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A Proposal for a Flexible Trend Specification in DSGE Models [1]

Martin Slanicay[2]

Abstract: In this paper I propose a flexible trend specification for estimating DSGE models on log differences. I demonstrate this flexible trend specification on a New Keynesian DSGE model of two economies, which I consequently estimate on data from the Czech economy and the euro area, using Bayesian techniques. The advantage of the trend specification proposed is that the trend component and the cyclical component are modelled jointly in a single model. The proposed trend specification is flexible in the sense that smoothness of the trend can be easily modified by different calibration of some of the trend parameters. The results suggest that this method is capable of finding a very reasonable trend in the data. Moreover, comparison of forecast performance reveals that the proposed specification offers more reliable forecasts than the original variant of the model.

Key words: DSGE model, trend specification, Bayesian estimation

JEL Classification: C51, C68, E32

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Motivation

DSGE models are models of the cyclical fluctuations of an economy, and most of them can therefore only be estimated on stationary data. However, most economic time series are non-stationary, contain trends or display breaks. This implies that these data must be transformed in order to make them stationary. There are many different approaches which try to extract trend components from the data, to make them stationary. However, each method extracts a different type of information from the data, and there is no professional consensus on what constitutes business cycle fluctuations. Detrending methods differ in their trend specifications as well as in the relationship they set up between trend and cyclical components. As a result, the stylized facts about the business cycle seem to differ substantially among detrending methods, even qualitatively (see Canova 1998). It seems that there is no general rule governing the transformation of

[1] The first, six-page-long draft of this paper was presented at the MME 2012 conference and published in the conference proceedings, see Slanicay (2012).

[2] Masaryk University, Faculty of Economics and Administration, Department of Economics, Lipová 41a, Brno 602 00, slanicay@mail.muni.cz

time series, and the suitability of each method depends on the particular situation and the research purpose.

The goal of this paper is to propose a flexible trend specification for estimating DSGE models on log differences. I demonstrate this flexible trend specification on a New Keynesian DSGE model of two economies, originally presented in Kolasa (2009), which I estimate on data from the Czech economy and the euro area, using Bayesian techniques. Consequently, I compare the estimation results of this proposed flexible trend specification with the estimation results of other methods commonly used within DSGE models, namely with the results of (i) demeaned log differences (original specification of the model), and (ii) the Hodrick-Prescott filter.

The rest of this paper proceeds as follows: the following section offers a review of the literature related to the issue of trend specification in DSGE models. Section 3 presents a non-technical overview of the model, while Section 4 discusses several issues related to the estimation of the model, namely: (i) the choice of the data, (ii) specification of the trends, and (iii) estimation results. In Section 5, I compare the estimation results from the proposed trend specification with results from the other methods. This comparison consists of a forecast performance comparison and an output gap comparison. Finally, Section 6 concludes.

Literature Review

There are essentially three possible approaches to the decomposition of time series into trend and cyclical components: (i) detrend the actual data, (ii) build-in a trend into the model, and (iii) use data transformations which, in theory, are likely to be void of non-cyclical fluctuations.

The first approach implies that the data are detrended out of the model and the model is then estimated on these detrended data. Mostly, these filtered trends are free of any economic interpretation. These methods are advantageous due to their universality and, in some cases (e.g. HP filter), simple implementation. On the other hand, one can argue that an arbitrary choice of a detrending method can significantly change the behaviour of the model, and the obtained results can substantially differ between different detrending methods (see Canova 1998, 2013). Moreover, many detrending methods are also applied on each time series individually, and these filtered trends can be inconsistent with each other. Canova and Ferroni (2011) propose a new method for estimating DSGE models based on combining the information provided by a variety of filters. They consider data filtered with alternative procedures as contaminated proxies of the relevant model-based variables, and estimate structural and nonstructural parameters jointly using a signal extraction approach.

The second approach means that the data are detrended within the model. The advantage of this approach consists of the fact that the decomposition of the data into the trend and cyclical components is performed by the model itself. It means that the model itself decides which part of the data belongs to the trend component and which part belongs to the cyclical component. Nevertheless, there are still many issues which depend on the researcher’s choice, such as some assumptions about the trend specification or the relationship between the trend and cyclical components, which make the previous objection concerning the arbitrary choice of detrending method still valid, if somewhat less so. It is often required that the trend components should satisfy a balanced growth path (henceforth BGP), which is a condition of long-term trend consistence that usually requires real variables, such as consumption, investment, output, real wage, etc. to have the same long-term growth rate. The BGP condition implies that some ratios, e.g. the consumption to output ratio or investment to output ratio, remain constant in the long run.

Aguiar and Gopinath (2007) show that shocks to trend growth, rather than transitory fluctuations around a stable trend, are the primary source of fluctuations in emerging economies. This can be seen as an argument for explicit modelling of the trend component within the model. Andrle (2008) also argues in favour of incorporating explicit (possibly structural) assumptions of trend behaviour. He claims that permanent shocks influence business cycle behaviour and ad-hoc detrended models *"must have hard times to explain the comovement of the data"* (Andrle, 2008, p. 1). Brůha (2011) proposes a small labour market model where he jointly models the trends and the cycles in a way which is slightly similar to the approach proposed in this paper. Canova (2013) proposes a new method for estimating cyclical DSGE models using raw data. This method is based on a flexible specification of the trend, which does not require the cyclical component to be solely located at business cycle frequencies.

The third approach is based on the fact that some transformations of the data may display fluctuations around a stable value, and after removing this stable value, which can be regarded as a steady state, the data may look stationary. A transformation of the data using log differences is very popular, where steady state values of these log differences can be interpreted as a steady state growth rate. For an example see Smets and Wouters (2003), where the ECB policy model is presented, or Adolfson et al. (2007), who present the "RAMSES" policy model of the Swedish central bank. Another popular method can be found in Cogley (2001) and McGrattan (2010). They suggest that the model be estimated using the data in the form of real "great ratios", i.e. shares of real consumption (investment, etc.) on the real GDP; this exploits the fact that these shares are very stable (in some countries). Therefore, after removing these shares' steady state values, the resulting deviations should look stationary. Similarly, Whelan (2006) suggests estimating the model using data in the form of nominal "great ratios", i.e. using the share of nominal consumption (investment, etc.) on the nominal GDP. The main pitfall of this method is that these ratios are not so stable in many countries, and the resulting deviations of these ratios from their "steady state" values therefore do not resemble stationary data at all.

The method proposed in this paper combines some elements from the second and the third approaches. I use data transformation in the form of log differences, however, the trend component is explicitly specified within the model in the form of an AR1 process around the steady state.

Model

This section briefly describes the model employed. It is a New Keynesian model of two economies, originally presented in Kolasa (2009).[3] Details of how the model was derived can be found in the Appendix, published on the journal's web-site.

The model assumes that there are only two economies in the world: a domestic economy (represented by the Czech economy) and a foreign economy (represented by the euro area). The problematic fact that one economy is much smaller than the other is solved by parameter n, which governs the relative size of the two economies.

The model assumes five types of representative agents in each economy. Households consume tradable and non-tradable goods produced by firms. There is an assumption of habit formation in consumption. Households trade bonds, too, and their intertemporal choice about consumption is influenced by preference shocks. Households supply labour and set wages on a monopolistically competitive labour market. Their labour supply is influenced by labour supply shocks, and their wage-setting is subject to a set of labour demand constraints and to the Calvo constraint on the frequency of wage adjustment (see Calvo, 1983). According to the Calvo constraint, each household resets its wage with probability $1-\theta_W$ and keeps its wage unchanged with probability θ_W in every period. Households also accumulate capital, which they rent to firms. Capital accumulation is subject to investment-specific technological shocks and to adjustment costs.

There are two types of firms in each economy: producers of tradable goods, and producers of non-tradable goods. Both of them employ a Cobb-Douglas production function with constant returns to scale. Productivity in both sectors is influenced by productivity shocks. Firms hire labour on the labour market and sell their goods on monopolistically competitive goods markets. They set prices on the goods market subject to a set of demand constraints and to the Calvo constraint on the frequency of price adjustment (see Calvo, 1983). According to the Calvo constraint, each firm resets its price with probability $1-\theta_H$ and keeps its price unchanged with probability θ_H in every period.

The fiscal authority collects lump-sum taxes and uses them for government expenditures and transfers to households, so that the state budget is balanced in each period. Government expenditures consist only of domestic non-tradable goods and are modelled as a stochastic AR1 process - a government expenditures shock. Given our assumptions about households, Ricardian equivalence holds in this model. The monetary authority follows a Taylor-type rule, and deviations from this rule are

[3] I depart from the original specification of the model in several aspects; nonetheless, these modifications are generally minor. For the readers' convenience, all of these modifications are mentioned in the Appendix, along with the description of the model. The Appendix can be read online, on the journal's web-site.

explained as monetary shocks. The model is closed with an assumption of a complete bond market and with an assumption of goods and labour markets clearing.

The model's behaviour is driven by seven structural shocks in both economies: a productivity shock in the tradable sector and the non-tradable sector, a labour supply shock, an investment efficiency shock, a consumption preference shock, a government spending shock, and a monetary policy shock. Except for the monetary policy shock, which is modelled as an IID process, all the other shocks are represented by an AR1 process. I allow for correlations between innovations of corresponding shocks in both economies.

Estimation

Data and Trends

The model is estimated using quarterly data from the Czech economy and the euro area 17[4] from the first quarter of 2000 to the first quarter of 2014.[5] The data series used were downloaded from the Eurostat web database. I use the following 14 time series (seven for each economy): real GDP (y), consumption (c), investment (i), HICP (p), real wage (w), short-term interest rate (r) and internal exchange rate (x) defined as prices of non-tradable goods (services and energy) relative to prices of tradable goods (others). Except for the nominal interest rates, all observables are seasonally adjusted and expressed as 100*log differences. The nominal interest rate is expressed as a quarterly rate in percent.

More details about the employed software, data and their seasonal adjustment, as well as the visual representation of the data can be found in the Appendix (online). Besides that, in the Appendix I also discuss several issues related to the estimation of the model, namely (i) the calibration of several parameters, (ii) the choice of the priors for the estimated parameters, and (iii) the results of the estimation.

Let us now describe the decomposition of the observables into the trend components and cyclical (model) components. u_t^{obs} and r_t^{obs} denote the observables, where $u \in \{y,c,i,p,w,x\}$; γ_t^u and γ_t^r denote the trend components; u_t and r_t denote the

[4] As the number of countries in the euro area grew during the period examined, the data for the euro area are not suitable for estimation because of breaks in the time series. It is therefore necessary to use proxy data for the euro area, in the form of an unchanging group of EMU countries for the relevant period. Nowadays, there are 3 possible options available from the Eurostat: EA 12, EA 17, and EA 18. I have chosen EA 17, however I have checked the sensitivity of the obtained results to the other two options and found no significant differences.

[5] I have also tried to estimate the model on two subsamples of the data - the pre-crisis period from 2000 to 2008 and the (post)-crisis period from 2008 to 2014. In both cases the proposed detrending method proved to be capable of finding very reasonable trends in the data and also led to more accurate forecasts than the original specification.

cyclical (model) components; and ε_t^u and ε_t^r are the trend shocks. Consequently, the decomposition of the observables can be written in the following form:

$$u_t^{obs} = \gamma_t^u + u_t - u_{t-1}, \qquad r_t^{obs} = \gamma_t^r + r_t,$$

$$\gamma_t^u - \gamma^u = \rho_u(\gamma_{t-1}^u - \gamma^u) + \varepsilon_t^u, \qquad \gamma_t^r - \gamma^r = \rho_r(\gamma_{t-1}^r - \gamma^r) + \varepsilon_t^r,$$

$$\gamma^u = mean(u_t^{obs}), \rho_u \in (0,1), \qquad \gamma^r = mean(r_t^{obs}), \rho_r \in (0,1).$$

The interpretation of the proposed trend specification is straightforward. The observable u_t^{obs} is expressed in log differences, i. e. approximately in the growth rates. Therefore, the observed growth rate u_t^{obs} is decomposed into the trend growth rate γ_t^u and the cyclical growth rate, expressed as a difference of two consecutive gaps $u_t - u_{t-1}$. The trend growth rate γ_t^u follows an AR1 process around the steady state growth rate γ^u which is given by the average growth rate. The trend shocks ε_t^u cause temporary deviations of the trend growth rate γ_t^u from the average growth rate γ^u. However, the effects of these temporary trend shocks are persistent to a certain degree, which means that the effects of such shocks do not disappear immediately but only over some time. The degree of persistence of such shocks is given by the parameters ρ_u. Note that while these trend shocks ε_t^u have temporary effects on the growth rates, they have permanent effects on the levels.

As regards decomposition of the interest rate r_t^{obs}, the interpretation is very similar. The observed interest rate r_t^{obs} is decomposed into the trend interest rate γ_t^r and the cyclical interest rate r_t. The trend interest rate γ_t^r follows an AR1 process around the steady state interest rate γ^r, given by the average interest rate. The trend shocks ε_t^r cause temporary deviations of the trend interest rate γ_t^r from the average interest rate γ^r. The effects of these temporary trend shocks are persistent to a certain degree, with the degree of persistence given by the parameter ρ_r.

The advantage of the proposed trend specification is that the trend component and the cyclical component are modelled together in one model, and the model itself decides which part of the data belongs to the trend component and which part belongs to the cyclical component. Nevertheless, there are still several things which depend on the researcher's choice. It is obvious that the standard deviations of trend shocks ε_t^u and ε_t^r and the persistence parameters ρ_u and ρ_r cannot be successfully estimated together because of the lack of identifiability. Therefore, I decided to calibrate the standard deviations of trend shocks ε_t^u and ε_t^r; and to estimate persistence parameters ρ_u and ρ_r.

I estimated ten variants of the model with different calibrations of the trend shocks ε_t^u and ε_t^r and with different prior settings of the persistence parameters ρ_u and ρ_r. I calibrated the standard deviations of trend shocks to some portion of the standard deviations of the observables u_t^{obs} and r_t^{obs}, namely: one half, one third, one quarter, one sixth, and one eighth. In my view, these portions represent reasonable values for the standard deviations of trend shocks. Values higher than one half would diminish the role of structural shocks and their propagation mechanism in the structural part of the model, while values smaller than one eighth would diminish the role of trend shocks and the results would, therefore, converge to the results of the original specification of the model estimated on demeaned log differences.

For each calibration of trend shocks I estimated two variants, which differ in the prior specification for the persistence parameters ρ_u and ρ_r. Both of them employ prior distribution Beta, however, in one case the prior mean is equal to 0.7 and prior std. deviation is equal to 0.1, while in the latter case the prior mean is equal to 0.5 and prior std. deviation is equal to 0.2. The former case can be regarded as a more "strict" informative prior, while the latter case represent rather "loose" uninformative prior.[6] This is why I refer to the proposed trend specification as a "flexible" specification, because the smoothness of the trend can be modified easily by different calibration of the standard deviations of trend shocks ε_t^u and ε_t^r and by the prior setting of the persistence parameters ρ_u and ρ_r.

Estimation Results

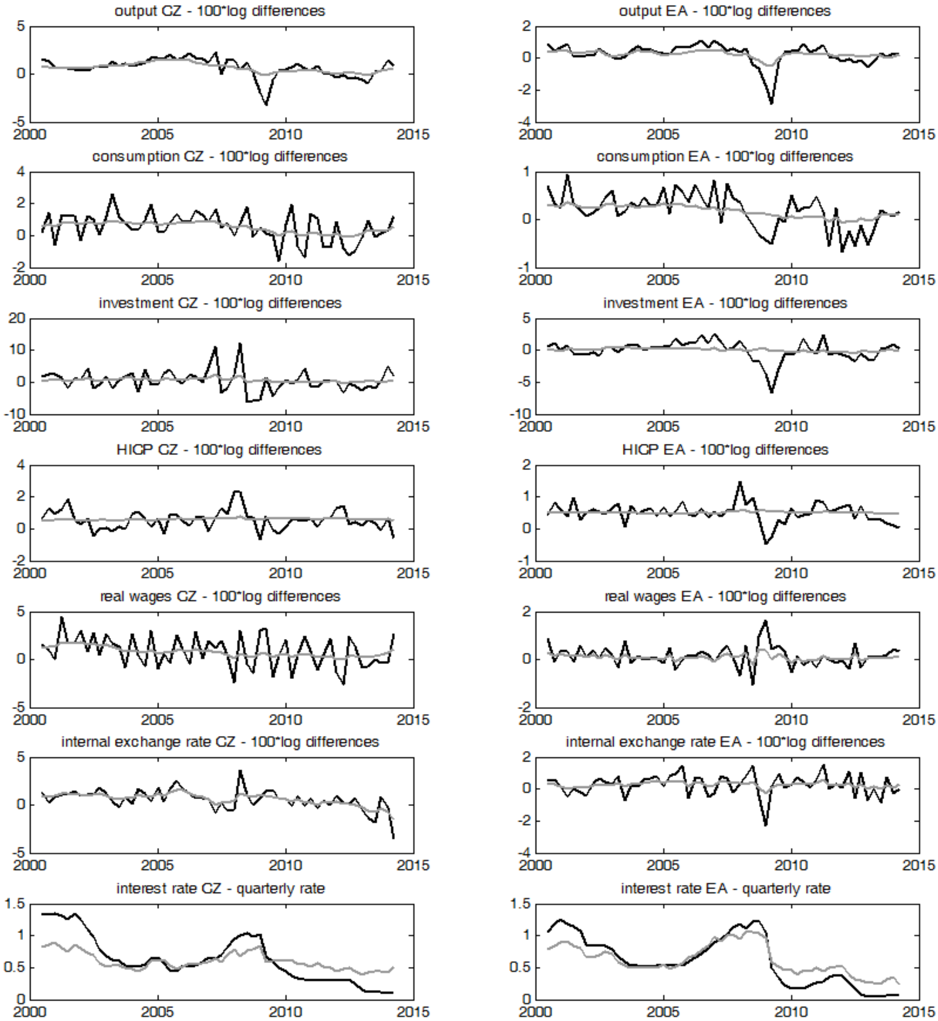
All variants of the model were estimated with the Random Walk Chain Metropolis-Hastings algorithm, using the Dynare toolbox for Matlab. I generated two independent chains for each variant, each with 2,000,000 draws. From each chain I used only the last 25% percent of the draws, i. e. the initial 1,500,000 draws from each chain were discarded. The average acceptance rate ranges from 20% to 28%, which is in line with informal recommendation for ideal acceptance rate, see for example Koop (2003).

The results suggest that this method is capable of finding very reasonable trends in the data. Figure 1 demonstrates this using a specification with the standard deviations of trend shocks calibrated to one third of the standard deviations of the observables, and persistence parameters estimated with "strict" prior.[7] The results of the remaining specifications can be found in the Appendix.

[6] I will henceforth use the terms "strict" and "loose" to refer to these different prior settings of the persistence parameters ρ_u and ρ_r.

[7] When working on this research, this particular specification was my first choice for how to describe the trend component.

Figure 1 Original Data - black line, Smoothed Trend - grey line



Source: author

We can see that while for some variables, e.g. investment and prices, the smoothed trend is very similar to the mean of the observable, for some variables (especially interest rates) the smoothed trend fluctuates more. However, this result is based on the employed calibration, and can be easily modified by calibrating the standard deviations of trend shocks differently. For the sake of comparability I decided to calibrate all trend shocks equally as a given portion of the standard deviation of the observables, however, it is also possible to calibrate the trend shocks differently for each variable.

Comparison with Other Methods

In this section, I compare the estimation results of my proposed flexible trend specification (henceforth FTS) with the estimation results of other methods, namely with the results of (i) demeaned log differences (henceforth DLD), and (ii) the Hodrick-Prescott filter (henceforth HP).

Comparison of Forecast Performance

It is possible to compare unconditional one-step-ahead predictions of the FTS model, the DLD model, and the naïve forecasts.[8] I can calculate the measure of fit of the in-sample predictions as the Root Mean Square Error (henceforth $RMSE$)

$$RMSE = \sqrt{\frac{\sum_{t=2}^{T}(x_t^f - x_t^{obs})^2}{T-1}},$$

where T is the number of observations, x_t^f is the unconditional one-step-ahead forecast for time t, and x_t^{obs} is the observed value in time t. We can also define "relative forecast performance" (henceforth RFP) as

$$RFP = \frac{RMSE_M}{RMSE_N},$$

where $RMSE_M$ denotes $RMSE$ of the model and $RMSE_N$ denotes $RMSE$ of the naïve forecasts. The RFP gives us a formal evaluation of the quality of the model forecast performance relative to the performance of the naïve forecasts. If the RFP is less than one, it indicates that the model's one-step-ahead forecast outperforms the naïve one-step-ahead forecast. On the other hand, if the RFP is greater than one, it indicates that the model does a "poor job" in explaining the movement of the particular observable because the naïve one-step-ahead forecast outperforms the model's one-step-ahead forecast.

Tables 1 and 2 display the calculated RFP for all model variants. We can see that all model specifications have trouble with forecasting of domestic output, as the model forecasts are almost always outperformed by the naïve forecasts. However, the FTS specifications reduce this pitfall. As regards other variables of interest, the FTS model's one-step-ahead forecast always outperforms the naïve one-step-ahead forecasts, which cannot be said of the DLD specifications. We can see that the DLD specifications also fail to forecast foreign inflation, since the naïve one-step-ahead forecast outperforms the DLD model's one-step-ahead forecast.

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[8] Naïve forecast is equal to the last observed value.

Table 1 Relative Forecast Performance - CZ Variables

variant	y^{obs}	c^{obs}	i^{obs}	p^{obs}	w^{obs}	x^{obs}	r^{obs}
dld	1.20	0.85	0.83	1.02	0.75	0.85	0.82
fts, 1/8, strict	1.14	0.84	0.82	0.91	0.72	0.84	0.80
fts, 1/8, loose	1.12	0.84	0.82	0.89	0.72	0.83	0.79
fts, 1/6, strict	1.11	0.84	0.82	0.86	0.72	0.84	0.79
fts, 1/6, loose	1.10	0.83	0.82	0.87	0.72	0.83	0.78
fts, 1/4, strict	1.07	0.82	0.81	0.84	0.71	0.84	0.81
fts, 1/4, loose	1.06	0.82	0.81	0.86	0.71	0.84	0.80
fts, 1/3, strict	1.03	0.81	0.82	0.88	0.71	0.84	0.88
fts, 1/3, loose	1.04	0.82	0.80	0.88	0.71	0.85	0.86
fts, 1/2, strict	0.98	0.82	0.81	0.87	0.72	0.86	0.88
fts, 1/2, loose	1.00	0.82	0.77	0.87	0.70	0.86	0.81

Source: author

Table 2 Relative Forecast Performance - EA Variables

variant	y^{obs*}	c^{obs*}	i^{obs*}	p^{obs*}	w^{obs*}	x^{obs*}	r^{obs*}
dld	0.97	0.89	0.93	1.11	0.85	0.72	0.86
fts, 1/8, strict	0.98	0.88	0.93	1.00	0.74	0.72	0.83
fts, 1/8, loose	0.98	0.88	0.93	0.98	0.74	0.72	0.83
fts, 1/6, strict	0.97	0.87	0.93	0.93	0.72	0.73	0.83
fts, 1/6, loose	0.97	0.87	0.93	0.94	0.72	0.72	0.84
fts, 1/4, strict	0.96	0.86	0.92	0.86	0.72	0.74	0.86
fts, 1/4, loose	0.96	0.86	0.92	0.89	0.71	0.72	0.86
fts, 1/3, strict	0.93	0.86	0.91	0.82	0.71	0.75	0.97
fts, 1/3, loose	0.95	0.86	0.92	0.84	0.68	0.72	0.91
fts, 1/2, strict	0.93	0.85	0.92	0.81	0.72	0.75	1.01
fts, 1/2, loose	0.95	0.84	0.93	0.83	0.68	0.71	0.94

Source: author

As far as the comparison of FTS and DLD is concerned, the FTS specifications are always better at forecasting eight time series: consumption (c^{obs} and c^{obs*}), real wage (w^{obs} and w^{obs*}), HICP (p^{obs} and p^{obs*}), domestic investment (i^{obs}), and domestic output (y^{obs}); for these, all variants of the FTS model outperform the DLD models. The evidence is rather mixed in the case of internal exchange rate (x^{obs} and x^{obs*}), interest rate (r^{obs} and r^{obs*}), foreign output(y^{obs*}), and foreign investment (i^{obs*}); there is no clear evidence that either the FTS variants or DLD variant provide more reliable forecasts of these variables. From an overall perspective it can be said that in general the FTS model provides better forecast performance than the original DLD specification.

Output Gap Comparison

As regards the economic implications, I can compare the output gap implied by the FTS and DLD model with the output gap obtained by HP filter, see Figure 2.[9] In the case of the Czech economy, the FTS output gap displays similar patterns to those shown by the HP output gap. For the euro area, all three output gaps display similar patterns, but the FTS output is usually in between the HP output gap and the DLD output gap. In my view, the DLD specification implies implausibly large output gap deviations in both economies. According to the DLD specification, in 2008 (just before the crisis) Czech output was 10 % above the trend and output in the euro area was 6 % above the trend. These values are strongly at odds with the common view in the profession on the magnitude of output gap fluctuations in both economies.

In general, it holds that the results of FTS variants with lower values attributed to trend shocks converge to the results of the DLD model while the results of FTS variants with higher values attributed to trend shocks converge to the results of the HP filter. In my view, therefore, the FTS model output gap is capable of providing a plausible description of the business cycle in both economies.

Figure 2 Output Gap, horizontal axis - timeline, vertical axis - output gap as a percentage deviation from the trend

Source: author

[9] For the sake of visibility I have decided to present the results of only one variant of the FTS model here, namely the "fts, 1/3, strict" variant.

Conclusion

In this paper, I have proposed a flexible trend specification for estimating DSGE models on log differences, and have demonstrated this flexible trend specification on a New Keynesian DSGE model of two economies, which had originally been presented in Kolasa (2009). The advantage of the proposed trend specification is that the trend component and the cyclical component are modelled together in one model, and the model itself decides which part of the data belongs to the trend component and which part belongs to the cyclical component. The proposed trend specification is flexible in the sense that smoothness of the trend can easily be modified by calibrating the trend parameters differently. The results suggest that this method is capable of finding very reasonable trends in the data. Moreover, a comparison of forecast performance reveals that the proposed specification offers more reliable forecasts than the original variant of the model.

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