European Commission

ISSN 2443-8022 (online)

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DISCUSSION PAPER 198 | JANUARY 2024

EUROPEAN ECONOMY

Economic and Financial Affairs

European Economy Discussion Papers are written by the staff of the European Commission's Directorate-General for Economic and Financial Affairs, or by experts working in association with them, to inform discussion on economic policy and to stimulate debate.

Authorised for publication by Géraldine Mahieu, Director for Investment, growth and structural reforms.

This paper exists in English only and can be downloaded from https://economy-finance.ec.europa.eu/ecfin-publications_en.

Luxembourg: Publications Office of the European Union, 2024

PDF ISBN 978-92-68-01763-0 ISSN 2443-8022 doi: 10.2765/11828 KC-BD-23-015-EN-N

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Abstract

The EU's Commonly Agreed Methodology (EUCAM) is used by the European Commission to estimate potential output and the output gap in order to appraise the productive capacity and the cyclical position of the EU economies. This paper assesses the robustness of the decomposition between trend and cyclical total factor productivity, two quantities involved in EUCAM which are notoriously difficult to disentangle in real-time. In 2010 EUCAM was extended to incorporate additional information about capacity utilisation in this detrending. The robustness of the trend-cycle decomposition of total factor productivity is assessed with respect to variations in the prior distribution of model parameters, in the set of indicators used to proxy capacity utilisation, and in the assumption of cyclical symmetry. The analysis shows that EUCAM is reasonably robust to the departures in model assumptions examined.

JEL Classification: C52, E32, D24.

Keywords: Business Fluctuations, Total Factor Productivity, Model Comparison.

Acknowledgements: We are grateful to Valerie Vandermeulen and to the members of the EPC's Output Gap Working Group for useful comments.

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ABBREVIATIONS

AT Austria

BE Belgium

BG Bulgaria

CY Cyprus

CZ Czechia

DE Germany

DK Denmark

EE Estonia

EL Greece

ES Spain

FI Finland

FR France

HU Hungary

HR Croatia

IE Ireland

IT Italy

LT Lithuania

LU Luxembourg

LV Latvia

MT Malta

NL Netherlands

PL Poland

PT Portugal

RO Romania

SE Sweden

SI Slovenia

SK Slovakia

EU14: AT, BE, DE, DK, EL, ES, FI, FR, IE, IT, LU, NL, PT, SE.

Post-2004 Accession Countries: BG, CY, CZ, EE, HR, HU, LT, LV, MT, PL, RO, SI, SK.

EU27: EU14 + Post-2004 Accession Countries.

EUCAM: European Union’s Commonly Agreed Methodology.

RMSRE: Root Mean Square Revision Error.

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1 INTRODUCTION

Potential output and the output gap provide essential tools to gauge the cyclical position of the economy and its productive capacity. In the frame of the economic and fiscal policy of the EU, the output gap enables the calculation of the structural budget balances of the Member States while potential output helps assessing the sustainability of public debts. Potential output is also relevant for evaluating the effectiveness of structural reforms aimed at boosting the productive capacity of EU countries. The European Commission estimates these two quantities by applying the EU's Commonly Agreed Methodology (EUCAM) discussed at the Economic Policy Committee's Output Gap Working Group and endorsed by the Ecofin Council (see Havik et al., 2014). As it relies on the Cobb-Douglas production function, EUCAM involves the estimation of trend and cyclical Total Factor Productivity (TFP), two quantities which are notoriously difficult to disentangle in real-time (see e.g. Kahn and Rich, 2007). In 2010, the previously used Hodrick-Prescott filter was replaced with a Bayesian model which exploits the link between the TFP cycle and capacity utilisation. This paper assesses the robustness of this upgraded TFP decomposition. The methodology is challenged with respect to variations in the prior distribution of model parameters, in the set of survey indicators used to proxy capacity utilisation, and in the assumption of cyclical symmetry. To assess robustness, the focus is put on the smoothness of potential growth, on the amount of commonality between the TFP cycle and capacity utilisation, and on the stability of the estimates across vintages. Special attention is paid to the variation recorded with respect to the EUCAM estimates.

Whenever possible, EUCAM makes use of economic knowledge so prior distributions are generally informative. For instance, the study of business cycles has led to the broad consensus that expansions typically last about eight years. Trend smoothness is also a strong requirement, motivated by the perception that permanent changes take place at a slower pace than transitory ones. Not all parameters can however benefit from such insights. Because prior distributions carry some degree of subjectivity, it is important to assess their impact on the estimation results. Traditional methods to analyse sensitivity to priors include the informal approach, the local and the global sensitivity analysis (Berger, Rios Insua, and Ruggeri, 2000). Local sensitivity analysis monitors the change in posterior estimates that follows from local perturbations in the baseline prior, with the advantage that the most influential parameters are easily identified. In the EUCAM context, it points out the importance of the prior distribution for the magnitude of the shocks to potential TFP growth. Emphasis is indeed put on small values, which is justified by the need to obtain potential growth estimates that respect the smoothness requirement in presence of noisy data. For the other parameters, the EUCAM priors do not appear very informative compared to the data: local variations in prior means are found to hardly affect the trend-cycle decomposition, even when compounded effects are taken into account. Local perturbations being arbitrary small, the local sensitivity analysis has however the drawback that any evidence of robustness remains questionable. It is thus worth completing it with an informal approach where more extreme departures from the baseline prior are examined. Following the suggestion of Ademmer et al. (2017), we focus on the model for capacity utilisation. We find that the TFP decomposition is generally robust to the prior for the parameters of the capacity utilisation equation.

Carstensen, Kiebner, and Rossian (2023) argue that incorporating further business cycle indicators could be advantageous. We thus experiment with the set of 12 domestic survey indicators utilised by Carstensen et al. (2023), which includes new orders in intermediate and production goods sectors, book orders, production expectations, the level of confidence in the main sectors plus the economic sentiment indicator. Not all these indicators measure capacity utilisation in a strict sense: new orders, book orders, and production expectations for instance may be expected either to anticipate the degree of commitment of resources rather than to describe its current level, or to be better related to the change in capacity utilisation. Similarly to Carstensen et al. (2023), the indicators are handled in one- and two-step procedures: the two-step approach replaces the EUCAM indicator of capacity utilisation with the first principal component of a subset of indicators, while the one-step approach adds all the 12 indicators at the cost of a modification of the original model. Variations in the TFP trend-cycle decomposition exceeding 1 pp. with both the one- and two-step approaches occur in seven countries. Note that a certain degree of sensitivity to the indicators must be deemed acceptable. Aggregating the indicators into a principal component yields a decomposition which is always closer to EUCAM compared to using all indicators in a disaggregated way, most probably because aggregating enables maintaining the original specification. Finally, no stabilisation effect appears: the revisions remain roughly equal across methods.

A prevailing view in the business cycle literature is that the economic cycle evolves following asymmetric patterns. Tests of skewness and coskewness indeed confirm the presence of asymmetry in TFP and capacity utilisation series from a majority of Member States. We thus compare EUCAM to alternative models for the TFP cycle which take asymmetry into account. We focus on the Kim and Nelson (1999) econometric implementation of the Friedman's (1993) plucking model. The original formulation however foresees a negative mean for the TFP cycle, which contrasts with EUCAM where the TFP cycle is centred on zero. We thus adapt the Kim and Nelson model to produce a zero-mean TFP cycle in spite of the alternating regimes. Given the outcome of the skewness and coskewness tests, a further model is tested where asymmetry lies both in the cyclical shocks and in the idiosyncratic shocks of capacity utilisation series. The analysis shows that extending EUCAM to account for asymmetries has only a moderate impact on the TFP decomposition.

Overall, the three exercises suggest that the TFP decomposition in EUCAM is reasonably robust to the departures in model assumptions examined. Three regularities appear: focusing on vintage Autumn 2022, (i) the estimation results are more stable in the 14 'old' Member States (EU14) compared to the post-2004 Accession Countries, (ii) for each country the potential growth estimates show more firmness than trend-cycle ones; across vintages, (iii) the changes in model assumptions explored do not lead to improvements in the stability of trend-cycle estimates. Regularity (i) can be expected to dissipate in the future with the incoming of additional observations. Regularity (ii) suggests that potential growth is better captured than the output gap, which is probably due to its larger persistence. Regularity (iii) is consistent with the possibility that the revisions in trend-cycle estimates are mostly due to the corrections in TFP data.

Section 2 describes the EUCAM model to detrend TFP. Section 3 investigates the sensitivity to prior distributions. Section 4 considers extending the set of indicators to proxy capacity utilisation. Section 5 discusses asymmetry in the TFP cycle. Section 6 concludes.

2 THE TFP MODEL IN EUCAM

In EUCAM, TFP is calculated using a Cobb-Douglas production function with constant return to scale and output elasticity to labour equal to 0.65. It is then assumed that the Solow residual $sr = \log TFP$ is made up of a trend p_t plus a cycle c_t which is related to the degree of capacity utilisation cu as in:

$$\begin{aligned} sr_t &= p_t + c_t \\ cu_t &= \mu_{cu} + \beta_{cu} c_t + e_{cut} \end{aligned} \quad (1)$$

where e_{cut} is an unobserved stochastic element. The link between capacity utilisation and the TFP cycle arises from an enriched formulation of the production function where capacity utilisation modulates the intensity of commitment of the input factors (Planas, Roeger, and Rossi, 2007). Trend TFP depends instead on the efficiency of the exploitation of the input factors implied by the level of technology and is thus unobserved. The trend and cycle components of TFP, and the idiosyncratic portion e_{cut} of capacity utilisation, evolve according to independent stochastic linear processes such as:

$$\begin{aligned} \Delta p_t &= \mu_p + \eta_{t-1} \\ \eta_t &= \phi_\eta \eta_{t-1} + a_{\eta t} \\ c_t &= 2\ A cos(2\pi/\tau) c_{t-1} - A^2 c_{t-2} + a_{ct} \\ e_{cut} &= \phi_{cu} e_{t-1} + a_{cut} \end{aligned} \quad (2)$$

where Δ denotes first-difference, and $a_{\ell t}$, $\ell = \eta, c, cu$, are normally-distributed white noises with variance V_ℓ. The use of stochastic models is consistent with the view that the TFP trend and cycle are inherently unstable. The cyclical fluctuations of c_t are described in terms of amplitude A and periodicity τ. A first-order autoregressive process is considered for e_{cut} in the case of FI, FR, and SI; for the other countries a simple white noise process is used, i.e. $\phi_{cu} = 0$ and $e_{cut} = a_{cut}$. Model (1)-(2) is fitted to the Solow residual augmented with two preliminary forecasts and to an indicator of capacity utilisation built upon survey information in industry, services, and construction sectors provided by the European Commission's Business and Consumer Survey (Havik et al., 2014). The estimation period starts in 1980 for EU14 and 1995 for the post-2004 Accession Countries, but few observations for the capacity utilisation indicator are missing in the first years.

3 SENSITIVITY TO PRIOR DISTRIBUTIONS

Model parameters and unobserved components are estimated in the Bayesian framework (Planas and Rossi, 2020). This requires eliciting a prior distribution for the model parameters, with the advantage that information provided by economic theory and empirical studies can easily be incorporated. Let the $p \times 1$ vector θ gather all parameters of model (1)-(2), i.e. $\theta = (A, \tau, V_c, \mu_p, \phi_\eta, V_\eta, \mu_{cu}, \beta_{cu}, \phi_{cu}, V_{cu})$ with maximum dimension $p = 10$. All parameters are assumed independent *a priori*, except μ_{cu}, β_{cu}, and V_{cu} which are given a Normal-Inverted Gamma-2 (NIG_2) structure (Bauwens, Lubrano, and Richard, 1999, p. 302). For each parameter, the prior distribution in current use is shown in Table 3.1 together with the median value of the prior means and standard deviations across EU27 countries. The priors are summarised in terms of median because of a strong heterogeneity across countries of the prior distribution of variance parameters.

Given the set of observations $y = (y_1, \cdots, y_T)$ where $y_t = (sr_t, cu_t)$, $t = 1, \cdots, T$, and the prior distribution $\pi(\theta|h_0)$ indexed by the vector of hyper-parameters h_0, Bayesian estimates of the cycle and potential growth are obtained as the posterior means $E(c_t|y, h_0)$ and $E(\Delta p_t|y, h_0)$.

Table 3.1 **Local sensitivity analysis - Median values across EU27**

	Prior distribution			$\sigma^2_{po}/\sigma^2_{pr}$	Average derivative $\|\| \frac{D_{\cdot\ell}}{T} \|\|$	
	Shape	μ_{pr}	σ_{pr}		Cycle	Pot. growth
V_η	IG_2	7.5×10^{-6}	7.5×10^{-6}	4.85	618.2	251.9
V_c	IG_2	1.0×10^{-3}	1.0×10^{-3}	0.01	4.29	1.75
V_{cu}	NIG_2	3.5×10^{-3}	3.5×10^{-3}	0.01	0.81	0.32
μ_{cu}	NIG_2	2.5×10^{-4}	3.1×10^{-2}	0.10	0.08	5.7×10^{-3}
μ_p	N	1.5×10^{-2}	1.0×10^{-2}	0.17	1.7×10^{-2}	7.3×10^{-3}
A	$B_{[0,.99]}$	0.42	0.17	0.45	1.0×10^{-2}	4.3×10^{-3}
β_{cu}	NIG_2	1.40	0.71	0.20	2.4×10^{-3}	1.0×10^{-3}
ϕ_η	$N_{[0,.99]}$	0.80	0.24	0.14	1.8×10^{-3}	0.9×10^{-3}
ϕ_{cu}	$N_{[-.97,.97]}$	0.0	0.40	0.17	1.8×10^{-3}	3.8×10^{-4}
τ	$B_{[2,ub]}$	8.0	3.2	0.72	1.0×10^{-3}	3.4×10^{-4}

Notes: μ_{pr} and σ_{pr} refer to the prior mean and standard deviation; $\sigma^2_{po}/\sigma^2_{pr}$ gives the posterior to prior variance ratio; subscript intervals like $[0,.99]$ refer to a truncation; for the periodicity parameter τ, the upper bound of the truncation interval $[2,ub]$ depends on the country, namely $ub = 32$ for EU14 and $ub = 17$ for post-2004 Accession Countries.

These posterior means are calculated by averaging the expected value of c_t and Δp_t given y and θ over the parameter posterior distribution $\pi(\theta|y,h_0)$ such that $\pi(\theta|y,h_0) \propto \pi(y|\theta)\pi(\theta|h_0)$, $\pi(y|\theta)$ being the likelihood function, as in $E(c_t|y,h_0) = \int E(c_t|y,\theta)\pi(\theta|y,h_0)d\theta$.

3.1. LOCAL SENSITIVITY ANALYSIS

How the unobserved components posterior mean varies following local departures in the prior mean of model parameters $E(\theta|h_0)$ can be understood through the first-order approximation:

$$E(c_t|y,h) \simeq E(c_t|y,h_0) + \sum_{\ell=1}^{p} \big(E(\theta_\ell|h) - E(\theta_\ell|h_0)\big) \frac{dE(c_t|y,h)}{dE(\theta_\ell|h)} \,|_{h=h_0}$$

where h represent the perturbed vector of hyper-parameters. Millar (2004) shows that the derivative of $E(c_t|y,h)$ respectively to the prior mean $E(\theta_\ell|h)$ is equal to the covariance between the expected value $E(c_t|y,\theta)$ and the derivative of the logarithm of the prior distribution $\pi(\theta_\ell|h)$ with respect to the prior mean $E(\theta_\ell|h)$. The first-order approximation can thus be written as:

$$\begin{aligned} E(c_t|y,h) &\simeq E(c_t|y,h_0) \\ &+ \sum_{\ell=1}^{p} \big(E(\theta_\ell|h) - E(\theta_\ell|h_0)\big) Cov\Big(E(c_t|y,\theta), \frac{d \log \pi(\theta_\ell|h)}{dE(\theta_\ell|h)} |h = h_0\Big) \end{aligned} \quad (3)$$

For each parameter, the first-derivative of the logarithm of the current prior distribution with respect to the prior mean, i.e. $d\log \pi(\theta_\ell|h)/dE(\theta_\ell|h)$, is given in Appendix. Equation (3) thus provides a simple method to evaluate the sensitivity of the EUCAM estimates in a given time-period to small departures in prior means.

Our interest mostly focuses on the estimates for all time-periods. Let v denote the $p \times 1$ vector of deviations in prior means with typical element $v_\ell = E(\theta_\ell|h) - E(\theta_\ell|h_0)$, and D the $T \times p$ matrix of derivatives with typical element $D_{t\ell} = Cov\big(E(c_t|y,\theta), d\log\pi(\theta_\ell|h)/dE(\theta_\ell|h)|_{h=h_0}\big)$. The first-order approximation (3) applied to the $T \times 1$ vector of cycle variables $c = (c_1, \cdots, c_T)'$ can be written as:

$$E(c|y,h) \quad \simeq \quad E(c|y,h_0) + Dv \tag{4}$$

A first question of interest is which parameter is most influential. If only the prior mean of parameter ℓ is changed by v_ℓ in a one-at-a-time (OAT) sensitivity analysis, then the deviation from the initial vector of cycle estimates is given by:

$$|| \, E(c|y,h) - E(c|y,h_0) \, || \quad = \quad || \, v_\ell D_{\cdot\ell} \, || = | \, v_\ell \, | \, || \, D_{\cdot\ell} \, ||$$

where $D_{\cdot\ell}$ represents the ℓ-th column of D and $|| \, D_{\cdot\ell} \, ||$ its L_2-norm. The larger the derivative norm $|| \, D_{\cdot\ell} \, ||$ and the larger the impact of a deviation v_ℓ from the prior mean. The norm of the vector of derivatives thus gives an indication about the relative importance of each parameter.

Table 3.1 shows the results for the EUCAM prior distributions in median value across EU27 countries. The derivative norm is displayed in average over the T time-periods. The parameters are sorted in decreasing order of importance with respect to cycle estimation. Median values are reported instead of averages due to the occurrence of outliers in the derivatives, especially for variance parameters. Table 3.1 also reports the ratio of the posterior to prior variance $\sigma^2_{po}/\sigma^2_{pr}$ for each parameter, still in median value. This ratio is advocated by Muller (2012) as a summary of the amount of data information relatively to the prior information. For instance, a ratio close to zero indicates that the data are much more informative than the prior so the prior is not influential. On the opposite a ratio greater than 1 indicates that the prior restrains the parameter, in which case a change in prior is likely to generate a change in the posterior mean.

With a median value of the posterior to prior variance ratio equal to 4.85, the prior distribution of the variance of the shocks to potential growth V_η is strongly restrictive[1]. The need to get potential growth estimates that respect the smoothness requirement justifies the elicitation of a prior distribution for V_η that emphasises small values. For most countries, choosing a less restrictive prior would lead to an excessively erratic trend estimate. For all other parameters, the prior distribution appears to be of limited importance. In particular, given the prior on V_η, the likelihood function pins well down the variance of the cyclical and idiosyncratic shocks. Among the non-variance parameters, with a median value of the posterior to prior variance ratio equal to 0.72, the most informative prior distribution regards the cycle periodicity τ for which use could be made of the empirical knowledge about business cycles. The derivatives in Table 1 confirm that for the trend-cycle decomposition, the most influential parameter is V_η: a change by one prior standard deviation in the prior mean of V_η implies a median shift by 0.5 pp. in the estimates of the cycle in each time-period - $100 \times 7.5\,10^{-6} \times 681.2 = 0.51$ pp. - and by 0.19 pp. for potential growth. More stability is recorded for the other parameters.

This analysis considers variations in one prior mean at a time. Compounded effects take place when all parameters are updated simultaneously, as in Basu, Jammalamdaka, and Liu (1996).

[1]There are few exceptions however, namely AT, CY, CZ, HR, IT, and MT, where the ratio is less than one.

In this case the deviation taken on average along the time dimension amounts to:

$$\frac{1}{\sqrt{T}} \mid\mid E(c|y,h) - E(c|y,h_0) \mid\mid \quad = \quad \sqrt{\frac{v'D'Dv}{T}}$$

The vector of deviations v being arbitrary, we concentrate on the one that implies the maximum discrepancy in posterior estimates. Following Muller (2012), we express the deviations in units of prior standard deviations. Let Σ_p denote the $p \times p$ matrix of prior variances, or marginal prior variance in the case of NIG_2 distributions. Some prior standard deviations may be excessively large for a local analysis in multidimensions, so we introduce a re-scaling with the $p \times 1$ vector of weights w. In the univariate case, the deviation v_ℓ can be expressed in units of the re-scaled prior standard deviation as in $v_\ell = u_\ell \times w_\ell \sigma_{pr\ell}$ for some u_ℓ with $u_\ell = \pm 1$ so that the deviation can assume positive or negative directions. This implies that $(v_\ell / w_\ell \sigma_{pr\ell})^2 = 1$. The multivariate analogue for a $p \times 1$ vector v of deviations is $v'(W'\Sigma_p W)^{-1} v = 1$ where W is a diagonal matrix with the rescaling weights w of its diagonal. For a given set of weights, we seek the vector v that solves:

$$\max \mid\mid E(c|y,h) - E(c|y,h_0) \mid\mid^2 \quad = \quad \max_{v:\, v'(W\Sigma_p W')^{-1}v=1} v'D'Dv$$

The problem is equivalent to finding $u = (W\Sigma_p W')^{-1/2} v$ such as:

$$u \quad = \quad \underset{u:\, u'u=1}{\text{argmax}}\; u'(W\Sigma_p W')^{1/2} D'D (W\Sigma_p W')^{1/2} u$$

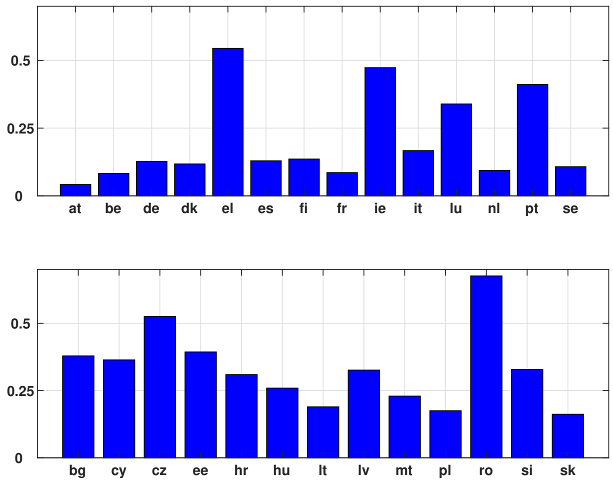
Let λ_1 denotes the largest eigenvalue of $(W\Sigma_p W')^{1/2} D'D (W\Sigma_p W')^{1/2}$. In terms of the L_2-norm, the maximum deviation achieved amounts to:

$$\max \mid\mid E(c|y,h) - E(c|y,h_0) \mid\mid \quad = \quad \sqrt{\lambda_1}$$

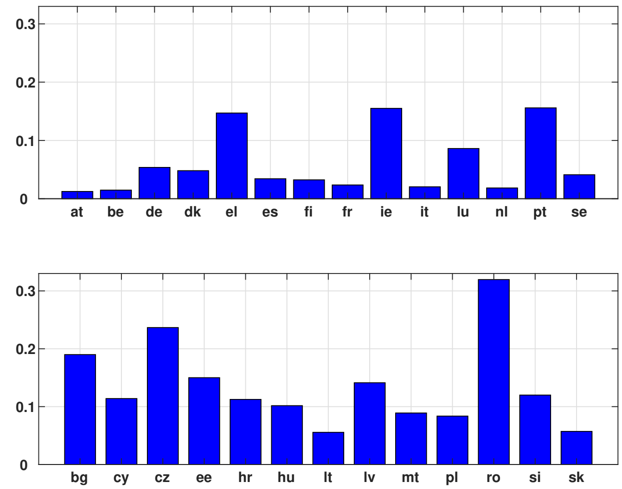
Dividing by $\sqrt{T}$ provides the maximum discrepancy on average for each time-period. Graph 3.1 and 3.2 show the maximum discrepancy $\sqrt{\lambda_1/T}$ in cycle and potential growth estimates for the EU27 countries (in pp.). Given the importance of the prior distribution of V_η highlighted in the OAT analysis, the prior for V_η is left unchanged so the results are conditional on this prior distribution. For the other parameters, changes in prior mean are allowed by up to one-fourth of the prior standard deviation for the variance parameters, and by up to one-half of the prior standard deviation for the remaining ones.

In Graph 3.1, the deviations in cycle estimates are smaller than one-half pp. in 24 cases. The largest discrepancies lie in the interval 0.5-0.67 pp.; they are recorded for CZ, EL, and RO. As expected, potential growth is more stable than the cycle estimates: the variations displayed in Graph 3.2 are smaller than one-quarter pp. in 26 cases. The maximum, one-third pp., is recorded for RO. In general, more instability is detected for the post-2004 Accession Countries: prior assumptions are more important because the sample size in this group of countries is reduced by 15 years compared to EU14.

Graph 3.1 **Maximum discrepancy in cycle estimates (pp.)**



Graph 3.2 **Maximum discrepancy in potential growth estimates (pp.)**



Notes: the maximum variation $\sqrt{\lambda_1/T}$ that can be recorded in each time-period is shown for deviations from prior means by up to 1/4 of the prior standard deviation in the case of variance parameters and by up to 1/2 of the prior standard deviation for the non-variance parameters; the analysis is conditional on the existing prior for V_η.

The evidence of robustness shown in Graph 3.1-3.2 may be seen as questionable since the change in prior means is arbitrary small, even though it is multidimensional. Larger prior variations give rise to larger discrepancies but the first-order approximation (4) looses accuracy. If local sensitivity analysis offers insights about the relative importance of prior and data information for each parameter and about the most influential priors, it inherits the limitations of the Taylor approximation. It is thus worth complementing it with the exploration of larger variations in prior distributions.

3.2. MORE EXTREME DEPARTURES IN PRIOR DISTRIBUTIONS

In their review of EUCAM, Ademmer et al. (2017) reported evidence of sensitivity of the TFP decomposition to the prior distribution of the parameters of the capacity utilisation equation in the case of IT. Referring to these priors, Ademmer et al. (2017) argued that "it is important to check their impact on the estimation results thoroughly". We address this concern using an informal approach (Berger, Rios Insua, and Ruggeri, 2000) where the importance of the prior of the parameters in the capacity utilisation equation (1) is assessed by comparison against using the flat alternative:

$$\begin{aligned} 5(\mu_{cu}+0.1) &= B(1.1,1.1) \\ \beta_{cu}/5 &= B(1.1,1.1) \\ V_{cu}/V_{cu}^{max} &= B(1.1,1.1) \end{aligned} \tag{5}$$

where $B(1.1, 1.1)$ denotes the Beta distribution with hyperparameters set equal to 1.1, which is almost uniform. The re-scaling of the variables in the left-hand-side of (5) imposes $\mu_{cu} \in [-0.1, 0.1]$, $\beta \in [0, 5]$, and $V_{cu} \in [0, V_{cu}^{max}]$, where V_{cu}^{max} is a given number, for instance the variance of capacity utilisation in a previous vintage. The prior distribution of the other parameters is left unchanged.

Flat priors constitute an extreme case in which no information is added on the side of the prior so the shape of the likelihood function is left unaltered in the posterior distribution. They are expected to highlight the salient features of the likelihood function, and thus to provide a simple tool to explore the model properties. For instance, in the case of DE, ES, HU, and PT, the flat prior (5) yields a very small posterior variance of the idiosyncratic component, leading to a correlation between capacity utilisation and the Solow residual cycle which is close to 1. This implies that the cycle is almost observed, so the resulting decomposition is invalid. Why the likelihood function puts emphasis on small values of V_{cu} can be understood by checking the dynamic properties of the data autoregressive transformation $\phi_c(L)cu_t$, where $\phi_c(L)$ is the autoregressive polynomial that drives the cycle fluctuations in (2). Writing it as $\phi_c(L) = 1 - \phi_{c1}L - \phi_{c2}L^2$ to simplify, the autoregressive transformation $\phi_c(L)cu_t$ satisfies:

$$\phi_c(L)cu_t = \phi_c(1)\mu_{cu} + \beta a_{ct} + (1 - \phi_{c1}L - \phi_{c2}L^2)a_{cut}$$

The capacity utilisation equation thus implies the following system of second moments:

$$\begin{aligned}
\gamma_0\big(\phi_c(L)cu_t\big) &= \beta^2 V_c + (1 + \phi_{c1}^2 + \phi_{c2}^2)V_{cu} \\
\gamma_1\big(\phi_c(L)cu_t\big) &= \phi_{c1}(-1 + \phi_{c2})V_{cu} \quad < 0 \\
\gamma_2\big(\phi_c(L)cu_t\big) &= -\phi_{c2}V_{cu} \quad > 0
\end{aligned} \tag{6}$$

where $\gamma_k\big(\phi_c(L)cu_t\big)$ refers to the lag-k covariance of $\phi_c(L)cu_t$. Given ϕ_{c1}, ϕ_{c2}, and V_c which are determined by the TFP block of equations, the system (6) is over-identified as there are only two parameters, β and V_{cu}, to describe three second moments. In addition, given the amplitude and periodicity parameters A and τ, the autoregressive coefficients are such as $\phi_{c1} = 2A\cos(2\pi/\tau) > 0$ and $-1 < \phi_{c2} = -A^2 < 0$, so first two autocovariances satisfy $\gamma_1(\phi_c(L)cu_t) < 0$ and $\gamma_2\big(\phi_c(L)cu_t\big) > 0$. When the data reject these restrictions, the smaller the value of V_{cu} the smaller the mismatch between the empirical and the model-based moments.

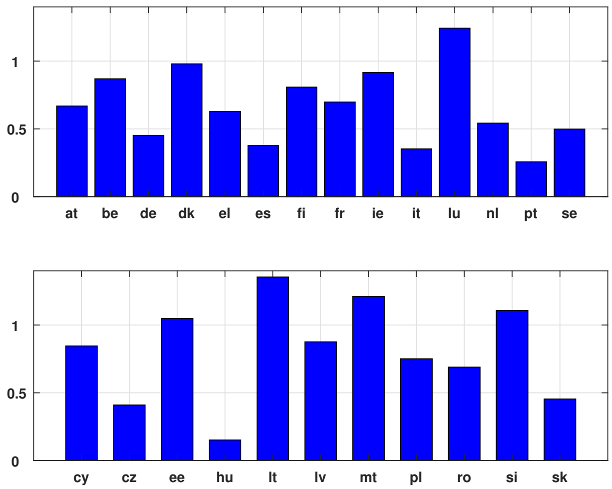
To make possible the use of flat priors also in the case of DE, ES, HU, and PT, the over-identifying restriction is relaxed by introducing a MA(1) term in the process describing the idiosyncratic component as in:

$$e_{cut} = a_{cut} + \theta_{cu}a_{cut-1} \tag{7}$$

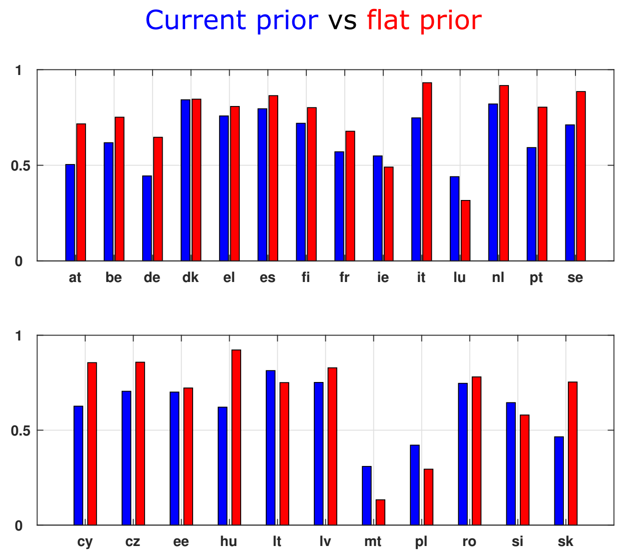
The variance of the idiosyncratic component becomes $V(e_{cut}) = V_{cu}(1 + \theta_{cu}^2)$. Given the flat prior $\theta_{cu} \sim B(1.1, 1.1) \times \mathrm{I}_{(-1,1)}$, the system of equations (1)-(2)-(7) is estimated using the flat priors (5) for $(\mu_{cu}, \beta, V_{cu})$. Hence the prior sensitivity analysis is conducted comparing the current results against the use of flat priors in the original

Empirical evidence is reported for 25 countries, namely EU27 minus BG and HR as EUCAM does not employ capacity utilisation data for these countries. Based on the Autumn 2022 vintage, Graph 3.3 shows the variance of the idiosyncratic component of capacity utilisation estimated with the flat prior in units of the EUCAM estimate. The ratio is calculated using the posterior modes. For 19 countries out of the 25 considered, the use of a flat prior leads to a smaller posterior variance of the idiosyncratic component. The current prior has thus a tendency to inflate the magnitude of the idiosyncratic component of capacity utilisation.

Graph 3.3 **Idiosyncratic component variance under flat priors in units of the current estimate**



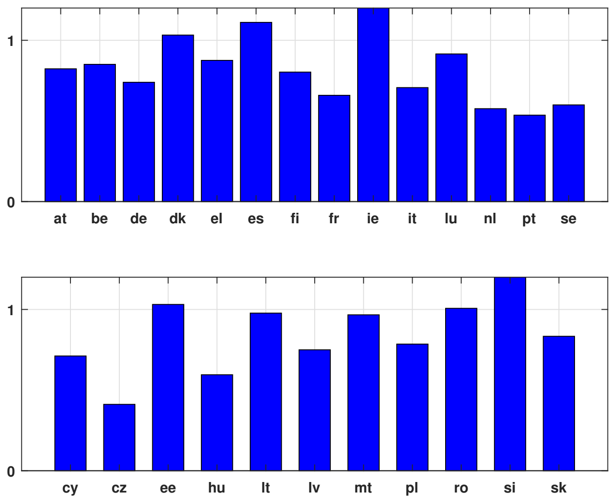
Graph 3.4 **Model-based correlation between capacity utilisation and the Solow residual cycle**



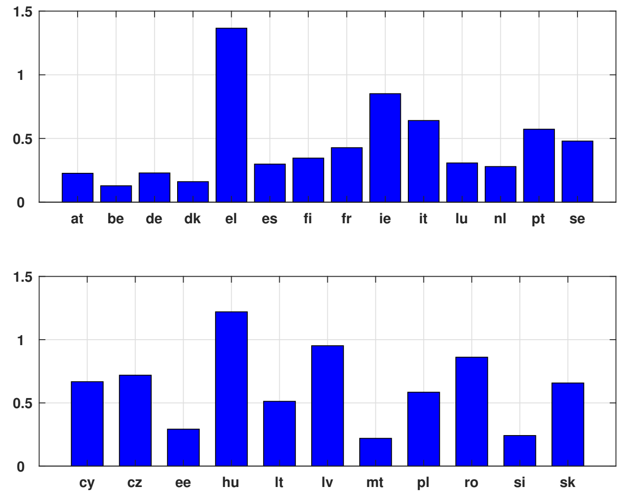
A increased magnitude of the idiosyncratic component can be expected to reduce the amount of commonality between capacity utilisation and the Solow residual cycle, especially if the posterior distribution of β_{cu} is stable. This is confirmed by Graph 3.4 which shows the model-based correlation, still calculated using the parameters posterior mode: it is seen that the correlation increases with the flat prior in all countries excepted IE, LU, MT, PL, and SI.

To summarise the impact of the flat prior on the trend smoothness, Graph 3.5 shows the inverse signal to noise ratio V_c/V_η, calculated using the posterior mode of each variance parameter, in units of the estimate obtained with the current prior. Values above one indicate that the flat prior increases the ratio V_c/V_η and thus yields a smoother trend. Most often the smoothest trend is obtained with the current prior. One possible explanation is that with the current prior, the variance of the cyclical shocks V_c increases together with the variance of the idiosyncratic term in order to hold steady the signal to noise ratio of the capacity utilisation equation, i.e. V_c/V_{cu}. This eventually leads to an increase in V_c/V_η and thus to potential growth estimates that are smoother. In such cases the current prior on V_{cu} contributes to the trend smoothness together with the prior on V_η.

Graph 3.5 **Inverse signal to noise ratio V_c/V_η, in units of the current estimate**

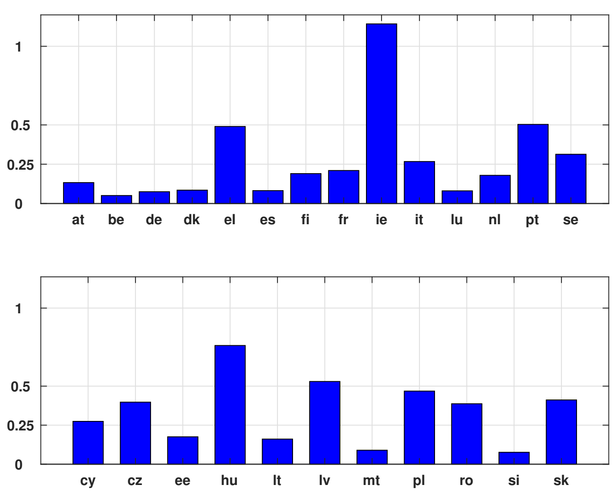


Graph 3.6 **Maximum absolute difference between cycle estimates in the years 2000-2022**



Graph 3.6 shows the maximum absolute variation in cycle estimates for the period 2000-2022 implied by the use of a flat prior for the parameter of the capacity utilisation equation. Only in the case of EL and HU a variation larger than 1.0 pp. is recorded. Potential growth is more stable than cycle estimates: the variations displayed in Graph 3.7 exceed 1 pp. only in the case of IE. As already noticed in the local analysis, the post-2004 Accession Countries show slightly more sensitivity to priors.

Graph 3.7 **Maximum absolute difference between potential growth estimates in the years 2000-2022**



3.3. CONCLUSION

EUCAM relies on a prior distribution for the magnitude of the shocks to potential TFP which puts emphasis on small values. This is justified by the need to obtain potential growth estimates that respect the smoothness requirement in presence of noisy data. For the other parameters, the

EUCAM priors do not appear very informative compared to the data: local variations in prior means hardly affect the trend-cycle decomposition, even when compounded effects are taken into account. The exploration of a more extreme alternative like a flat prior for the parameters of the capacity utilisation equation reveals that trend smoothness is favoured at the cost of a slight reduction in commonality between capacity utilisation and the Solow residual cycle. Nevertheless, the trend-cycle decomposition of the Solow residual appears to be generally robust to the prior of the capacity utilisation equation parameters. Slightly more instability is observed for the post-2004 Accession Countries compared to the EU14 group due to a smaller sample size. EL, IE, and HU are countries where more sensitivity to priors could be detected.

4 ROBUSTNESS TO SURVEY INDICATORS

4.1. ALTERNATIVE INDICATORS

EUCAM takes into consideration the degree of capacity utilisation in the economy. To build the measure of capacity utilisation called CUBS, EUCAM merges an indicator of resource utilisation in industry (CU) together with two economic sentiment indicators that account for resource utilisation in service and construction sectors; details can be found in Annex 3 of Havik et al. (2014). Since univariate methods are not considered, a certain degree of sensitivity to the indicators must be deemed acceptable. Still, it is worth ascertaining that EUCAM delivers a TFP decomposition that does not depend excessively on the set of indicators used to proxy capacity utilisation. For this robustness check, we take as starting point Carstensen et al. (2023) who argue that augmenting EUCAM with additional business cycle indicators can stabilise significantly the TFP decomposition across vintages: they report a 25% reduction in revisions in the concurrent estimates on average across the five largest economies of the euro area. We thus check the robustness of the TFP decomposition to the proxies used for capacity utilisation while also revisiting the empirical evidence reported by Carstensen et al. (2023).

We focus on the 12 domestic survey indicators labelled SUR in Carstensen et al. (2023) which are provided by the European Commission Business and Consumer Surveys: in addition to CU, the SUR group includes new orders in total industry (NO), intermediate, and production goods sectors, book orders (BO), production expectations (PE), and the level of confidence in industry, services, consumers, retail, and construction sectors which are aggregated into the economic sentiment indicator (ESI). Carstensen et al. (2023) also consider domestic hard and international indicators but their results suggest the SUR group is the most relevant one to stabilise the TFP gap estimates. Not all the SUR indicators measure capacity utilisation in a strict sense: new orders, book orders, and production expectations for instance may be expected to anticipate the degree of commitment of resources rather than to describe its current level. Nevertheless, and although Carstensen et al. (2023) find it advantageous for forecasting, we do not experiment with time-shifting the indicators. Instead the indicators are handled in one- and two-step procedures similarly to Carstensen et al. (2023): the two-step approach replaces the CUBS indicator in (1) with the first principal component of CU, NO, BO, PE, and the ESI, while the one-step approach complements CUBS with all 12 indicators. In the one-step approach, model (1)-(2) is augmented with the measurement equations:

$$ind_{\ell t} = \beta_\ell c_t + e_{\ell t} + e_t \qquad \ell = 1, \cdots, 12 \tag{8}$$

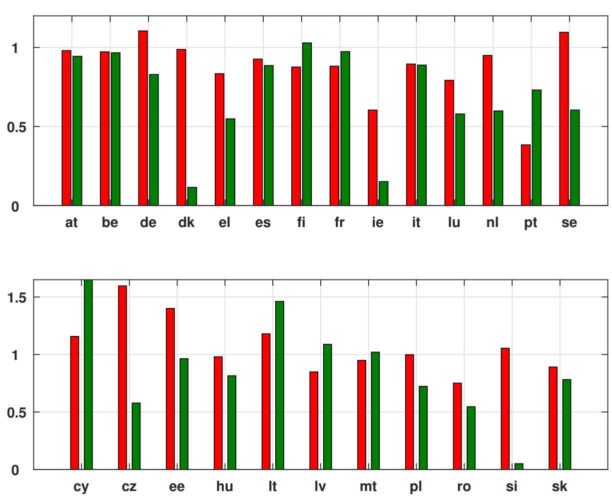
No constant term appears in (8) as the indicators are centered. Compared to (1), equation (8) contains two white noises: $e_{\ell t}$ which is purely idiosyncratic, and e_t which captures the common movements in the indicators which do not have cyclical recurrence. Omitting this common shock leads to estimating a very small variance of the idiosyncratic shocks $e_{\ell t}$ and thus to a cycle estimate that sticks to the cross-section average of the indicators. This eventually produces potential TFP estimates that are excessively erratic. In order to facilitate model comparison, all survey indicators are re-scaled to the empirical variance of CUBS so that the current prior distribution for β_{cu} and V_{cu} can be used for β_ℓ, $V(e_{\ell t})$, $\ell = 1, \cdots, 12$, and $V(e_t)$.

4.2. EMPIRICAL COMPARISON

Graph 4.1 shows the inverse signal to noise ratio V_c/V_η in units of the current estimates; values greater than one indicate further smoothness. Most often, the one-step approach leads to estimating a more erratic potential TFP. Relying on the first principal component only delivers a potential whose smoothness is more similar to EUCAM. This suggests that the differences between the EUCAM and SUR decompositions are mainly due to the change in model specification.

Graph 4.1 **Inverse signal to noise ratio, in units of current estimates**

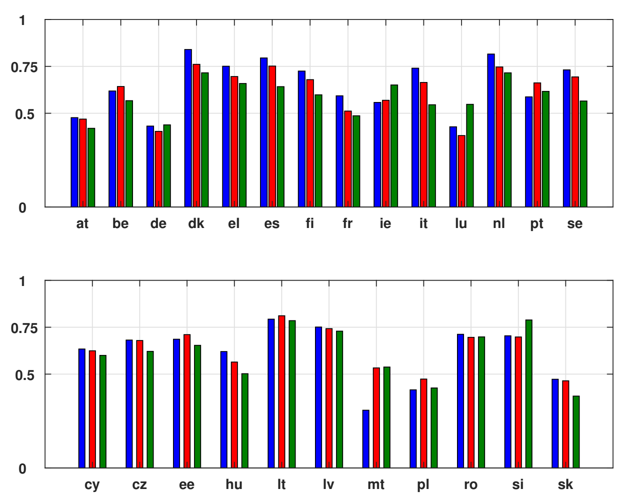
Principal component, all survey indicators



Notes: a ratio V_c/V_η larger than one in units of the current estimate indicates further smoothness.

Graph 4.2 **Model-based correlation between capacity utilisation indicators and the Solow residual cycle**

EUCAM, principal component, all survey indicators



Notes: for the one-step approach, the maximum correlation across indicators is shown.

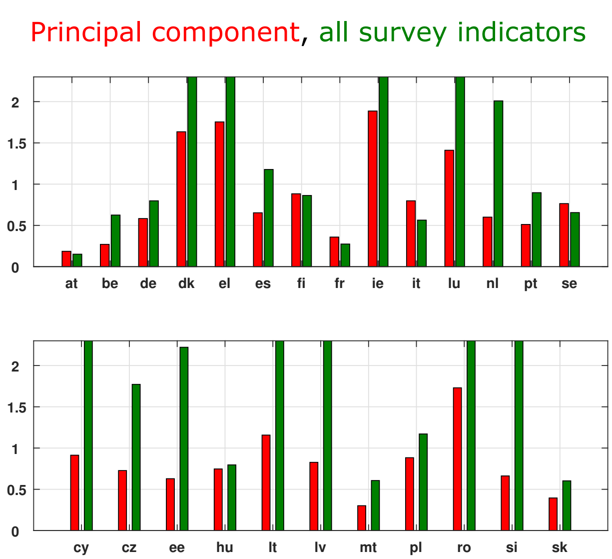
Graph 4.2 shows the model-based correlation between the TFP cycle and, respectively, CUBS, the first principal component, and the SUR indicators. The correlation is calculated using the posterior mode of the model parameters. In the SUR case where the correlation is indicator-dependent, Graph 4.2 shows the maximum value across indicators[2]. It is seen that the one-step approach

[2] In the one-step approach, the correlation is maximised with ESI in seven cases, namely CZ, EE, ES, FI, IE, MT, SK, with CUBS in six cases, namely EL, FR, HU, IT, PT, SE, with CU in five cases, namely BE, DE, DK, NL, PL, and with BO in four cases, namely AT, CY, LU, SI. The sentiment index in industry, construction, and services, provides the largest correlation with the TFP cycle only once in the case of LT, RO, and LV, respectively. NO, BO, and PE instead never appear as most informative indicators.

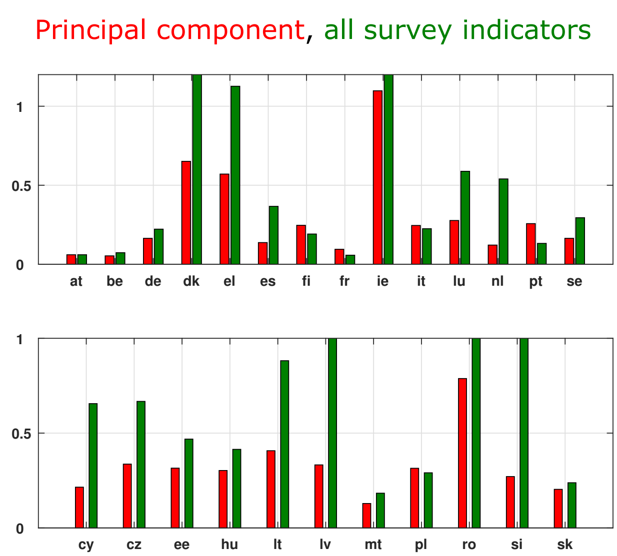
SUR always reduces commonality, most probably because of the additional noise variable e_t that captures the non-cyclical dependence between indicators. Comparing the three approaches, the amount of commonality between the auxiliary variables and the TFP cycle is maximised using CUBS in 60% of the cases, namely nine out of EU14 and six out of the eleven post-2004 Accession Countries.

Graph 4.3 and 4.4 show the maximum absolute discrepancy with respect to the EUCAM cycle and potential growth estimates which is recorded when resorting to the new indicators. According to Graph 4.3, variations in trend-cycle decomposition exceeding 1 pp. with both the one- and two-step approaches occur in seven cases, namely DK, EL, IE, LT, LU, RO, and SI. Potential growth estimates in Graph 4.4 show more stability since variations exceeding 0.5 pp. with both approaches are recorded in only four cases, namely DK, IE, RO, and SI. Most often, aggregating the indicators into a principal component yields a decomposition which is closer to EUCAM compared to using all indicators. The change in model specification may thus play a role. For instance, in the case of DK we could check that the variation in trend-cycle decomposition reduces to 1 pp. if PE and the three new-order series are related to the first-difference of the Solow residual cycle instead of its level. Such a specification also yields a decomposition which differs from EUCAM by 0.6 pp. only compared to 2.0 pp. with the plain one-step approach in the case of NL. For ES and PL, the discrepancy reduces to less than 1.0 pp. when PE and the three new-order series are excluded from the data set.

Graph 4.3 **Maximum absolute distance to the EUCAM TFP cycle estimates Vintage Autumn 2022, period 2000-2022 (pp.)**



Graph 4.4 **Maximum absolute distance to EUCAM TFP potential growth estimates Vintage Autumn 2022, period 2000-2022 (pp.)**



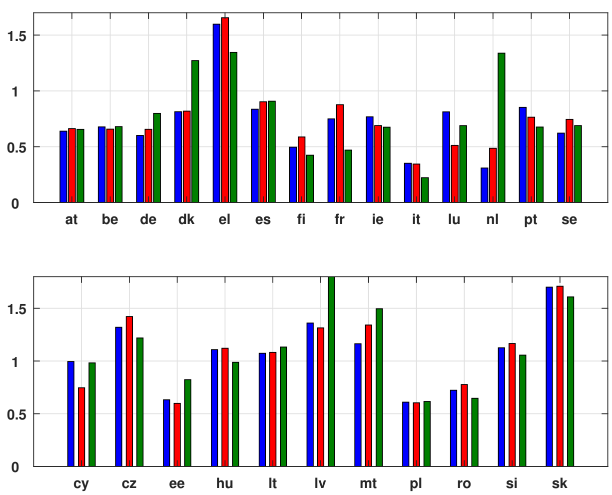
Finally, we check whether the use of additional indicators helps stabilising the decomposition across vintages. To make the exercise as realistic as possible, both real-time TFP data and real-time prior distributions are utilised. The survey indicators are instead not revised. The stability of the TFP decomposition across vintages 2013-2022 is measured by the root mean squared revision error (Rmsre) defined as:

$$\text{Rmsre} \quad = \quad \sqrt{\sum_{\ell=2014}^{2022} (c^{\ell}_{\kappa+\ell-2014} - c^{\ell-1}_{\kappa+\ell-2014})/9} \tag{9}$$

where the superscript ℓ refers to the vintage year, and the subscript κ to the concurrent time-period in vintage 2013, i.e. the time-period corresponding to year 2013 in vintage 2013. The difference $c^{\ell}_{\kappa+\ell-2014} - c^{\ell-1}_{\kappa+\ell-2014}$, $\ell = 2014, \cdots, 2022$, measures the one-step revision in the cycle estimate for time-period $\kappa + \ell - 2014$ due to the vintage update from $\ell - 1$ to ℓ.

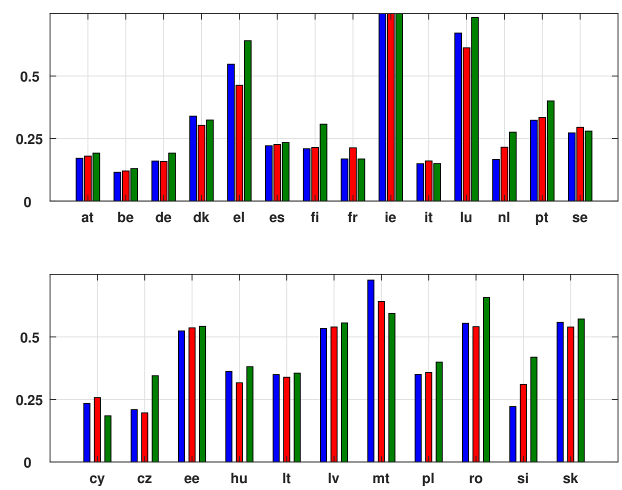
Graph 4.5 **Rmsre in TFP cycle estimates, vintages 2013-2022**

EUCAM, principal component, all survey indicators



Graph 4.6 **Rmsre in potential growth estimates, vintages 2013-2022**

EUCAM, principal component, all survey indicators



Graph 4.5 shows the Rmsre in cycle estimates. Not much difference can be seen between the three methods: on average across countries, the Rmsre in cycle estimates obtained with CUBS, the two- and the one-step approach is equal to 0.88, 0.89, and 0.97 pp., respectively. These values represent roughly 50% of the cross-country average standard error of the EUCAM cycle estimates obtained in Autumn 2022. The only cases where a reduction in Rmsre greater than 20% is observed are CY and LU with principal component and FR, IT, and PT with all indicators. There are also cases where the new indicators inflate instability, like for instance for DK and NL where the increase in Rmsre exceeds 50%.

Graph 4.6 focuses on potential growth. In the case of IE, the abnormal size of the one-step revision, almost 2 pp., is explained by a strong instability in the TFP vintages which follows from the relocation of some intellectual property assets to this country by a small number of firms which have perturbed the calculation of capital stock. Excluding IE, the average across countries of the Rmsre with the CUBS, the two-, and the one-step method amounts to 0.34, 0.34, and 0.38 pp. respectively, which represents roughly 45% of the cross-country average standard error of potential growth in the Autumn 2022 vintage. A 20% reduction in Rmsre is recorded only for CY with all indicators. Otherwise, the new indicators do not help stabilising potential TFP growth estimates compared to CUBS [3].

[3] This outcome does not confirm the results in Carstensen et al. (2023) who report a 25% decrease in revisions

4.3. CONCLUSION

Complementing CUBS with further survey indicators does not seem to improve the TFP decomposition, at least along the dimensions we explored. The one-step approach where all indicators are included without aggregation always reduces the amount of commonality between the TFP cycle and the indicators compared to EUCAM. Aggregating the indicators into a principal component yields a decomposition which is closer to EUCAM compared to the one-step approach, most probably because it preserves the model specification contrary to the one-step alternative which requires removing further noise from the indicators. Also, some indicators like new-orders and production expectations are sometimes more related to the change in TFP cycle rather than to the cycle level. No stabilisation effect appears: EUCAM and the two-step approach yields the equal revisions on average across countries, while the one-step approach increases the magnitude of revisions by roughly 10%, still on average across countries.

5 ROBUSTNESS TO ASYMMETRY MODELLING

Since the first contributions by Neftci (1984), Falk (1986), and Sichel (1993, 1994), many empirical studies have reported evidence of asymmetric patterns in cyclical macroeconomic variables, leading to the prevailing view that the economic cycle evolves asymmetrically. If TFP behaves accordingly, taking asymmetry into consideration may be expected to improve the trend-cycle decomposition. To check whether TFP and CUBS series from EU27 embody asymmetric patterns, we test the significance of the squared moment coefficient of skewness of the univariate innovations in the Solow residual and in the CUBS series, say $\mathcal{I}_{\ell t}$ with standard deviation σ_ℓ, $\ell = sr, cu$, and of the aggregate coskewness which involves the mixed third-moments. These statistics are defined by:

$$
\begin{aligned}
Sk_\ell^2 &= E(\frac{\mathcal{I}_{\ell t}^3}{\sigma_\ell^3})^2 \qquad\qquad \ell = sr, cu \\
ACosk &= 3E(v_{srt}^2 v_{cut})^2 + 3E(v_{srt} v_{cut}^2)^2 \qquad (10)
\end{aligned}
$$

where v_{srt} and v_{cut} denote the standardised innovations[4]. Properly rescaled by $6/T$, the empirical counterparts of (10) are asymptotically χ_d^2-distributed with respectively $d = 1$ and $d = 2$ degrees of freedom. Considering both univariate skewness and aggregate coskewness offers some insights into the source of asymmetry. For instance, since in the EUCAM model $(1) - (2)$ the cyclical shocks a_{ct} are common to the two endogenous variables, significance of aggregate coskewness suggests the presence of asymmetry in the cyclical shocks. In the absence of coskewness, significance of univariate skewness suggests the presence of asymmetry in the shocks to potential growth and to the idiosyncratic portion of capacity utilisation. The empirical results are shown in Table 5.1 for EU27 countries minus BG and HR. All calculations are made using the Autumn 2022 data vintage. Significant values are displayed in bold, the 5% critical value of χ_d^2 distribution with one and two degrees of freedom being respectively equal to 3.84 and 5.99.

following the addition of new survey indicators to proxy capacity utilisation. Possible reasons for the different outcome include the focus on vintages 2013-2022 instead of 2005-2021 in Carstensen et al. (2023), a two-step approach that is simpler than in Carstensen et al. (2023), and the use of real-time priors instead of the Autumn 2021 prior in Carstensen et al. (2023) which may have increased the revision errors.

[4] The standardisation is made by post-multiplying the $T \times 2$ matrix of innovations in model (1)-(2) by their empirical variance-covariance matrix raised to power -1/2.

For 23 countries out of the 25 examined, asymmetry is detected in either or both of the Solow residual and CUBS. The countries where no evidence of asymmetry appears are CY and PL. EE and EL are the only instances where the skewness of TFP is significant but not the coskewness, suggesting asymmetry in the shocks to potential growth. There are 13 countries, namely AT, BE, CZ, EE, FR, IT, LU, LV, MT, PT, RO, SE, and SK, where asymmetry is detected in CUBS while coskewness is not significant, as if asymmetry were present in the idiosyncratic component of CUBS. Coskewness is found significant for nine countries, namely DE, DK, ES, FI, HU, IE, LT, NL, and SI: in these cases asymmetry seems related to the shocks to the TFP cycle. These observations suggest extending the EUCAM model for TFP to account for asymmetry in the TFP cycle and in the idiosyncratic component of CUBS, while leaving unchanged the distribution of the shocks to potential.

Table 5.1 **Tests of skewness and coskewness, vintage Autumn 2022**

	Univariate skewness		Coskewness
	$\log TFP$	CUBS	
AT	1.20	**7.09**	0.58
BE	0.12	**5.49**	1.63
CY	0.00	1.47	0.14
CZ	0.01	**16.25**	0.97
DE	**5.83**	**7.71**	**4.79**
DK	**4.94**	0.95	**4.69**
EE	**5.51**	**3.77**	3.16
EL	**4.29**	2.40	4.22
ES	**34.95**	2.25	**10.32**
FI	**6.93**	**2.84**	**6.74**
FR	1.77	**5.02**	4.31
HU	**2.96**	**4.83**	**5.03**
IE	0.55	**15.86**	**14.19**
IT	0.58	**7.38**	0.96
LT	**6.11**	**11.00**	**9.48**
LU	0.74	**16.24**	3.44
LV	2.01	**14.63**	2.93
MT	0.27	**8.75**	1.22
NL	**4.54**	**7.68**	**13.34**
PL	0.01	0.66	1.41
PT	1.67	**8.07**	2.20
RO	0.19	**3.51**	1.80
SE	1.43	**2.81**	1.59
SI	**6.22**	**10.08**	**8.60**
SK	1.50	**3.87**	4.54

Notes: the 10% critical value of a χ^2_d with one and two degrees of freedom are respectively equal to 2.71 and 4.61.

To incorporate asymmetry we turn to the Kim and Nelson (1999) econometric implementation of the plucking model put forward by Friedman (1993). Friedman built the plucking model upon the observation that stronger expansions tend to follow deeper recessions but stronger booms are not necessarily followed by deeper recessions. Hartley (2021) confirmed the plucking hypothesis in a panel regression involving 169 countries, and Mills and Wang (2003) successfully tested the Kim and Nelson model on GDP data from the G-7 countries. As it includes a trend-cycle decomposition, the Kim and Nelson model fits well into the EUCAM framework, but some adaptation remains necessary.

5.1. ADAPTING THE KIM AND NELSON MODEL TO ACCOUNT FOR ASYMMETRY

Kim and Nelson introduce asymmetry in a trend-cycle decomposition by substituting the standard Gaussian assumption for the cyclical shocks with a mixture of normal distributions as in:

$$\phi_c(L)c_t = \begin{cases} a_{ct} & S_t = 1 \\ -\lambda_c + (1+\delta_c)a_{ct} & S_t = 0 \end{cases} \tag{11}$$

where S_t is a discrete latent variable which evolves according to a Markov process. During normal regimes $(S_t = 1)$, the cycle loads shocks with variance $V(a_{ct}) = V_c$ and it has a zero mean. Imposing $\delta_c > 0$ and $\lambda_c > 0$, during recessions ($S_t = 0$) the shocks take a larger variance $V\big((1+\delta_c)a_{ct}\big) = (1+\delta_c)^2 V_c$ while the cycle shows a negative shift driven by parameter λ_c. The parameter λ_c thus captures asymmetry in the cyclical shocks. Kim and Nelson also let the discrete variable S_t control the magnitude of the shocks to level of the trend, but since EUCAM does not foresee shocks to the level of potential, only potential growth evolving stochastically in (2), this feature is irrelevant in our framework and is left ignored.

A straightforward incorporation of equation (11) in EUCAM is however ineffective due to an incompatibility with the prior distribution in current use for V_c. Indeed, on average across EU27 minus BG and HR, the current prior mean for V_c is such as $E(V_c) = 9 \times 10^{-4}$: this implies that, *a priori*, 95% of the cyclical shocks lie into the interval ± 6 pp., roughly. The current prior distribution for V_c is thus sufficiently large to accommodate the large negative shocks which characterise the years 2009 and 2020. In order to detect recessions, the prior variance of cyclical shocks in normal regimes must be reduced. In addition, equation (11) implies an unconditional mean for the cyclical component which is strictly negative since $E(c_t) = -\text{Pr}(S_t = 0)\lambda_c/\phi_c(1)$. This contrasts with the zero-mean assumption for the cyclical component in EUCAM. Therefore, to enable the detection of recessions and to ensure comparability with EUCAM, equation (11) is updated to:

$$\phi_c(L)c_t = \begin{cases} \frac{\text{Pr}(S_t=0)}{\text{Pr}(S_t=1)}\lambda_c + \delta_c a_{ct} & S_t = 1 \\ -\lambda_c + a_{ct} & S_t = 0 \end{cases} \tag{12}$$

where the parameter δ_c, $0 < \delta_c < 1$, tempers the magnitude of cyclical shocks in normal times while the constant $\frac{\text{Pr}(S_t=0)}{\text{Pr}(S_t=1)}\lambda_c$ ensures $E(c_t) = 0$. The constant $\frac{\text{Pr}(S_t=0)}{\text{Pr}(S_t=1)}\lambda_c$ makes the cyclical shocks preponderantly positive during normal regimes, which can thus also be interpreted as expansion periods.

We experiment with the re-formulated Kim and Nelson model (12) incorporated into the EUCAM equations (1)-(2), which we label Model 1. Table 5.1 however provides some evidence of asymmetry in the idiosyncratic component of capacity utilisation. We thus also experiment with Model 2 where, in addition to (1)-(2)-(12), the process governing the idiosyncratic movements of capacity utilisation in (2) is extended to:

$$(1-\phi_{cu}L)e_{cut} = \begin{cases} \frac{\text{Pr}(S_t=0)}{\text{Pr}(S_t=1)}\lambda_{cu} + \delta_{cu} a_{cut} & S_t = 1 \\ -\lambda_{cu} + a_{cut} & S_t = 0 \end{cases} \tag{13}$$

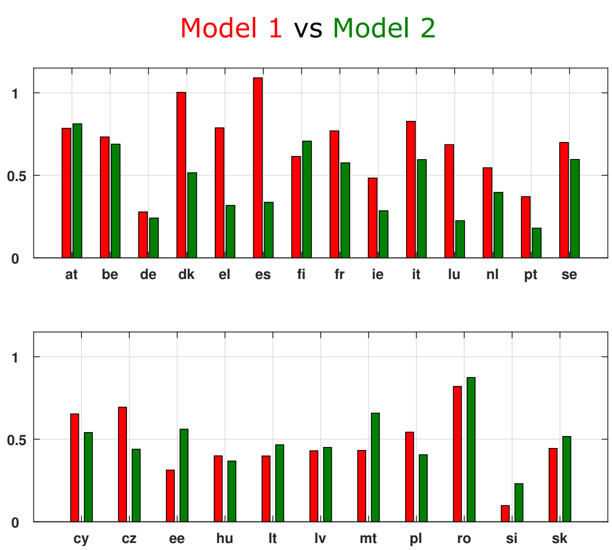
In (13), the idiosyncratic shocks of capacity utilisation are described with a mixture distribution which mimics the one specified in (12) for the cyclical shocks. Both processes depend on the same latent variable S_t, so capacity utilisation and the TFP cycle switch between regimes contemporaneously. Model 1 and Model 2 are fitted using the flat prior $B(1.1, 1.1)$ for δ_c and δ_{cu}, and $B(1.1, 1.1)_{[0,0.2]}$ for λ_c and λ_{cu}, in addition of the EUCAM priors for the other parameters.

5.2. EMPIRICAL COMPARISON

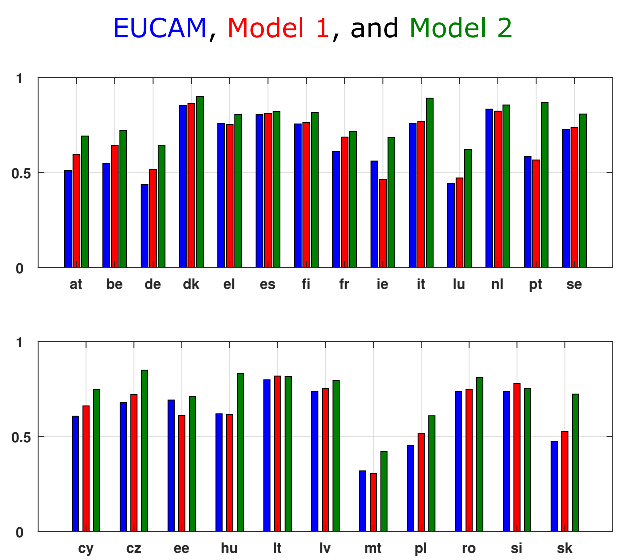
Regarding the 2009 recession, the two asymmetric models provide roughly similar posterior inference: Model 1 detects the 2009 trough in 16 cases against 20 for Model 2. More variations occur with respect to the Covid pandemic episode: the 2020 recession is detected in 7 countries with Model 1 against 23 with Model 2. Overall, Model 2 infers that all countries of the panel have undergone at least one recession, while with Model 1 there are five countries, BE, CY, CZ, LU, and RO, where no recession is spotted. Allowing for contemporaneous regime changes in the TFP cycle and in the idiosyncratic component of capacity utilisation as in (13) helps identifying recessions.

Graph 5.1 shows the inverse signal to noise ratio obtained with the two non-linear models in units of the EUCAM estimate. In the non-linear models the inverse signal to noise ratio amounts to $\big(P(S_t = 1)\delta_c^2 V_c + P(S_t = 0)V_c\big)/V_\eta$. The larger the ratio and the smoother the trend, so when given in units of the EUCAM estimate, values above one indicate that the non-linear model yields a trend that is smoother than in EUCAM. It is seen that, most often, taking asymmetry into account yields potential TFP estimates which are more erratic than EUCAM's ones. This feature follows from the re-scaling of the variance of the cyclical shocks through δ_c which shrinks the prior mean of $V(\delta_c a_{ct})$ and thus also the prior mean of the inverse signal to noise ratio: the prior $\delta_c \sim B(1.1, 1.1)$ indeed reduces the prior mean of $V(\delta_c a_{ct})/V(a_{\eta t})$ during expansions to roughly one-third of its value in EUCAM[5]. On average across countries, Model 1 yields an inverse signal to noise ratio close to 0.6 in units of the EUCAM estimate against 0.5 for Model 2.

Graph 5.1 **Inverse signal to noise ratio in units of the EUCAM estimates**



Graph 5.2 **Model-based correlation between the TFP cycle and CUBS**



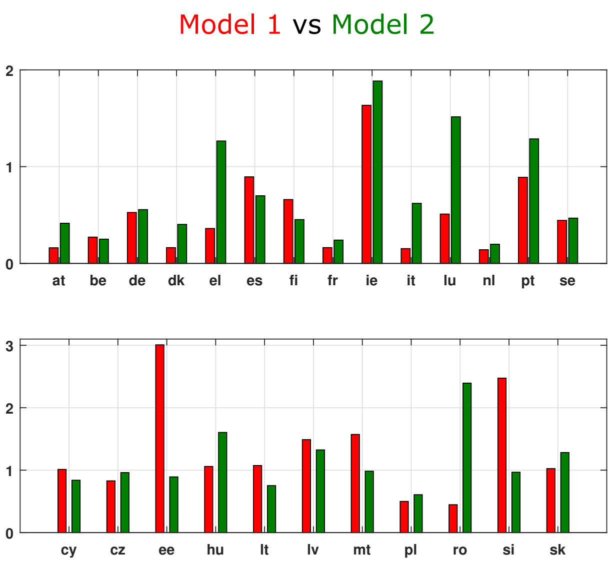
[5] Prior independence implies $V(\delta_c a_{ct}) = E(\delta_c^2)V(a_{ct}) = \big(V(\delta_c) + E(\delta_c)^2\big)V(a_{ct}) \simeq V(a_{ct})/3$.

Graph 5.2 shows the model-based correlation between CUBS and the Solow residual cycle in EUCAM vs the two asymmetric alternatives. The larger the correlation and the larger the weight put on the capacity utilisation indicator in the estimation of the TFP cycle; in case of a zero-correlation, the TFP decomposition corresponds to the one obtained in univariate modelling. The average across countries amounts to 0.64, 0.66, and 0.75, respectively. EUCAM and Model 1 yields a similar correlation between CUBS and the TFP cycle while Model 2 foresees more commonality due to the decrease in the magnitude of the idiosyncratic movements in CUBS during normal regimes implied by the tempering parameter δ_{cu}.

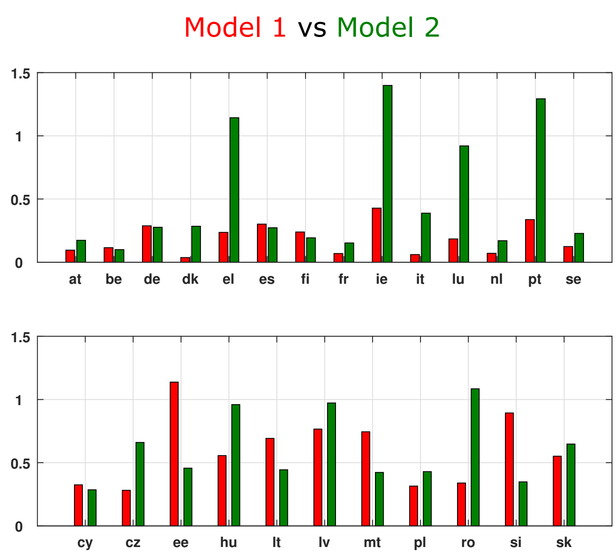
Graph 5.3 shows the maximum difference in the post-2000 years between cycle estimates obtained with the two asymmetric models compared to EUCAM. The maximum difference exceeds 1 pp. with both models for only one country among EU14, namely IE, and for three countries among the eleven post-2004 Accession Countries, namely HU, LV, and SK. Again, more instability is observed for this last group of countries. Slightly more departure is recorded with Model 2: on average across countries, the absolute difference with respect to EUCAM amounts to 0.80 pp. for Model 1 against 0.85 pp. for Model 2. Model 2 tends to generate larger departures than Model 1 as it estimates a more erratic potential growth, following the decrease in the inverse signal to noise ratio illustrated in Graph 5.1.

Potential growth is more stable: as can be seen in Graph 5.4, differences larger than 0.5 pp. are recorded with both alternative models only for HU, LT, and SK. Focusing on EU14, it is seen that Model 2 can lead to differences of about 1 pp. in the case of EL, IE, LU, and PT, while Model 1 always yields differences smaller than 0.5 pp. On average across countries the maximum difference amounts to 0.28 with Model 1 against 0.40 pp. with Model 2.

Graph 5.3 **Maximum absolute distance to EUCAM cycle estimates, Vintage Autumn 2022, period 2000-2022 (pp.)**



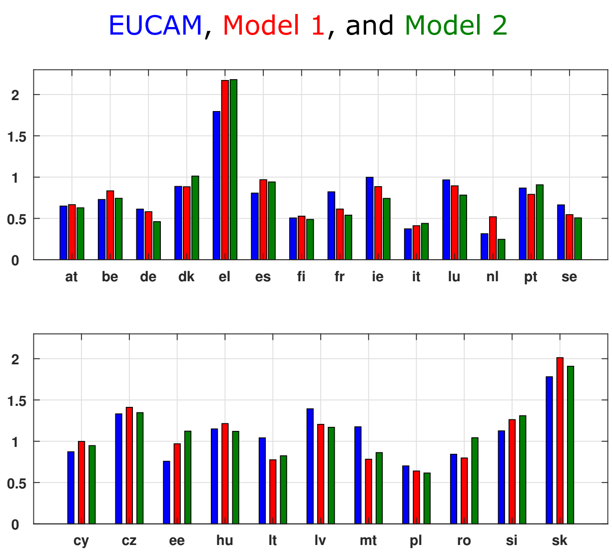
Graph 5.4 **Maximum absolute distance to EUCAM potential growth estimates, Vintage Autumn 2022, period 2000-2022 (pp.)**



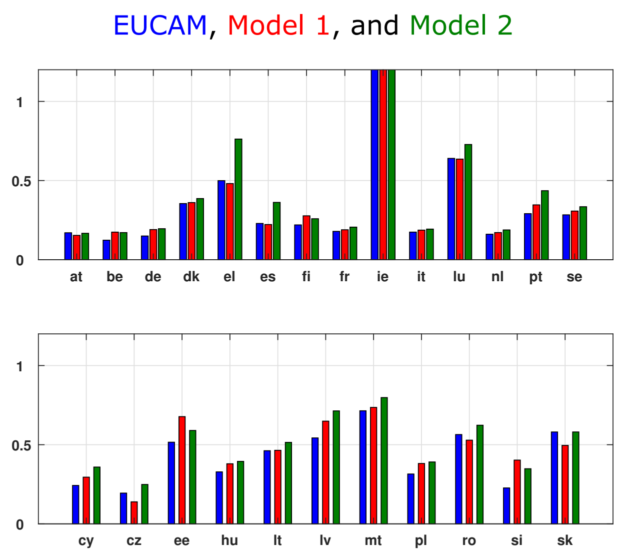
Graph 5.5 and Graph 5.6 show the Rmsre in cycle and potential growth estimates obtained with EUCAM vs the two asymmetric alternatives. The Rmsre is calculated as in (9), making use of

both real-time data vintages and real-time prior distributions which thus vary across vintage. The three specifications yield a similar stability of concurrent cycle estimates: the cross-country average Rmsre amounts to 0.93, 0.93, and 0.92 pp., respectively. These revisions represent 50% of the cross-country average standard deviation of the Solow residual cycle calculated with the Autumn 2022 data vintage. Again, potential growth is more stable across vintages: the cross-country average Rmsre amounts to 0.40, 0.43, and 0.48 pp., respectively, and more instability is observed for the post-2004 Accession countries. The large revisions recorded for IE, around 1.9 pp. with all methods, are due to data instability.

Graph 5.5 **Rmsre in TFP cycle (pp.), vintages 2013-2022**



Graph 5.6 **Rmsre in potential TFP growth (pp.), vintages 2013-2022**



5.3. CONCLUSION

The TFP model in EUCAM is compared to two alternative specifications which allow for asymmetry in cyclical shocks and in the idiosyncratic component of capacity utilisation. These asymmetric models are built upon the Kim and Nelson econometric specification of Friedman's plucking model. They are motivated by the results of Mardia test. By introducing a latent variable which controls the succession of expansions and recessions, the asymmetric models provide a richer inference compared to EUCAM. Yet fitting these two models necessitates tuning the EUCAM prior distributions, which eventually hampers model comparison. In particular, it is seen that both asymmetric models increase the variability of potential TFP, and that the correlation between the TFP cycle and CUBS rises in presence of asymmetry in the idiosyncratic component of CUBS: both outcomes are related to the tempering of shocks in normal regimes which is necessary to detect recessions. The trend-cycle decomposition of the Solow residual provided by the two asymmetric models remains however close to the EUCAM's one: on average across countries, the maximum departure lies below 1 pp. No improvement is obtained regarding revision errors. The EUCAM trend-cycle decomposition of TFP seems thus reasonably robust to alternative specifications which take asymmetry into account.

6 OVERALL CONCLUSION

Potential output and the output gap are essential ingredients of the economic and fiscal policy of the EU. The European Commission estimates both quantities by applying the methodology known as EUCAM which has been agreed between Member States. This methodology involves a decomposition of TFP into trend and cyclical components that makes use of information provided by capacity utilisation. Because disentangling trend and cyclical productivity in real-time is notoriously difficult, it is important to thoroughly assess the robustness of this decomposition. The robustness of the EUCAM decomposition of TFP is examined with respect to variations in prior distributions, in the set of survey indicators, and in the assumption of cyclical symmetry. Robustness to prior distributions is explored via a local sensitivity analysis and an informal approach. The local sensitivity analysis evidences that the EUCAM prior emphasises small values for the magnitude of the shocks to potential TFP, which is justified by the smoothness requirement for potential growth in a context of noisy data. For the other parameters, the EUCAM priors do not appear very informative compared to the data: local variations in prior means hardly affect the trend-cycle decomposition, even when compounded effects are taken into account. The exploration of a more extreme alternative like a flat prior for the parameters of the capacity utilisation equation reveals that trend smoothness is favoured at the cost of a slight reduction in the commonality between capacity utilisation and the Solow residual cycle. Nevertheless, the trend-cycle decomposition appears to be generally robust to the prior of the parameters in the capacity utilisation equation.

Turning to the robustness to the selection of survey indicators, we experiment with the inclusion of the 12 survey indicators considered in Carstensen et al. (2023). Two strategies are tested: a one-step approach where all indicators are inserted through a model update, and a two-step approach which substitutes CUBS with the first principal component of a subset of indicators while leaving unchanged the EUCAM specification. Due to the model update, the one-step approach always reduces the amount of commonality between the TFP cycle and the indicators compared to EUCAM. It follows that the one-step approach yields a decomposition which is farther to EUCAM compared to the two-step approach: the average discrepancy across countries amounts to 1.86 pp. against 0.86 pp. Therefore, complementing CUBS with further survey indicators leaves the TFP decomposition stable when the indicators are aggregated into a principal component which is substituted to CUBS, but more variation is recorded when the indicators are inserted altogether in an enlarged model. Whatever the approach, no stabilisation effect appears: the revisions remain roughly equal.

Next, the TFP model in EUCAM is compared to alternative specifications which allow for asymmetry in the TFP cyclical shocks and in the idiosyncratic component of capacity utilisation. These extensions are motivated by the results of univariate and bivariate tests of skewness. Two asymmetric models built upon the Kim and Nelson econometric specification of Friedman's plucking model are considered. The introduction of a latent variable which controls the succession of expansions and recessions provides a richer inference compared to the linear specification in EUCAM. Yet fitting these two models necessitates tuning the EUCAM prior distributions, which eventually hampers model comparison. For instance, it is seen that both asymmetric models increase the variability of potential TFP, and that the correlation between the TFP cycle and CUBS rises when asymmetry is also allowed in the idiosyncratic component of CUBS: both outcomes are related to the tempering of shocks in normal regimes which is necessary to detect recessions. The trend-cycle decomposition of the Solow residual provided by the two asymmetric models remains close to the EUCAM's one, since on average across countries, the maximum departure lies below 1 pp. No improvement are obtained regarding revision errors. Overall, the EUCAM trend-cycle decomposition of TFP seems robust to alternative specifications which take asymmetry into account. Given the additional complexity, these results do not justify extending EUCAM to asymmetric models.

The TFP decomposition in EUCAM can thus be seen as reasonably robust to the departures in model assumptions examined. Three regularities are worth noticing: focusing on vintage Autumn 2022, (i) the estimation results are more stable in EU14 than in the post-2004 Accession Countries, (ii) for each country the potential growth estimates show more firmness than trend-cycle ones; across vintages, (iii) the alternative model assumptions explored yield no improvement with respect to revision errors. Regularity (i) can be expected to dissipate in the future with the incoming of additional observations. Regularity (ii) suggests that potential growth is better captured than the output gap, which is probably due to its larger persistence. Regularity (iii) is consistent with the possibility that the revisions in trend-cycle estimates are mostly due to the corrections in TFP data.

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APPENDIX

To evaluate the partial derivatives of the posterior unobserved component estimates with respect to the prior means in (3), one needs the derivatives $\frac{d \log \pi(\theta_\ell|h)}{dE(\theta_\ell|h)}$. They are provided below: terms which are constant with respect to θ_ℓ and thus irrelevant to the covariance with $g(\theta) = E(c|y, \theta, h)$ in (3) are written as cst, and to simplify the subscript ℓ is omitted. The EUCAM prior distributions involve the following three cases:

- Normal given $V(\theta)$: if $\pi(\theta) = N(E(\theta), V(\theta))$, then $\log(\theta) = cst - \frac{1}{2V(\theta)}\big(\theta - E(\theta)\big)^2$ and:

$$\frac{d \log \pi(\theta)}{dE(\theta)} = \frac{\theta - E(\theta)}{V(\theta)}$$

- Beta: if $\pi(\theta) = Beta(a, b)$, $\log \pi(\theta) = -\log B(a, b) + (a-1)\log\theta + (b-1)\log(1-\theta)$, then $E(\theta) = \frac{a}{a+b}$ and:

$$\begin{aligned}\frac{d \log \pi(\theta)}{dE(\theta)} &= cst + \frac{\partial (a-1)\log\theta}{\partial a}\Big/\frac{\partial E(\theta)}{\partial a} + \frac{\partial (b-1)\log(1-\theta)}{\partial b}\Big/\frac{\partial E(\theta)}{db} \\ &= cst + \log\theta\frac{(a+b)^2}{b} - \log(1-\theta)\frac{(a+b)^2}{a}\end{aligned}$$

  For the periodicity parameter, the support is extended to $lb - ub$ instead of $(0, 1)$. In this case $E(\theta) = lb + (ub - lb)\frac{a}{a+b}$ so the derivative above must be divided by the support length $ub - lb$.

- IG_2: if $\pi(\theta) = IG_2(s, \nu)$, $\log \pi(\theta) = cst - \frac{\nu+2}{2}\log\theta - \frac{s}{2\theta}$, then $E(\theta) = \frac{s}{\nu-2}$ and:

$$\begin{aligned}\frac{d \log \pi(\theta)}{dE(\theta)} &= \frac{\partial \log \pi(\theta)}{\partial s}\Big/\frac{\partial E(\theta)}{\partial s} + \frac{\partial \log \pi(\theta)}{\partial \nu}\Big/\frac{\partial E(\theta)}{\partial \nu} \\ &= -\frac{1}{2\theta}(\nu - 2) + \frac{(\nu-2)^2}{2s}\log\theta\end{aligned}$$

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