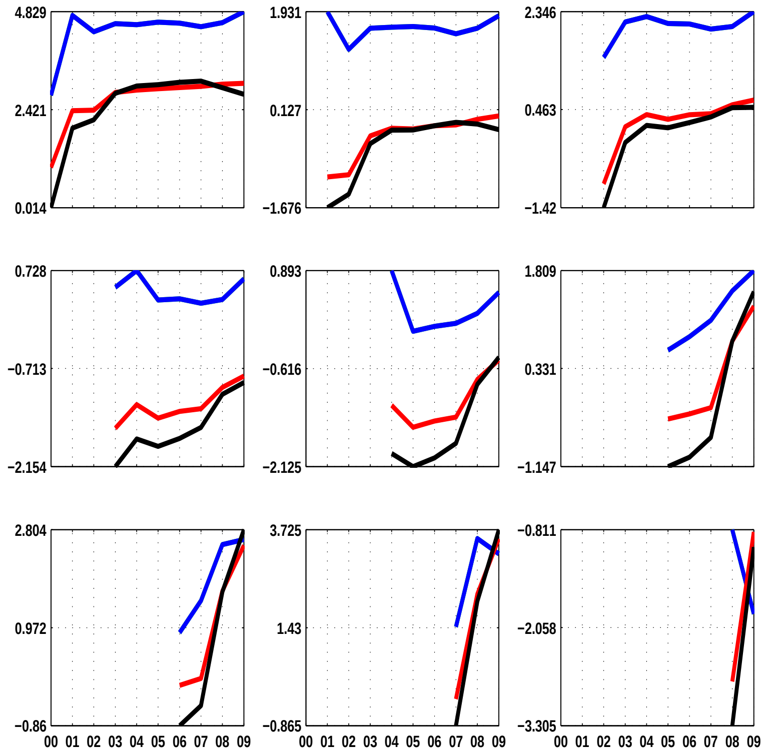
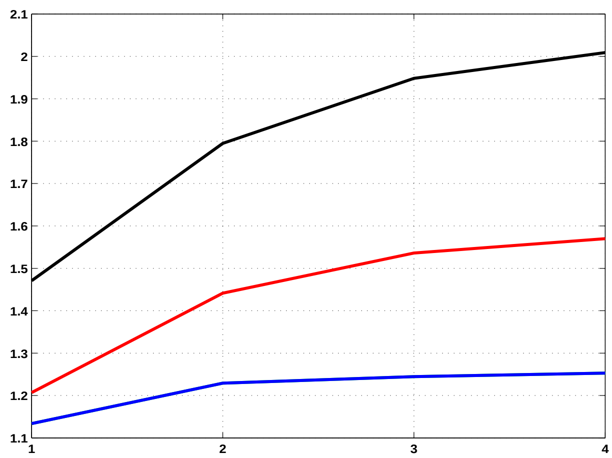


Figure 5 LU Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 LU Real-time vintages
Paths followed by the 2000-2008 cycle estimates

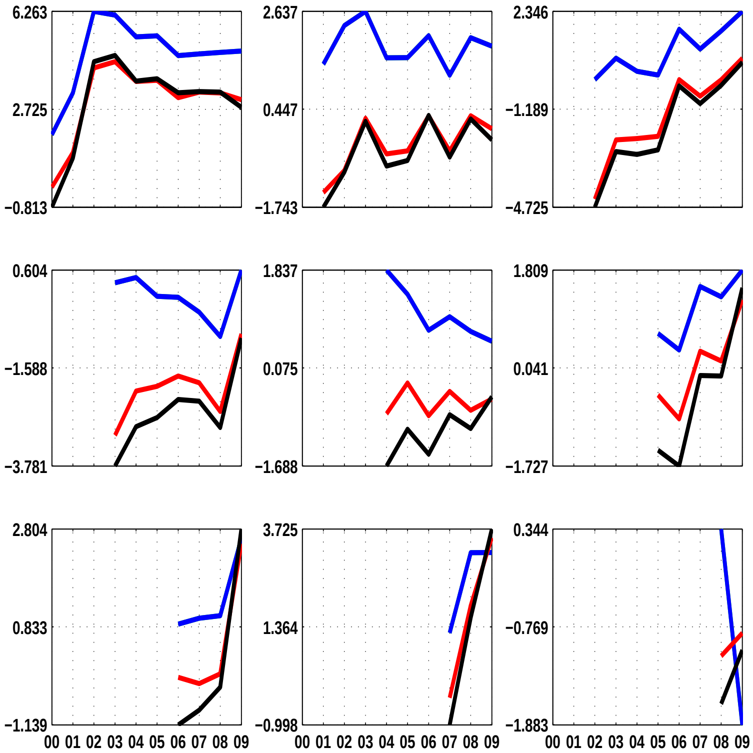
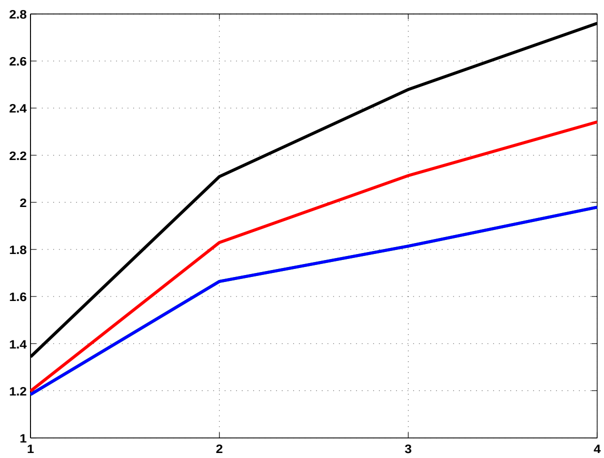


Figure 7 LU Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for LU:

- **TFP data** Real-time data show large enough revisions.
  CU data There is a level shift in 1998 in the CUI series. No BS series available.
  Link TFP-CU The β-coefficient is significantly different from 0 with a posterior mode above one as expected.
  Revisions The bivariate model yields less revisions than univariate and HP decompositions both with the 2009 data and the real-time vintages.

The bivariate estimates uses the capacity utilisation series to identify a cyclical peak in 2000-2001. The HP filter estimates instead a negative TFP gap, particularly in 2001 which is subsequently revised to become positive. The 2008 gap estimated with the CUI series has a large revision in 2009. Most often BS series yield better results but it is not available for LU.

4.10 Netherlands

Figure 1
TFP vintages plus CU series

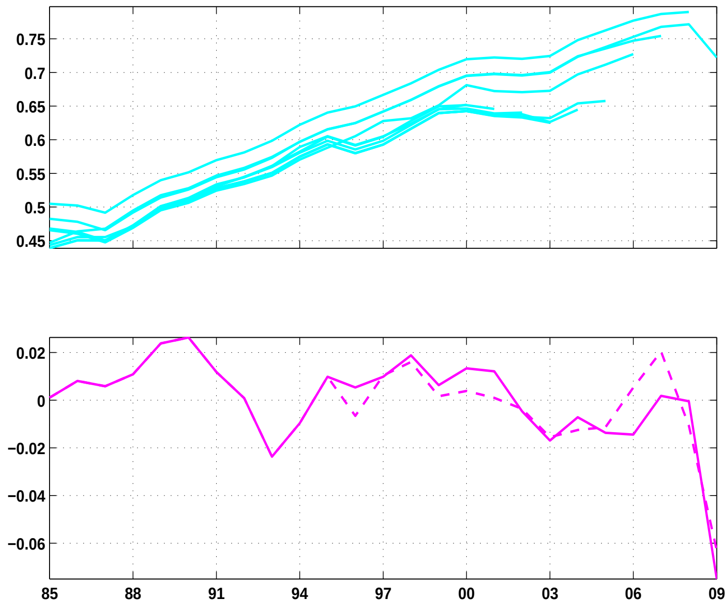


Figure 2 NL Vintage 2009
Trend growth and cycle $(\times 100)$

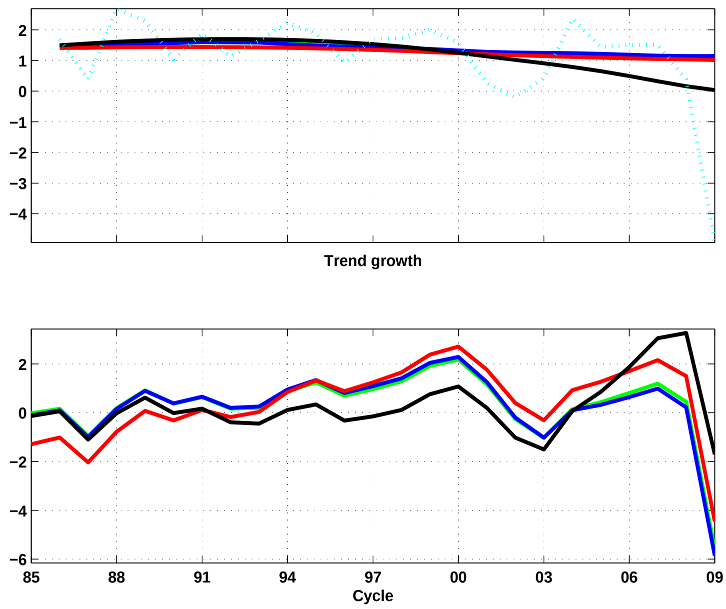


Figure 3 NL Vintage 2009

Prior and posterior distributions, 2009 vintage

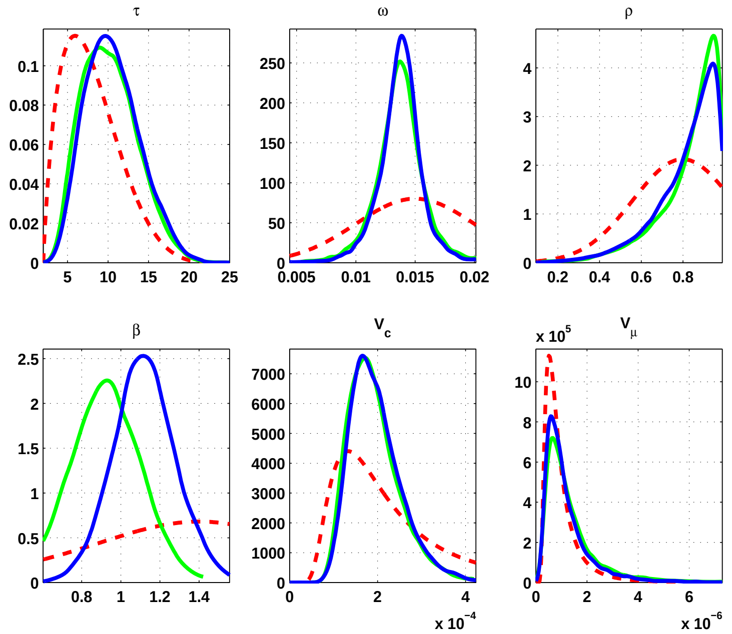


Table 1 NL Full sample estimation, 2009 vintage

Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \quad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}/(1-\delta L)$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	δ	β	V_{CU}
CUI										
	0.014	0.95	0.6×10^{-6}	0.57	9.65	16.6×10^{-5}	-0.001	0.78	1.11	8.9×10^{-5}
	(0.002)	(0.15)		(0.15)	(3.32)		(0.01)	(0.18)	(0.16)	
BS										
	0.014	0.95	0.7×10^{-6}	0.57	8.99	17.2×10^{-5}	-0.003	0.66	0.93	10.9×10^{-5}
	(0.002)	(0.15)		(0.15)	(3.34)		(0.01)	(0.22)	(0.18)	

Figure 4 NL Vintage 2009
Paths followed by the 2000-2008 cycle estimates

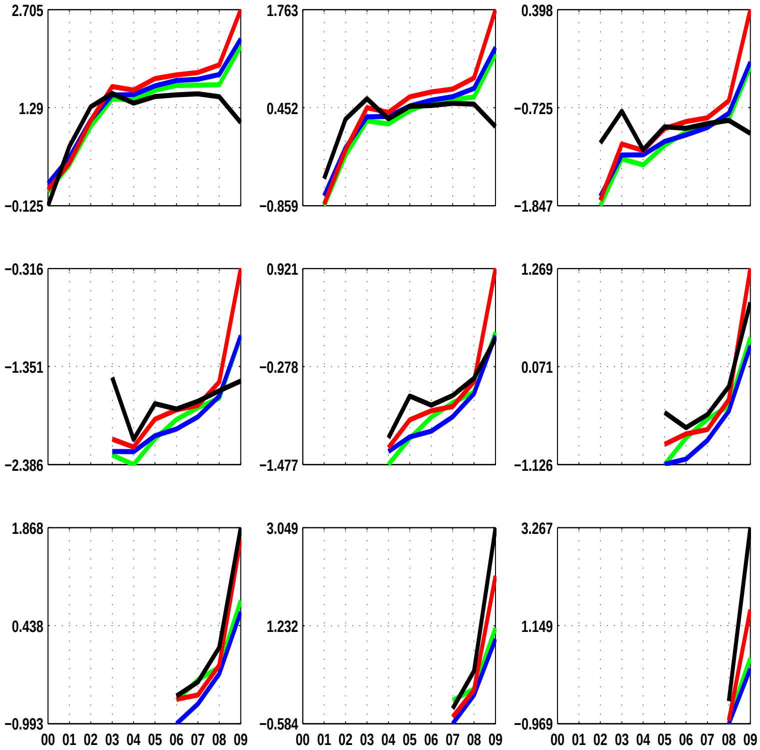


Figure 5 NL Vintage 2009
Revisions standard deviation $(\times 100)$

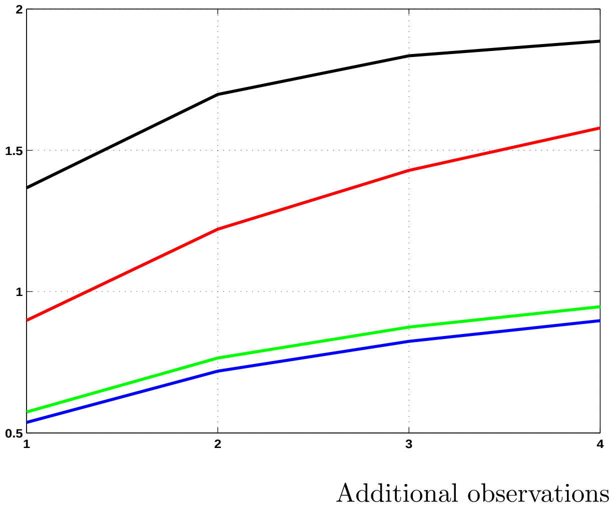


Figure 6 NL Real-time vintages
Paths followed by the 2000-2008 cycle estimates

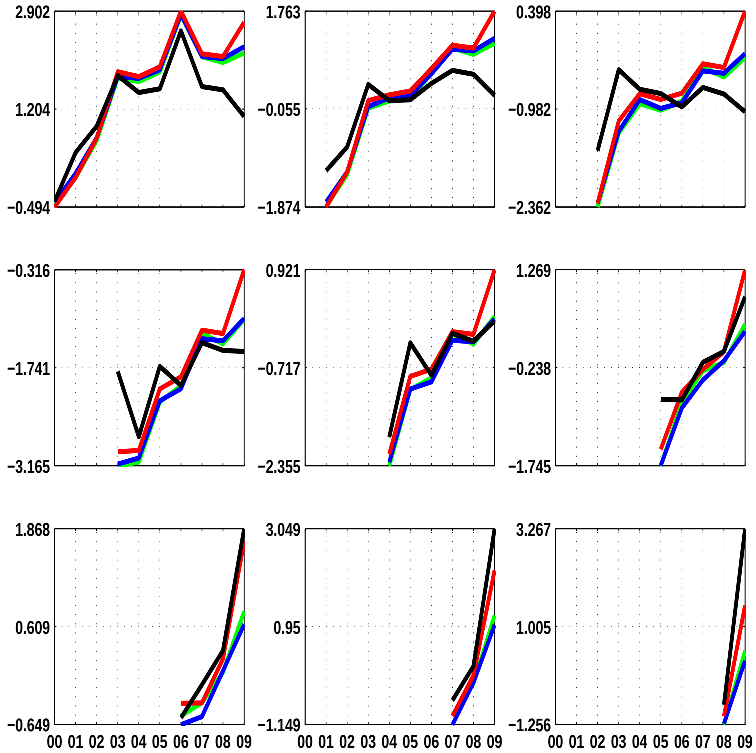
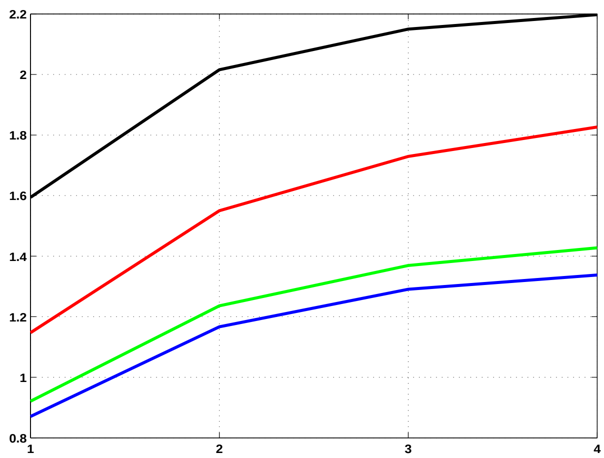


Figure 7 NL Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for NL:

- **TFP data** The vintages are stable until 2005 included. The next vintages show both a level shift and a change in the series growth between 1995 and 2000.
  CU data The two series are quite similar. Both have a large dip in 2009.
  Link TFP-CU The β-coefficient is significantly different from 0. When CUI is used, the β-posterior mode is larger than 1.0 and greater than when using BS.
  Revisions The bivariate model yields less revisions both with the 2009 data and the real-time vintages, with both CUI and BS series.
  CUI vs. BS: The results are very close.

The largest difference beween HP and bivariate estimates appear in the 2006-2009 years for which HP gaps are heavily revised with sign switch.

4.11 Portugal

Figure 1
TFP vintages plus CU series

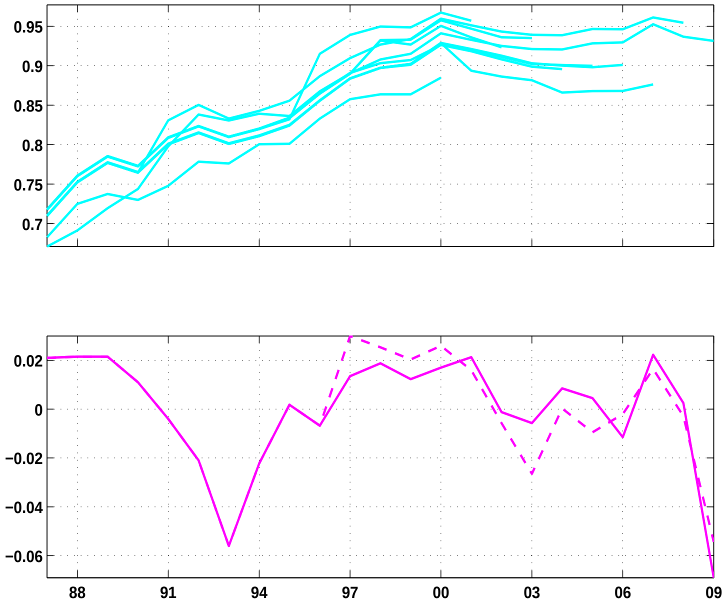


Figure 2 PT Vintage 2009
Trend growth and cycle ($\times 100$)

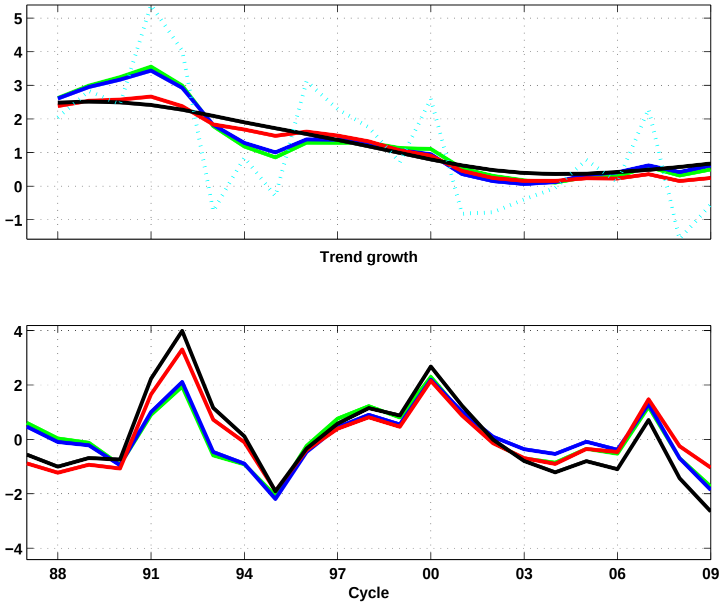


Figure 3 PT Vintage 2009

Prior and posterior distributions, 2009 vintage

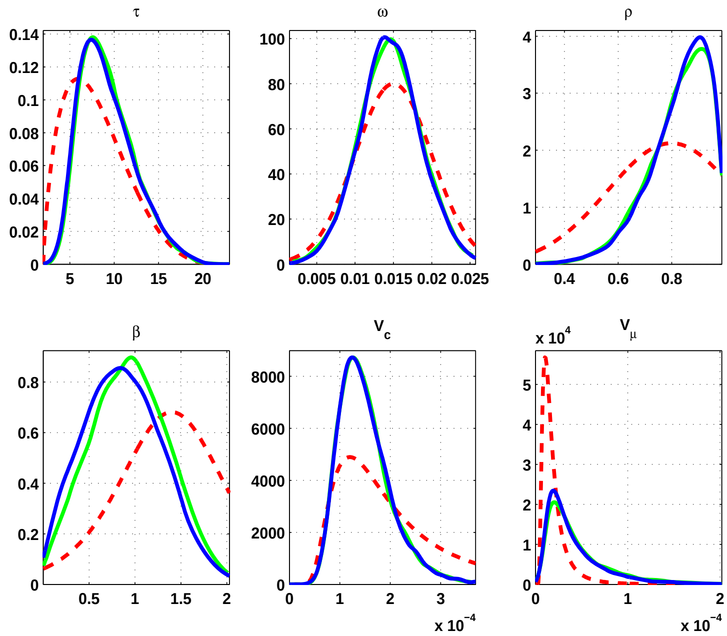


Table 1 PT Full sample estimation, 2009 vintage

Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \qquad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	β	V_{CU}
CUI									
	0.014	0.91	19.7×10^{-6}	0.43	7.38	12.5×10^{-5}	0.001	0.84	50.6×10^{-5}
	(0.004)	(0.11)		(0.13)	(3.09)		(0.01)	(0.43)	
BS									
	0.015	0.91	19.9×10^{-6}	0.45	7.59	12.5×10^{-5}	0.001	0.96	48.2×10^{-5}
	(0.004)	(0.12)		(0.13)	(3.01)		(0.01)	(0.42)	

Figure 4 PT Vintage 2009
Paths followed by the 2000-2008 cycle estimates

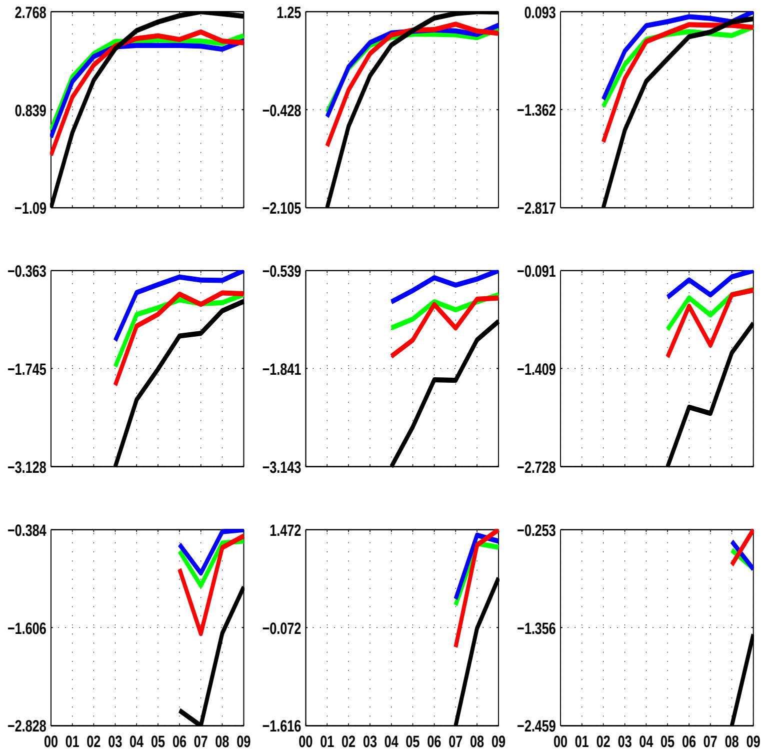


Figure 5 PT Vintage 2009
Revisions standard deviation ($\times 100$)

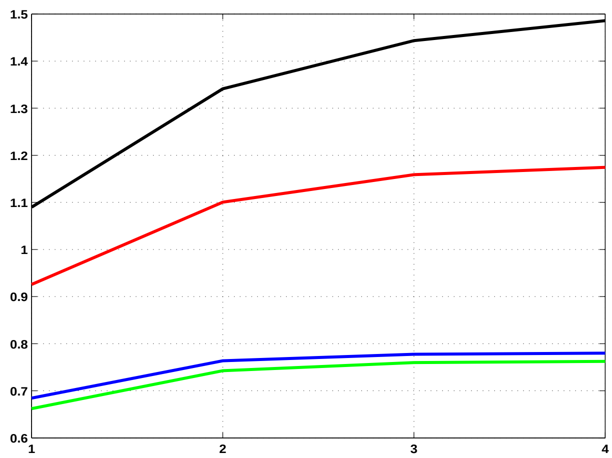


Figure 6 PT Real-time vintages
Paths followed by the 2000-2008 cycle estimates

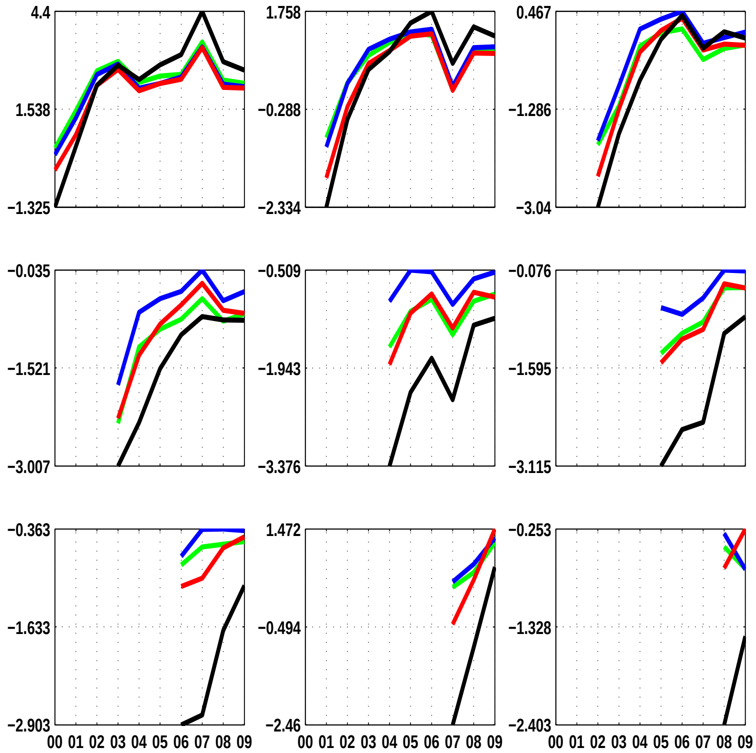
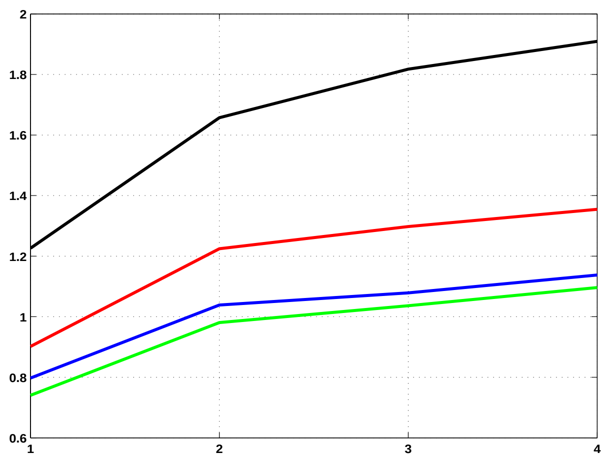


Figure 7 PT Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for PT:

- **TFP data**: large revisions in the vintages.
  CU data : There is a large dip in the series in 1993. The BS and CUI series are similar.
  Link TFP-CU The β-coefficient is significantly different from 0.
  Revisions: the bivariate model yields less revisions than univariate and HP decompositions both with the 2009 data and the real-time vintages, with both CUI and BS series.
  CUI vs. BS: slightly less revisions are obtained with the BS series.

The largest differences between HP and the bivariate estimates occur in the last five years. 2007 is particularly bad for HP.

4.12 United Kingdom

Figure 1
TFP vintages plus CU series

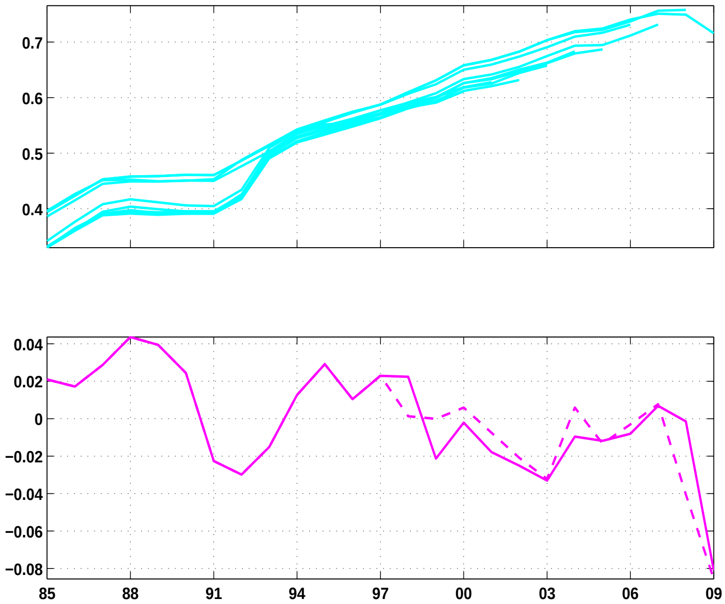


Figure 2 UK Vintage 2009
Trend growth and cycle $(\times 100)$

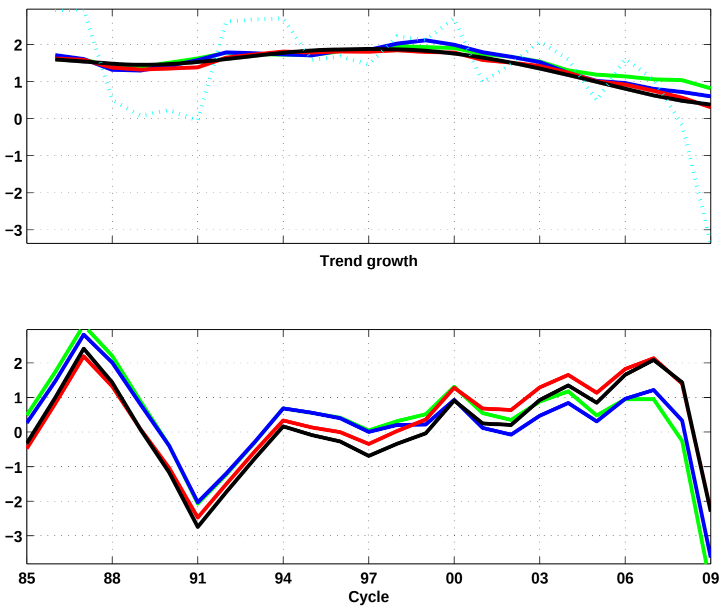


Figure 3 UK Vintage 2009
Prior and posterior distributions, 2009 vintage

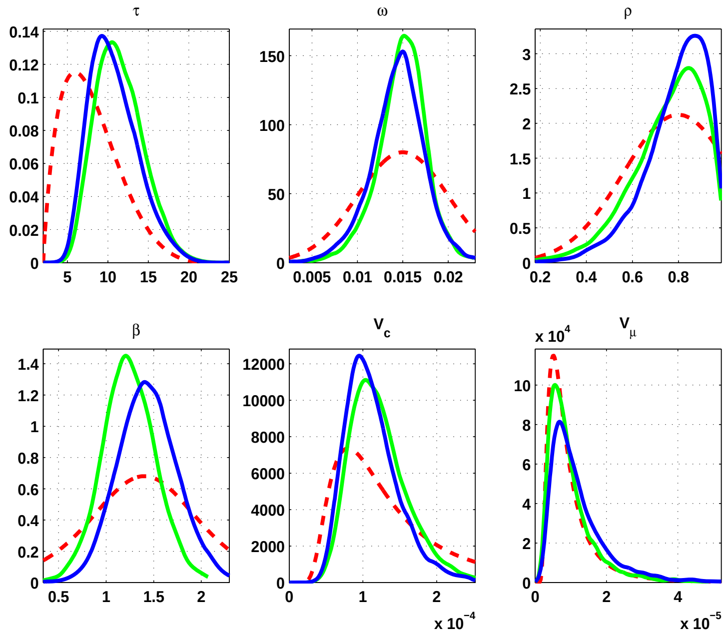


Table 1 UK Full sample estimation, 2009 vintage
Posterior modes and standard deviations

TFP: $\Delta p_t = \mu_t \quad (1-\rho L)\mu_t = (1-\rho)w + a_{\mu t} \quad (1 - 2A cos(2\pi/\tau)L + A^2L^2)c_t = a_{ct}$

CU: $CU_t = \mu_{CU} + \beta c_t + a_{CUt}/(1-\delta L)$

	w	ρ	V_μ	A	τ	V_c	μ_{CU}	δ	β	V_{CU}
CUI										
	0.015	0.87	6.9×10^{-6}	0.65	9.3	9.5×10^{-5}	-0.003	0.78	1.4	25.3×10^{-5}
	(0.003)	(0.14)		(0.13)	(2.95)		(0.01)	(0.21)	(0.32)	
BS										
	0.015	0.84	5.6×10^{-6}	0.69	10.48	10.3×10^{-5}	-0.004	0.77	1.2	27.7×10^{-5}
	(0.003)	(0.15)		(0.12)	(2.9)		(0.01)	(0.22)	(0.29)	

Figure 4 UK Vintage 2009
Paths followed by the 2000-2008 cycle estimates

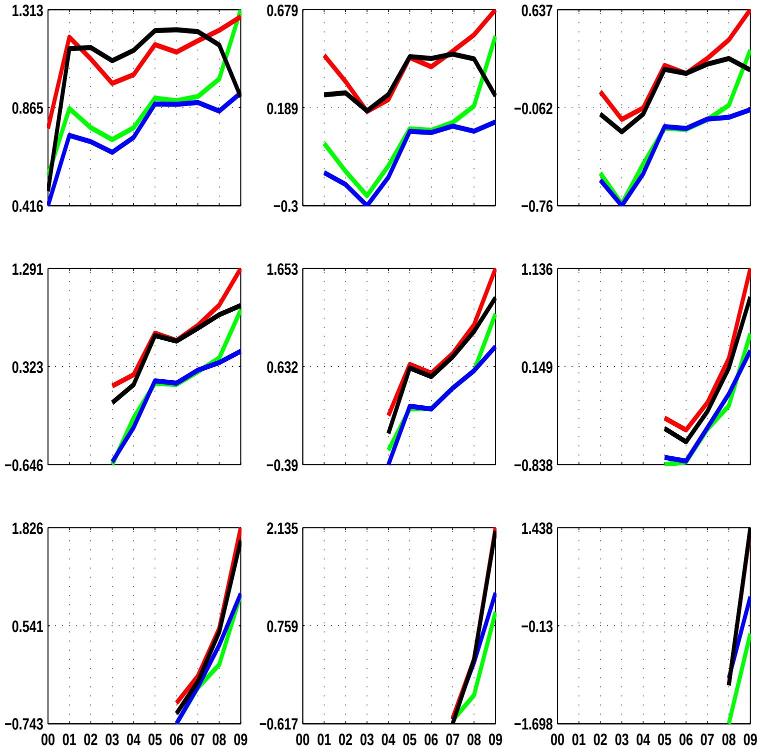
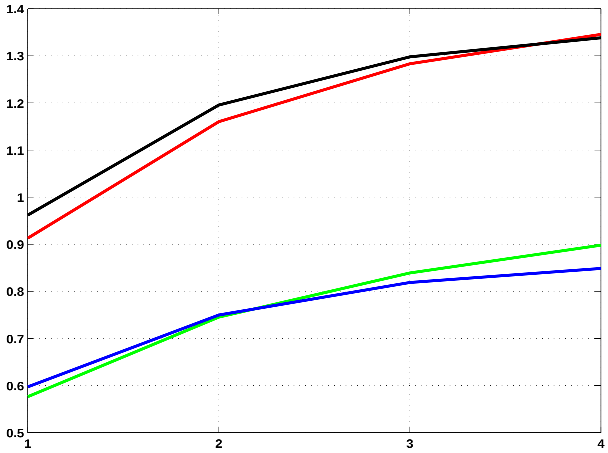


Figure 5 UK Vintage 2009
Revisions standard deviation $(\times 100)$



Additional observations

Figure 6 UK Real-time vintages
Paths followed by the 2000-2008 cycle estimates

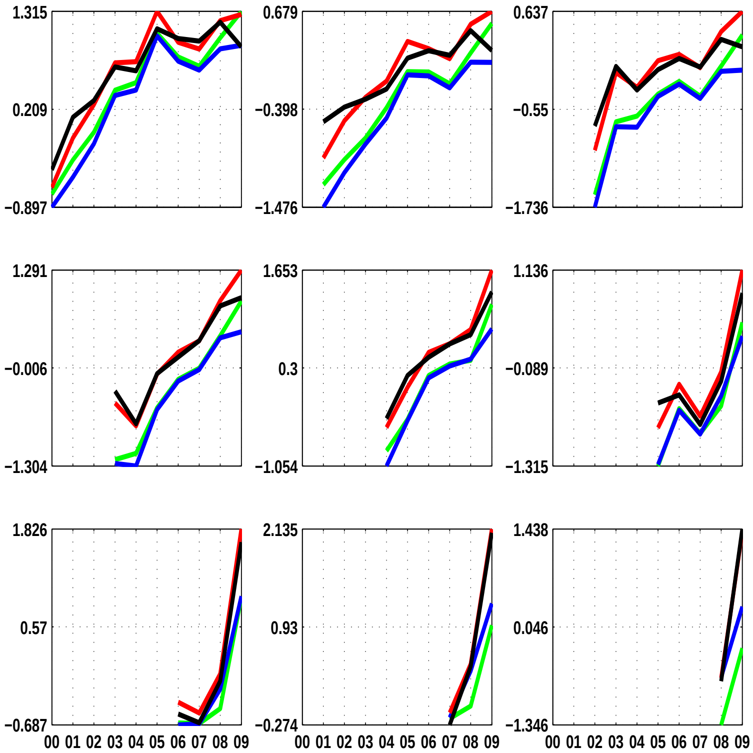
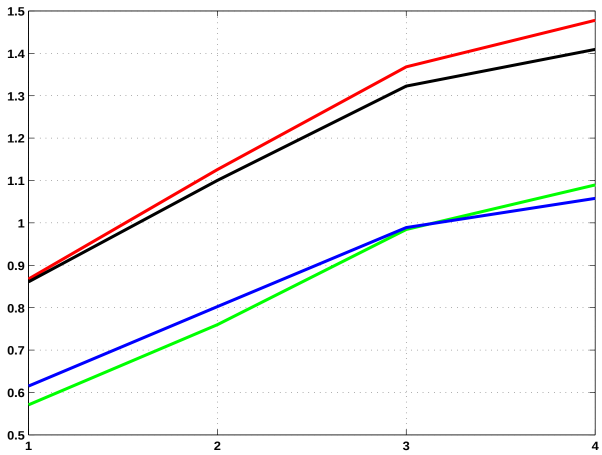


Figure 7 UK Real-time vintages
Revisions standard deviation $(\times 100)$



Additional observations

Summary for UK:

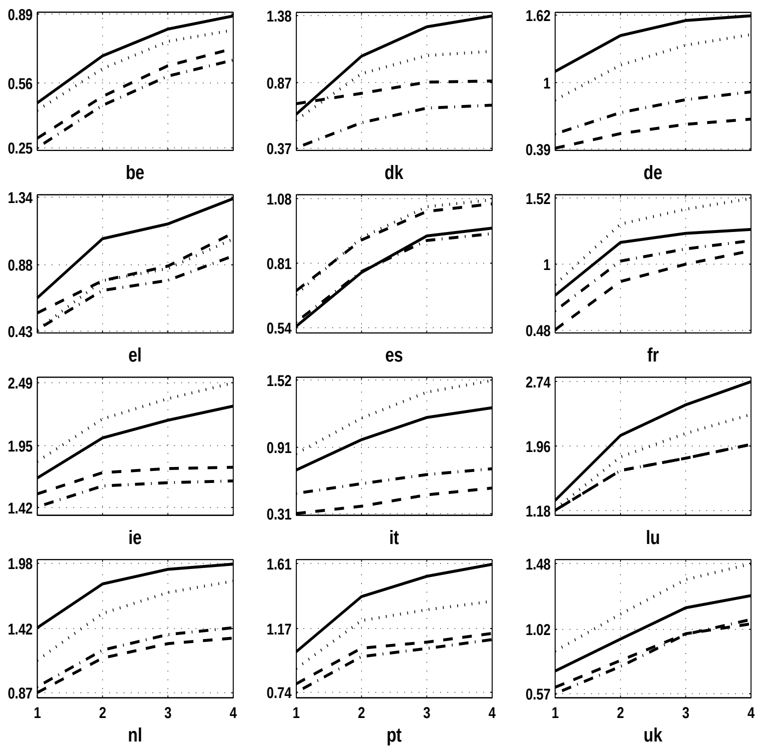
- **TFP data** The 2006-2009 vintages show large differences in the first sample-half with respect to the other vintages. All series show cyclical fluctuations in the 1985-1993 years that disappear afterwards.
  CU data The BS series is slightly more variable in the last years.
  Link TFP-CU The β-coefficient is significantly different from 0. It takes larger values when CUI is used instead of BS.
  Revisions Bivariate model using the CUI and BS series dominate with both 2009 data and real-time dataset.
  CUI vs. BS The two series yield similar results.

For all years 2000-2008, the real-time concurrent estimates obtained with the three methods go through large positive revisions with a sign switch. Concurrent TFP gap estimates are systematically excessively pessimistic.

5 Conclusion

The figure below puts together the revisions standard deviation recorded in real-time for all countries. It can be seen that in all cases the bivariate method improve over the univariate approach. This shows that CU series do have informative content for TFP. The CU improvement makes the bivariate approach more reliable in real-time than HP for all cases. CU series give a better outcome than BS in three cases, ie. DE, IT and FR, BS dominates for DK, ES, IE, and the two series give equivalent results for the other countries. The β-coefficient is significant for all countries, with posterior mode higher than one except for EL.

Real-time vintages
Revisions standard deviation ($\times 100$)



The analysis thus shows that especially around boom bust episodes, the use of cyclical indicators leads to less revisions and sign changes of the TFP gap.

6 Appendix

6.1 IG-priors for variance parameters

Table A1
Mean and standard deviation of IG-variance priors

	BE	**DE**	**DK**	**EL**	**ES**	**FR**	**IE**	**IT**	**LU**	**NL**	**PT**	**UK**
$V_c(\times 10^{-4})$	1.6	1.6	1.6	1.7	2.0	1.6	14	1.6	3.8	2.6	2.4	1.6
$V_\mu(\times 10^{-6})$	2.4	2.4	22	20	1.2	8.0	40	2.0	20	1.0	20	10
$V_{CU}(\times 10^{-4})$	4.8	16.3	9.3	2.8	3.1	3.6	12.8	1.8	6.4	1.8	9.3	5.1

The prior distribution of variance parameters are tuned so that mean and standard deviations are equal.

6.2 Correlations between CU series.

Table A2 Correlations between CU series

	Corr(CUI,BS)	Corr(CUI,PMI)	Corr(BS,PMI)
BE	.917	—	—
DE	.862	.906	.863
DK	.824	—	—
EL	.660	—	—
ES	.733	.868	.766
FR	.647	.792	.742
IE	.881	.837	.862
IT	.927	.883	.920
NL	.827	—	—
PT	.918	—	—
UK	.929	.784	.828

7 References

Denis C., Mc Morrow K. and Roeger W. (2002), "Production function approach to calculating potential growth and output gaps - estimates for the EU Member States and the US", European Economy, Economic Papers nr. 176, European Commission.

Denis C., Grenouilleau D., Mc Morrow K. and Roeger W. (2006), "Calculating potential growth rates and output gaps - A revised production function approach", European Economy, Economic Papers nr. 246, European Commission.

European Commission (2005), "New and updated budgetary sensitivities for the EU budgetary surveillance", ec.europa.eu/economy_finance/sg_pact_fiscal_policy/sg_programmes9085_en.htm.

European Commission (2008), *Public finance in EMU - 2008*, European Economy, 4-2008, Brussels: European Commission.

Hodrick R.J. and E.C. Prescott (1997), "Post-war U.S. business cycle: an empirical investigation", *Journal of Money, Credit and Banking*, 29, 1, 1-16.

Kuttner K. (1994), "Estimating potential output as a latent variable", *Journal of Business and Economic Statistics*, 12, 3, 361-368.

Marcellino, M. and A. Musso (2008), "Real time estimates of the euro area output gap". European University Institute, mimeo.

Pierce, D.A. (1980), "Data Revisions in Moving Average Seasonal Adjustment procedures", *Journal of Econometrics*, 14, 1, 95-114.

Planas C. and Rossi A. (2004), "Can inflation improve the real-time reliability of output gap estimates?", *Journal of Applied Econometrics*, 121-133.

Planas C., Rossi A., and Fiorentini G. (2008), "Bayesian analysis of the output gap", *Journal of Business & Economic Statistics*, 19, 1, 18-32.

Proietti T., Musso T., and Wastermann T. (2007), "Estimating potential output and output gap for the euro area: a production function approach ", *Empirical Economics*, 33, 85-115.

Runstler, G. (2002), "The information content of real-time output gap estimates: an application to the euro area". European Central Bank Working Paper 182.

Stock J. and Watson M. (1998), "Median unbiased estimation of coefficient variance in a time-varying parameter model", *Journal of the American Statistical Association*, 349-358.