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The sensitivity of DSGE models' results to data detrending

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Editorial

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The sensitivity of DSGE models' results to data detrending[*]

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July 14, 2009

Abstract

This paper aims to shed light on potential pitfalls of different data filtering and detrending procedures for the estimation of stationary DSGE models. For this purpose, a medium-sized New Keynesian model as the one developed by Smets and Wouters (2003) is used to assess the sensitivity of the structural estimates to preliminary data transformations. To examine the question, we focus on two widely used detrending and filtering methods, the HP filter and linear detrending. After comparing the properties of business cycle components, we estimate the model through Bayesian techniques using in turn the two different sets of transformed data. Empirical findings show that posterior distributions of structural parameters are rather sensitive to the choice of detrending. As a consequence, both the magnitude and the persistence of theoretical responses to shocks depend upon preliminary filtering.

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1 Introduction

This paper analyzes the consequences of alternative preliminary data detrending and filtering methods for the estimation of stationary Dynamic Stochastic General Equilibrium (DSGE) models. DSGE models generally aim to explain business cycle fluctuations, therefore the model equations derived from optimizing agents are usually log-linearized around the steady state to describe the behavior of the stationary variables as they fluctuate in response to shocks. Since many macroeconomic time series are instead highly persistent and possibly non-stationary, the estimation of the model requires to transform the data consistently with the model assumptions. However, at this stage the applied macroeconomist faces a number of detrending and filtering procedures, which are common in empirical studies, including deterministic detrending, stochastic detrending and differencing.

This paper argues that even if it is well known that alternative detrending methods produce different moments in the cyclical components of the data (see, e.g. Canova (1998)) or may generate spurious business cycles (e.g. King and Rebelo (1993), Harvey and Jaeger (1993), Cogley and Nason (1995)), there is little evidence on the effects they produce on the estimation of the current generation of structural DSGE models. Since monetary business cycle models are emerging as widespread tools for forecasting and quantitative policy analysis, we believe that it is important to understand to what extent the transmission of the structural shocks and their contributions in explaining the dynamic of macroeconomic variables can be affected by preliminary ad hoc detrending approach.

For this purpose, this paper analyzes the effects of alternative preliminary data transformations using a typical New Keynesian model as the one developed by Smets and Wouters (2003) and currently employed to support policymaking at the European Central Bank. This model features nominal price and wage rigidities amid a number of real and nominal frictions which help to fit macroeconomic data. Using Bayesian estimation and validation techniques, Smets and Wouters (SW, henceforth) show that the estimated model is able to compete with more standard, unrestricted time series models, such as VARs, in out-of-sample forecasting. However, by removing sample means and extracting a separated (linear) trend from each observable in advance, the authors do not incorporate uncertainty about low-frequency components into their analysis.

In order to investigate to what extent their quantitative results are sensitive to preliminary ad hoc data transformations, we extract cyclical components from seven euro area macroeconomic time series using two widely used detrending and filtering methods: linear detrending (as in SW) and Hodrick-Prescott (HP) filtering. After comparing the properties of business cycle components in terms of volatility, persistence and co-movement with the real GDP, we estimate the model through likelihood-based methods using in turn the two different sets of transformed data. As a consequence, the first set of estimates replicates the SW empirical findings.

The results of this paper are twofold. First, we document that a number of business cycle *regularities* in the euro area vary widely across detrending methods, such as the amplitude of the fluctuations, the degree of comovement with real GDP and the phase shift of a variable relative to the overall business cycle. Moreover, when data are linearly detrended, consumption turns out to be more volatile than output contradicting the consumption smoothing hypothesis and, real wage which is commonly considered as much less variable than GDP, presents a relative high standard deviation.

Second, this paper shows that posterior estimates of the structural parameters are rather sensitive to what kind of trend-removal is applied. For instance, the Calvo price parameter, the inertial behavior of inflation and therefore, the slope of the hybrid Phillips curve depend upon preliminary data transformations. As a consequence, the impulse responses computed using the two sets of transformed data differ. Using a deterministic trend, the responses are characterized by a higher magnitude and persistence.

The remainder of this paper is organized as follows. Section II reviews the model. Section III studies the properties of the cyclical components used in the empirical exercise and their sensitivity to the choice of detrending. The estimation of the model is discussed in section IV. Section V explores the consequences for policy analyses. Section VI concludes.

2 The Smets and Wouters model

A new generation of monetary business cycle models with sticky prices and wages (the New Keynesian or New Neoclassical Synthesis (NNS) models) has become an important tool for both policy analysis and forecasting in central banking. These models combine the rigor of the Real Business Cycle (RBC) approach, characterized by the derivation of behavioral relationships from optimizing agents with the introduction of nominal rigidities (typically Calvo or Taylor-type contracts) which imply monetary non neutralities.

SW have developed a medium-scale monetary DSGE model in the new Keynesian tradition based on work by Christiano, Eichenbaum, and Evans (2005). Using euro area data, they show that the model is sufficiently rich to capture most of the statistical features of the main macroeconomic time series, as long as a sufficient number of structural shocks is considered. Applying Bayesian estimation techniques, SW show that even relatively large models can be estimated as a system. The full information approach delivers a more efficient estimate of the structural model parameters and it also provides a consistent estimate of the structural shock processes driving economic developments. On the basis of the marginal likelihood and Bayes factors, SW also point out that the estimated DSGE models perform quite well in forecasting compared to standard and Bayesian vector autoregressions (VARs and BVARs).

The Appendix reports a short description of the log-linearized version of the model whereas we refer to SW for details on the micro-foundations. The economy consists of a final-good producing firm, a continuum of intermediate-good producing firms, a continuum of households and a monetary authority. Households maximize a non-separable utility function in consumption and labour effort over an infinite life horizon. Consumption appears in the utility function relative to a time-varying external habit variable that depends on past aggregate consumption. Each household provides differentiated labour inputs so that there is some monopoly power over wages. This results in an explicit wage equation and allows for the introduction of sticky nominal wages as in the Calvo model (households are allowed to reset their wage each period with an exogenous probability). Households rent capital services to firms and decide how much capital to accumulate given certain costs of adjusting the capital stock. The introduction of variable capital utilization implies that, as the rental price of capital changes, the capital stock can be used more or less intensively according to some cost schedule.[1] Firms produce differentiated goods, decide on labour and capital inputs, and set prices according to the Calvo model. The Calvo model in both wage and price-setting is augmented by the assumption that prices that are not re-optimized in a given period are partially indexed to past inflation rates. Prices

[1]See, King and Rebelo, 2000.

are therefore set as a function of current and expected marginal costs, but are also determined by the past inflation rate. The marginal cost of production depends on the wage and the rental rate of capital. Similarly, wages also depend on past and expected future wages and inflation. Finally, the model is closed with a generalized Taylor rule, where the interest rate is set as a function of the deviation of inflation from a time-varying inflation objective and the theoretically consistent output gap (output in deviation from the efficient flexible price level of output). The model contains ten exogenous shocks, which are assumed to be orthogonal to each other. Six of these shocks are modelled as autoregressive processes of order one: total factor productivity, the investment-specific technology shock, the intertemporal preference shock, the labour supply shock, government spending and the inflation objective of the monetary authorities. The first five of these exogenous shocks are assumed to affect the flexible-price level of output that enters the central bank's reaction function as its target level for output. The rationale for this assumption is that those shocks derive from technology and preferences, and should therefore be accommodated from a welfare perspective. The remaining four shocks are assumed to be white noise: a price and wage mark-up shock, an equity premium shock and a traditional interest rate (or monetary policy) shock. Because these shocks are assumed to create inefficient temporary disturbances to the economy, they do not enter the calculation of the flexible-price output level used in the central bank's reaction function. As a result these shocks are more likely to create a trade-off between inflation and output gap stabilization.

3 The properties of the cyclical components

Business cycle components are extracted from seven euro area macroeconomic time series. These are the real GDP, real consumption, real investment, the GDP deflator, real wages, employment and the short-term nominal interest rate. The data are taken from the latest version of the Euro Area Wide Model database which has been constructed by the staff of the Econometric Modelling Division of the ECB (see, Fagan et al., 2001). As in Smets and Wouters (2003), the data span the period 1970:Q2 - 1999:Q4 though, in the empirical analysis, the 1970s are only used to initialize the estimates. Real variables are expressed as 100 time the log. The inflation rate is measured by the log of the quarterly changes in the GDP deflator. The nominal short-term interest rate is expressed on a quarterly basis.

Throughout the paper we compare the consequences stemming from the use of the two following data transformations:

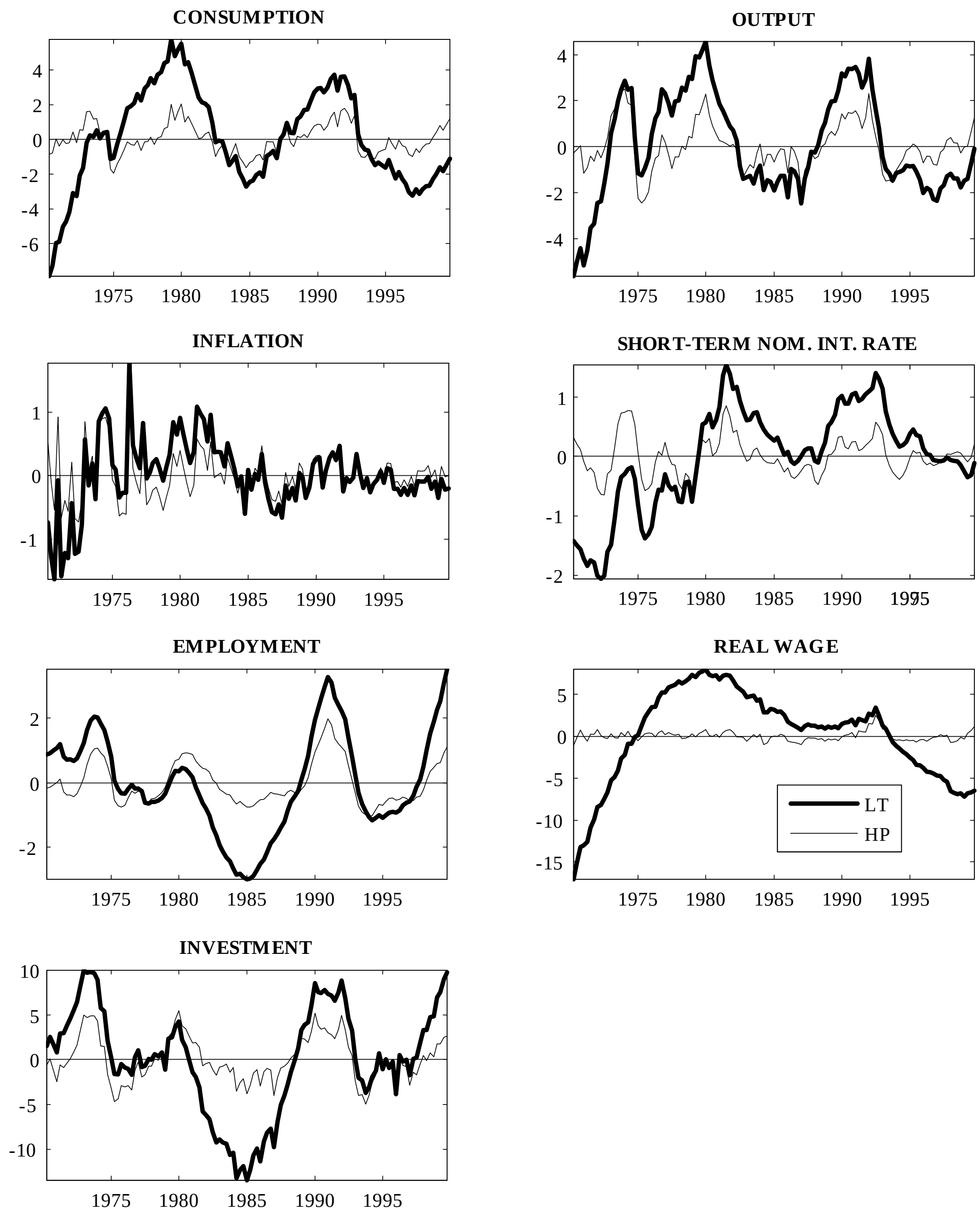
a) Following SW, all variables are demeaned and linearly detrended. The short-term interest rate is detrended with the same linear trend in inflation (LT);

b) All variables are independently HP filtered with smoothing parameter, $\lambda = 1600$ (HP).

Before proceeding to the estimation of the model, as in Canova (1998), we document that a number of business cycle *regularities* vary widely across detrending methods, such as the amplitude of the fluctuations, the degree of comovement with real GDP and the phase shift of a variable relative to the overall business cycle.

Figure 1 presents a plot of the cyclical components. The thin line represents the HP filtered data whilst the bold line is the LT cyclical behavior. Figure 1 shows the obvious fact that the two estimated business cycle components are significantly different across the two detrending methods. Since by construction the fit of the linear trend is worse that the fit of the HP trend, business cycle components extracted using a simple linear trend present a marked persistency and a higher variability compared to the HP filtered data. Concerning the real wage series, the comparison of the two cyclical components is even problematic.

Figure 1 – Cyclical components of Euro area macro data



Note: Thin line - HP filter (λ=1600). Solid line - LT cyclical behavior.

Summary statistics reported in the next sub-section highlight that also not obvious facts as relative variabilities, correlations and the phase shift of a variable relative to the overall business cycle differ across the two methods. The origins of such a difference should be sought in the assumptions about the properties of the trend implied by the two alternative methodologies.

Table 1.1 - Descriptive statistics for cyclical components of series, 1970-1999

	st.dev.	Relative variability (as % of GDP)					
Method	GDP	Consum.	Invest.	Real wages	Employm.	Inflation	Short-term nom. rate
LT	2.22	1.24	2.70	2.46	0.69	0.25	0.38
HP	1.02	0.85	2.48	0.56	0.66	0.36	0.32

LT assumes that the trend component is a deterministic process which can be approximated with a linear function of time. Since it cannot fully eliminate stochastic trends which characterize many macroeconomic time series, LT can bias the estimate of the cyclical component by partially allocating trend components into the cyclical ones. This clearly produces cycles of longer length and higher variability. On the other hand, the HP filter extracts a trend which is stochastic but it moves smoothly over time. Singleton (1988) shows that, when applied to stationary time series, the HP filter is a rough approximation to a high-pass filter, damping fluctuations which last longer than eight years per cycle (in quarterly data) and passing shorter cycles without change.[2] However, when it is applied to trend-stationary time series, the HP filtering is conceptually equivalent to a two-step operation: linearly detrend the data and then apply the HP filter to deviations from trend. Thus, the HP filter is like a high pass filter on deviations from trend. This may reduce the persistence and the volatility of the HP cyclical components in comparison with linear detrended data.

Moreover, if applied to difference-stationary time series, the filter does not operate like a high pass filter. Cogley and Nason (1995) show that, in this case, the HP filter is equivalent to a two-step linear filter: difference the data to make them stationary and then smoothing them with an asymmetric moving average filter. This operation strongly amplifies growth cycles at business cycle frequencies and damps long- and short-run fluctuations. As a consequence, the filter can create artificial persistence as well as business cycle periodicity and comovement even if none are present in the original data. In this respect, applying the HP filter to an integrated process is similar to detrending a random walk (Nelson and Kang, 1981).[3]

3.1 Descriptive statistics

Table 1.1 and 1.2 summarize the properties of the cyclical components by reporting few moments of the distribution and some short-term cross correlations. Table 1.1 presents the standard deviation of the cyclical component of GDP and the standard deviation of the remaining variables as percentage of GDP standard deviation. The standard deviation of the real GDP is more than double compared to the HP filter (2.22 against 1.02), however the fact that the absolute standard deviation of GDP is higher using LT is not a finding since it is obtained by construction. The most important findings are instead the differences concerning relative variabilities. In this

[2] A high pass filter removes low frequency or long cycle components and allows the high frequency or short cycle components to pass through.

[3] Nelson and Kang show that regressing a random walk series on a deterministic time trend generates residuals exhibiting spurious cycles.

respect, two main results emerge. First, the LT filter produces (relative) volatility statistics that exceed those of the HP filter and, for some variables, by a large amount. For instance, the relative variability of the real wage is four times higher using LT (2.46 compared to 0.56). The pattern described above is reversed for inflation since the HP filter produces the highest measure of cyclical volatility.[4]

Second, using a simple linear trend, the relative volatility of consumption and real wage seems to be at odds with common stylized facts of the business cycle (see, e.g. Kydland and Prescott, 1990, Stock and Watson, 1999). Indeed, we find that in this case consumption is relatively more volatile than output (1.24) contradicting the consumption smoothing hypothesis and the real wage rate, which is commonly considered as much less variable than GDP, presents a relative high standard deviation (2.46).

Table 1.2 - Descriptive statistics for cyclical components of series, 1970-1999

			Cross correlations with GDP $(corr(x_t, y_{t+k}))$								
	series	k	-4	-3	-2	-1	0	1	2	3	4
	GDP		0.72*	0.82*	0.90*	0.96*	1.00				
	Consumption		0.79*	0.85*	0.89*	0.92*	0.94*	0.91*	0.87*	0.82*	0.74*
	Investment		0.12	0.20*	0.28*	0.34*	0.40*	0.43*	0.44*	0.44*	0.43*
LT	Employment		0.25*	0.30*	0.34*	0.37*	0.37*	0.39*	0.39*	0.38*	0.36*
	Real wage		0.72*	0.72*	0.71*	0.69*	0.67*	0.62*	0.57*	0.51*	0.44*
	Inflation		0.61*	0.60*	0.64*	0.65*	0.60*	0.53*	0.44*	0.31*	0.21*
	Short-term rate		0.60*	0.59*	0.57*	0.52*	0.45*	0.34*	0.21*	0.09	-0.04
	GDP		0.22*	0.44*	0.65*	0.85*	1.00				
	Consumption		0.25*	0.38*	0.51*	0.63*	0.78*	0.73*	0.64*	0.54*	0.39*
	Investment		0.31*	0.47*	0.63*	0.77*	0.89*	0.80*	0.69*	0.55*	0.39*
HP	Employment		0.58*	0.69*	0.77*	0.79*	0.73*	0.61*	0.45*	0.28*	0.11
	Real wage		0.34*	0.34*	0.30*	0.32*	0.31*	0.18	0.06	-0.04	-0.16
	Inflation		0.20*	0.25*	0.37*	0.42*	0.32*	0.22*	0.09	-0.15	-0.24*
	Short-term rate		0.50*	0.61*	0.67*	0.64*	0.50*	0.27*	0.001	-0.25*	-0.43*

"*" indicates that the statistic is significant at 5%

Statistics presented in Table 1.2 provide information on the degree of co-movement of the cyclical behavior of each series with the cyclical component of real GDP. Specifically, this is the correlation between x_t and y_{t+k} where x_t is the transformed series listed in the second column and y_{t+k} is the $k-$quarter lead of the filtered logarithm of real GDP. A large positive correlation at $k = 0$ indicates procyclical behavior of the series; a large negative correlation at $k = 0$ indicates countercyclical behavior; and a maximum correlation at, for example, $k = -1$ indicates that the cyclical component of the series tends to lag the aggregate business cycle by one quarter. For each variable, the upper part of the table reports co-movements in the LT case whereas the lower part presents correlation coefficients for the HP filtered data. Table 1.2. suggests that the correlation between output and the other real macroeconomic variables is very sensitive to the choice of detrending. This result implies important consequences for those variables which are

[4] Inflation contains sizable high-frequency components which are not removed by the HP filter. As a result, the variability of inflation is slightly higher using this filtering procedure.

commonly considered having systematic relationship to the business cycle, such as consumption and investment. For instance, consumption presents a strong procyclical pattern (correlation at zero is 0.94 and 0.78, respectively) but the magnitude of the cross-correlations with real GDP decreases when the data are HP filtered. Investment behaves in a strong procyclical manner when data are HP filtered whereas it turns out to be only slightly procyclical with a lead using LT. The contemporaneous correlation between employment and GDP is 0.73 using the HP filter, however the correlation becomes larger when employment is shifted back by about half a year suggesting that employment lags the cycle. On the contrary, results related to the LT method provide evidence that employment is nearly contemporaneous with a slight lead. Real wages turn out to be strongly procyclical when the raw data series are linearly detrended. The cross-correlations indicate that real wages lag the cycle by approximately one year. However, the values of the cross-correlation with real GDP decrease greatly using the HP filter. Finally, both the cyclical components of inflation and of the short-term nominal interest rate are strongly procyclical and lag the business cycle. These patterns are clearly evident in the figures even though the magnitude of the cross-correlations fall when the data are HP filtered for inflation and increase for the short-term nominal interest rate.

Figure 2 presents the autocorrelation function of the filtered data. Not surprisingly, the pattern of serial dependencies differs across the two methods whereas LT generally produces higher serial correlation coefficients. Next section shows how the discrepancy in the autocorrelation functions rebounds on parameter estimates, in particular of those designate to capture the observed persistence in the data.

4 Empirical analysis

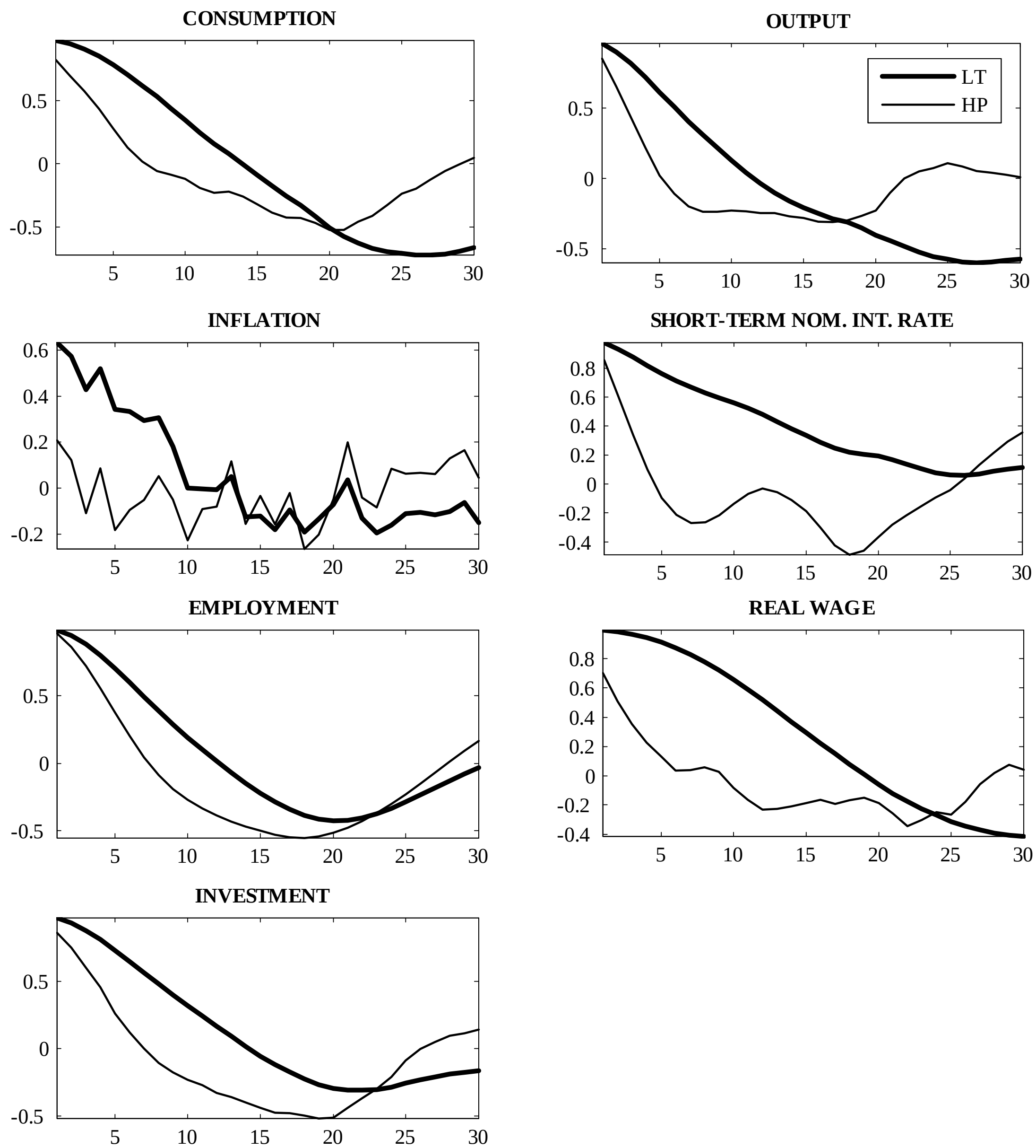
This section illustrates the estimation of the model using the above alternative sets of transformed data. Full-system Bayesian estimation methods are applied in order to bring the DSGE model to the data. Bayesian techniques, which have become a popular tool for the analysis of DSGE models, thanks to the work of, among others, Schorfheide (2001), Smets and Wouters (2003) and Rabanal and Rubio-Ramirez (2005), have advantages over the traditional maximum likelihood methods when dealing with potential model misspecification and identification problems.[5]

We solve the system of linear rational expectation equations (1) - (14) in Appendix A using standard solution methods. The Kalman filter as in Sargent (1989) is then applied to evaluate the likelihood function associated with the linear state-space system. In a Bayesian framework, the likelihood function is then combined with diffuse prior distributions to compute the posterior densities of the model parameters. Marginal prior distributions are listed in Table 3 and 4; priors are adopted from SW and are kept fixed during the exercise.[6]

[5] The interested reader is referred to the book by Canova (2005).

[6] To replicate the SW findings, we also use the same calibration. The discount factor β is calibrated to be 0.99 which implies an annual steady-state real interest rate of 4 percent. The depreciation rate τ is set equal to 0.025 per quarter, which implies an annual depreciation on capital equal to 10 percent. We set α =0.30, which roughly implies a steady-state share of labor income in total output of 70 percent. The share of steady-state consumption in total output is assumed to be 0.6, while the share of steady-state investment is assumed to be 0.22. This corresponds more or less to the average share of output and investment in total euro area output over the estimation period. It also implies a steady-state capital output ratio of about 2.2. In addition, we also need to fix the parameter capturing the markup in wage setting as this parameter is not identified. We set λ_w equal

Figure 2 – Autocorrelation functions



Finally, a random walk Metropolis-Hastings algorithm is used to generate 500,000 draws from the posterior distributions. All parameters are initialized at their posterior mode values

to 0.5, which is somewhat larger than the findings in the microeconometric studies by Griffin (1996) based on U.S. data.

computed by directly maximizing the (log) posterior distribution using the quasi-Newton BFGS method as in the `csminwel.m` algorithm by C. Sims. The variance of the innovation in the Metropolis-Hastings has been set in order to get an acceptance rate of about 35%. Recursive means from multiple chains are then used to check for convergence of the Markov chain generated by the Metropolis-Hastings algorithm to the posterior of interest.

4.1 Estimation results

Posterior distributions of structural parameters obtained using the two alternative detrended and filtered data (LT and HP) are compared in Tables 2 and 3. The tables present the estimated posterior mean, the 5th, 50th, and 95th percentiles of the posterior distributions and the estimated posterior mode. Column 3 reports the estimates for the LT case and thus this basically replicates the SW estimation results.[7] Column 4 presents posterior statistics for the HP filtered data. Throughout this section, the discussion is focused on those parameters which appear more sensitive to preliminary data transformation.

Starting from the parameters describing the price setting behavior of firms, we find that the posterior distribution of the Calvo price parameter, ξ_p, largely varies across the two detrending methods. The posterior median of ξ_p is 0.94 using LT which implies an average duration of prices in the Euro Area equals to 4 years. However, using the HP filtered data, the estimated average duration of price contracts drops to 1 and a-half year.

The posterior median of the price indexation parameter γ_p, which characterizes the inertial behavior of inflation, is 0.40 using the HP filter and it raises to 0.56 with LT. This implies that the relative importance of the backward versus forward looking components in explaining the inflation dynamics depends partially on the preliminary definition of the cycle. Moreover, since the slope of the NK Phillips curve is a function of both ξ_p and γ_p, then it turns out that price elasticity to real marginal cost greatly varies across the two detrending methods. Specifically, the slope of the Phillips curve is 6 times larger using the HP filter (0.02 compared to 0.003 in the LT approach).

Concerning the parameter characterizing the consumption equation, the median of the posterior distributions of the elasticity of intertemporal substitution σ_c and the habit persistence parameter h are not surprisingly higher when LT is used. Consequently, an expected 1% increase in the short term interest rate for four quarters has an impact on consumption more than double when the data are previously HP filtered (0.4 compared to 0.2).

It appears that another key difference in the results between the two estimations concerns the structural shocks. Focusing on the autoregressive parameters, one can observe that the HP filter produces smaller estimates in comparison with LT. For instance, the posterior median of the productivity shock is 0.92 when we use a deterministic trend and 0.82 in the case of the HP filter. Similar findings emerge for the remaining structural shocks, in particular for the government spending and for the consumption preference shocks.

On the basis of the higher variability characterizing the LT cyclical components, it should not be surprising that the standard errors are estimated to be in general larger using LT method in comparison with the HP filter.

[7] We find that the posterior distributions of two parameters differ substantially from those reported in SW. These parameters are the autocorrelation coefficient of the technology shock and the Calvo price parameter. These differences can be due to the use of a rectified log-linearized version of the model with respect to the version appeared in SW.

Table 2 - Prior and posterior distributions of structural parameters

	Prior distributions			Posterior distribution (LT)					Posterior distribution (HP)				
name	density	mean	st. dev.	mode	mean	5th	50th	95th	mode	mean	5th	50th	95th
Investment adj. costs	Normal	4	1.5	6.70	6.91	5.07	6.88	8.86	2.92	3.80	2.14	3.69	5.83
Fixed cost	Normal	1.45	0.25	1.00	1.02	0.63	1.01	1.42	1.29	1.23	0.85	1.23	1.62
σ consumption utility	Normal	1	0.375	1.48	1.52	1.07	1.51	1.99	1.16	1.18	0.76	1.16	1.65
σ labour utility	Normal	2	0.75	2.30	2.38	1.45	2.35	3.38	2.15	2.27	1.32	2.25	3.30
Habit in consumption	Beta	0.7	0.1	0.63	0.65	0.53	0.65	0.76	0.51	0.54	0.41	0.54	0.67
Calvo wages	Beta	0.75	0.05	0.68	0.69	0.62	0.69	0.76	0.76	0.75	0.67	0.75	0.82
Calvo prices	Beta	0.75	0.05	0.94	0.94	0.92	0.94	0.76	0.84	0.86	0.82	0.86	0.89
Calvo employment	Beta	0.5	0.15	0.76	0.76	0.71	0.76	0.81	0.67	0.66	0.60	0.66	0.72
Indexation wages	Beta	0.75	0.15	0.46	0.49	0.26	0.48	0.75	0.62	0.55	0.30	0.55	0.81
Indexation prices	Beta	0.75	0.15	0.54	0.56	0.40	0.56	0.74	0.38	0.41	0.24	0.40	0.62
Capital util. adj. cost	Normal	0.2	0.075	0.24	0.23	0.13	0.23	0.34	0.22	0.23	0.12	0.23	0.34
r_π	Normal	1.7	0.1	1.69	1.69	1.52	1.69	1.85	1.68	1.67	1.51	1.68	1.84
$r_{\Delta\pi}$	Normal	0.3	0.1	0.18	0.19	0.11	0.19	0.27	0.19	0.19	0.11	0.19	0.28
r lagged interest rate	Beta	0.8	0.1	0.94	0.94	0.91	0.95	0.97	0.90	0.92	0.84	0.92	0.97
r_y	Normal	0.125	0.05	0.07	0.07	0.02	0.07	0.13	0.10	0.09	0.02	0.09	0.17
$r\Delta_y$	Normal	0.0625	0.05	0.13	0.13	0.10	0.13	0.17	0.20	0.16	0.10	0.17	0.23

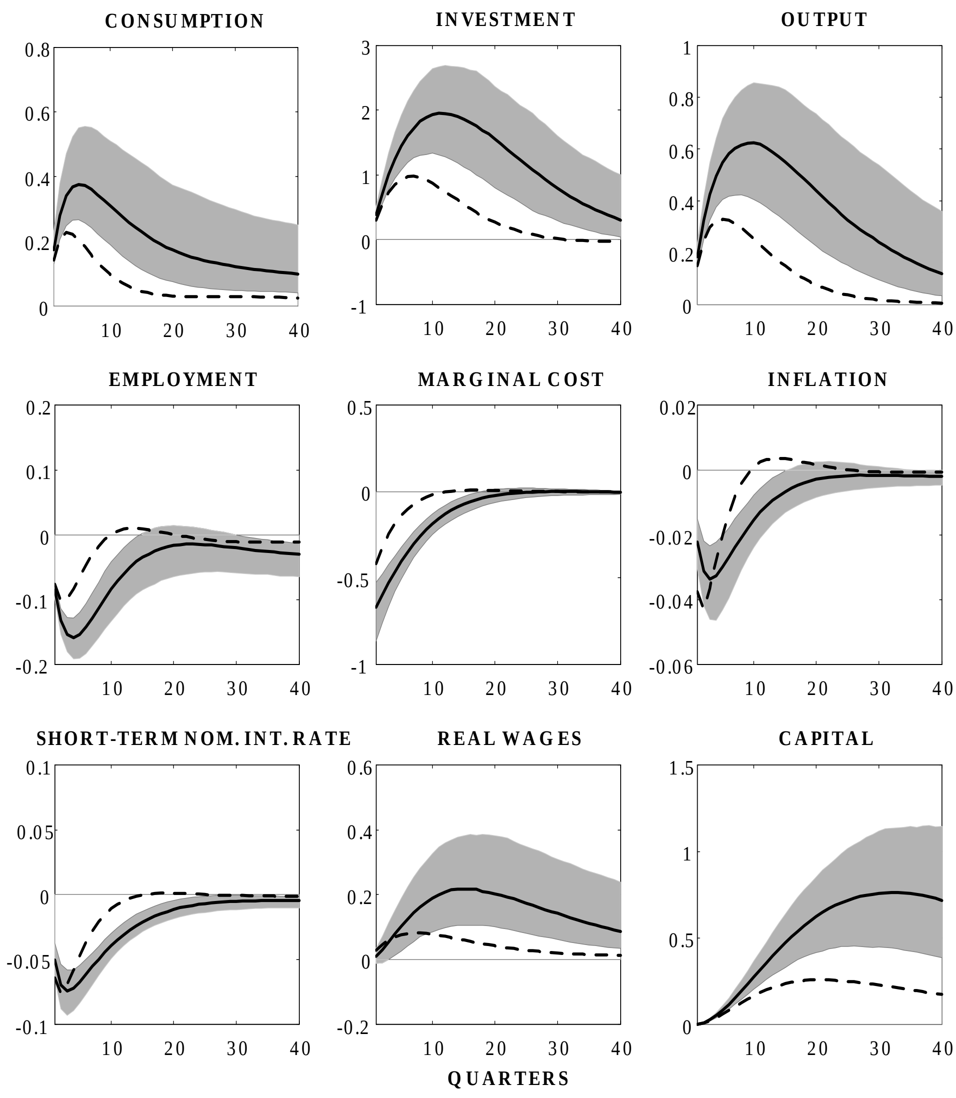
Table 3 - Prior and posterior distribution of shock processes

	Prior distribution			Posterior distribution (LT)					Posterior distribution (HP)				
name	density	mean	st.dev.	mode	mean	5th	50th	95th	mode	mean	5th	50th	95th
ρ productivity shock	Beta	0.85	0.1	0.93	0.92	0.86	0.92	0.97	0.83	0.82	0.74	0.82	0.89
ρ inflation objective shock	Beta	0.85	0.1	0.92	0.85	0.65	0.87	0.97	0.92	0.85	0.65	0.87	0.97
ρ consump. preference shock	Beta	0.85	0.1	0.84	0.82	0.74	0.82	0.88	0.62	0.61	0.46	0.62	0.75
ρ govern. spending shock	Beta	0.85	0.1	0.95	0.95	0.90	0.95	0.98	0.82	0.81	0.71	0.82	0.92
ρ labour supply shock	Beta	0.85	0.1	0.96	0.95	0.90	0.95	0.98	0.96	0.87	0.63	0.91	0.97
ρ investment shock	Beta	0.85	0.1	0.57	0.56	0.43	0.56	0.69	0.26	0.27	0.16	0.26	0.39
σ productivity shock	Inv. Gamma	0.4	2*	0.61	0.66	0.49	0.64	0.87	0.39	0.43	0.33	0.42	0.55
σ inflation obj. shock	Inv. Gamma	0.02	2*	0.01	0.02	0.01	0.01	0.04	0.01	0.04	0.01	0.01	0.16
σ consump. preference shock	Inv. Gamma	0.2	2*	0.42	0.54	0.30	0.50	0.91	0.42	0.49	0.29	0.46	0.77
σ govern. spending shock	Inv. Gamma	0.3	2*	0.31	0.32	0.28	0.32	0.36	0.28	0.29	0.25	0.28	0.33
σ labour supply shock	Inv. Gamma	1	2*	3.14	3.55	2.30	3.44	5.18	2.12	2.72	1.64	2.55	4.46
σ investment shock	Inv. Gamma	0.1	2*	0.42	0.43	0.32	0.43	0.55	0.47	0.49	0.41	0.49	0.58
σ interest rate shock	Inv. Gamma	0.1	2*	0.10	0.10	0.08	0.10	0.13	0.04	0.06	0.03	0.06	0.10
σ equity premium shock	Inv. Gamma	0.4	2*	0.19	0.34	0.13	0.27	0.82	0.19	0.33	0.13	0.27	0.74
σ price-markup shock	Inv. Gamma	0.15	2*	0.16	0.16	0.14	0.16	0.19	0.16	0.17	0.14	0.17	0.20
σ wage-markup shock	Inv. Gamma	0.25	2*	0.22	0.22	0.19	0.22	0.26	0.24	0.24	0.20	0.24	0.28

5 Implications for policy analysis

This section shows that monetary policy analyses conducted through stationary DSGE models are sensitive to preliminary data detrending methods.

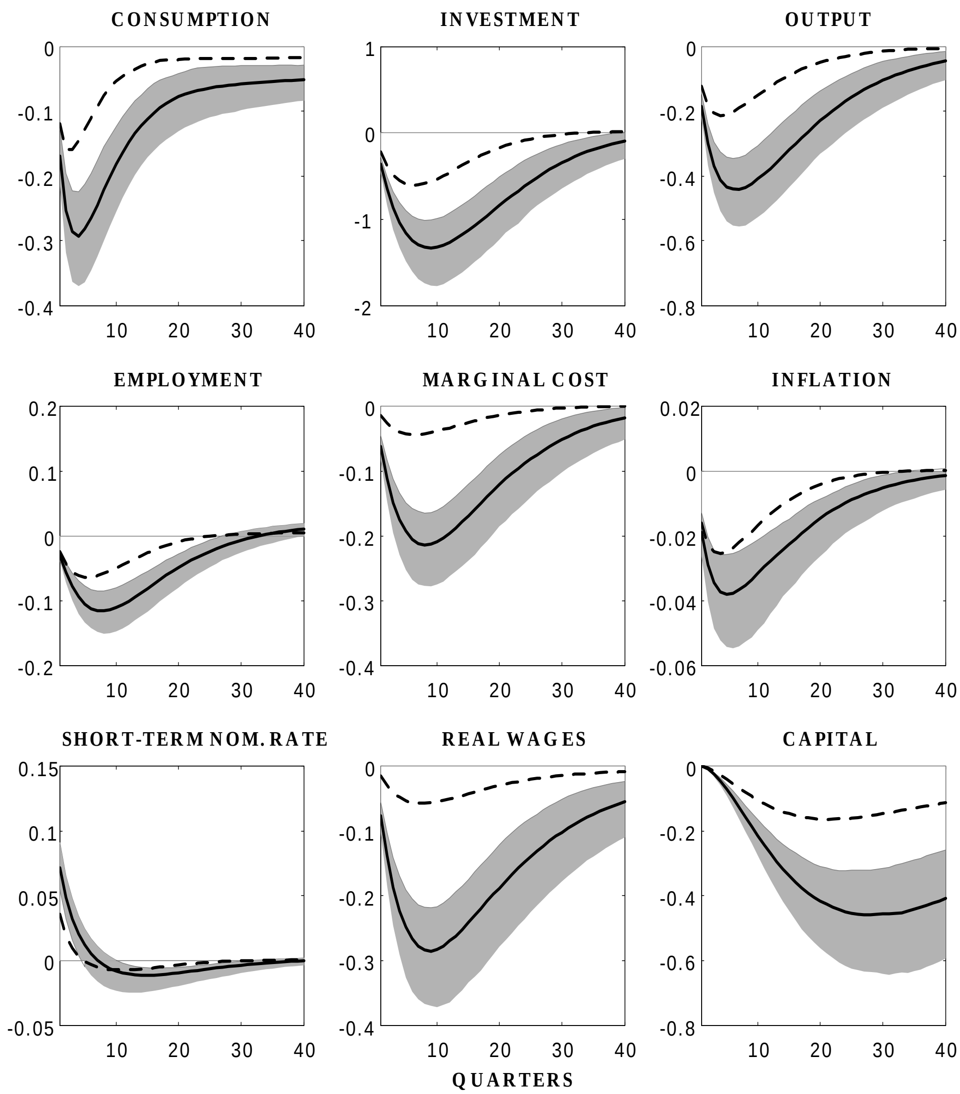
Figure 3 – Responses to a technology shock



Note: HP (dashed line) vs LT (solid line). The IRFs are based on the posterior median.

Figure 3 and 4 report impulse responses to a technology and monetary policy shocks, respectively. Figures plot the posterior median responses with 0.95 probability bands (grey area) obtained using the LT (solid line) and the posterior median responses coming from the HP filter (dashed line).

Figure 4 - Responses to a monetary policy shock



Note: HP (dashed line) vs LT (solid line). The IRFs are based on the posterior median.

Following a productivity shock, Figure 3 shows that, output, consumption, and investment rise, while employment falls. The technology shock causes the marginal cost to drop leading to a fall in inflation and a raise in real wages. By comparing the responses under the two cases, it emerges that the estimated impulse responses in the HP case lie outside the LT probability band. Both the magnitude and persistence of responses are larger when a deterministic trend is used to compute cyclical components of the data. In particular, in response to a one-standard deviation productivity shock, output increases by approximately 20 basis points in the LT case, it reaches its maximum at 60 basis points after ten quarters and then slowly dies out. In the HP filter case, output increases initially for the same amount however, it reaches the maximum at 30 basis points after approximately five quarters. The half-lives of the shock are estimated to be about 6 and 3 years for the LT and HP filter, respectively. Similar patterns emerge for the remaining variables.

Following a temporary monetary policy tightening, Figure 4 shows that the short-term nominal interest rate rises but the increase is more than double in the LT case. Indeed, we find that a one-standard deviation monetary shock corresponds to a 8-basis points move in the short-term interest rate for LT and 3-basis points move for the HP case. This produces a hump-shaped fall in output, consumption and investment, however the magnitude of the response depends on preliminary data transformation. For instance, focusing on output, we observe that, after a temporary monetary policy shock, output falls by approximately 18 basis points in the LT case, it reaches a peak at 40 basis points after six quarters, and then slowly returns to the baseline. In the HP filter case, output decreases initially for the same amount, however it reaches its minimum after five quarters at 20 basis points. For more than 4 years, the impact on GDP in the LT case is larger than the maximum value of the response obtained using the HP filter.

In line with the stylized facts following a monetary policy shock, real wages fall, although the maximum impact on this variable is three times larger in the LT case (about 27 basis points compared to 9 basis points).

6 Conclusions

The extraction of cyclical movements about trends is a long-standing problem of empirical business cycle research. This literature has already emphasized how the mechanical application of detrending methods in general, and the HP filter in particular, may lead to collections of stylized business cycle facts with questionable value. This paper shows that cyclical components extracted using different methods have different properties in terms of relative variability, persistence and cross-correlations with real GDP.

Since DSGE models are good approximations about a steady state, they are a natural candidate to study business cycle fluctuations. However, this requires the definition of what business cycle components of the data are. Many studies on this area of research seem to forget this key point, indeed there are several examples in which means are removed and filters are mechanically applied to a wide range of macroeconomic time series without paying serious attention to the stochastic properties of the series analyzed.

Using a medium-sized DSGE model as in Smets and Wouters (2003), this paper provides evidence that different preliminary ad hoc data transformations affect posterior estimates of the model structural parameters. For instance, the Calvo price parameter, the inertial behavior of inflation and therefore, the slope of the hybrid Phillips curve are rather sensitive to the choice of detrending. These findings not only show that uncertainty about trends matters but they could raise the conjecture that the little consensus about the value of the slope of the New Keynesian Phillips curve could partially depend upon the use of different transformed data.

Moreover, macroeconomists often discuss the sizes of these structural parameters comparing them e.g. to micro data. An important implication emerging from this simple analysis is that such comparisons with micro evidence are fragile exercises. Should we compare to micro data the Calvo parameter from LT data, or from the HP detrended data?

Finally, when the estimated model is used to compute the responses of endogenous variables to structural shocks, one can observe that impulse responses computed using the two sets of detrended data are different. Using a deterministic trend, the responses are characterized by a higher magnitude and persistence.

The results in this paper strongly encourage future research to integrate the modeling of long- and short-run macrodynamics.

7 Appendix A

7.1 The log-linearized model

In what follows, the "^" above a variable denotes log-deviations from the steady-state.

The dynamics of *aggregate consumption* is given by:

$$\begin{aligned}\hat{C}_t &= \frac{h}{1+h}\hat{C}_{t-1} + \frac{h}{1-h}E_t\hat{C}_{t+1} - \frac{1-h}{\sigma_c(1+h)}(\hat{R}_t - E_t\hat{\pi}_{t+1}) \\ &\quad + \frac{1-h}{\sigma_c(1+h)}\widehat{\varepsilon}_t^b. \end{aligned} \tag{1}$$

Consumption $\hat{C}_t$ depends on the ex ante real interest rate $\hat{R}_t - E_t\hat{\pi}_{t+1}$ and, with external habit formation, on a weighted average of past and expected future consumption. When $h = 0$, this equation reduces to the traditional forward-looking consumption equation. In this specification the interest elasticity of consumption depends not only on the intertemporal elasticity of substitution σ_c, but also on the habit persistence parameter (h). A high degree of habit persistence will tend to reduce the impact of the real rate on consumption for a given elasticity of substitution. Finally, $\widehat{\varepsilon}_t^b$ represents a preference shock affecting the discount rate that determines the intertemporal substitution decisions of households. This shock is assumed to follow a first-order autoregressive process with an i.i.d. normal error term:

$$\widehat{\varepsilon}_t^b = \rho_b\widehat{\varepsilon}_{t-1}^b + \eta_t^b. \tag{2}$$

The *investment equation* is given by:

$$\hat{I}_t = \frac{1}{1+\beta}\widehat{I}_{t-1} + \frac{\beta}{1+\beta}E_t\widehat{I}_{t+1} + \frac{\varphi}{1+\beta}\widehat{Q}_t + \widehat{\varepsilon}_t^I, \tag{3}$$

where $\varphi = 1/\bar{S}''$. The capital adjustment costs is a function of the change in investment rather than its level, as in Christiano et al. (2005). This introduces an additional dynamics in the investment equation, which is useful in capturing the hump-shaped response of investment to various shocks including monetary policy shocks. A positive shock to the investment-specific technology, $\widehat{\varepsilon}_t^I$, increases investment in the same way as an increase in the value of the existing capital stock $(\widehat{Q}_t)$. This investment shock is also assumed to follow a first-order autoregressive process with an i.i.d. normal error term:

$$\widehat{\varepsilon}_t^I = \rho_I\widehat{\varepsilon}_{t-1}^I + \eta_t^I. \tag{4}$$

The corresponding *Q equation* is given by:

$$\widehat{Q}_t = \frac{\overline{r}^k}{1-\tau+\overline{r}^k}E_t\widehat{r}_{t+1}^k + \frac{1-\tau}{1-\tau+\overline{r}^k}E_t\widehat{Q}_{t+1} - (\widehat{R}_t - \widehat{\pi}_{t+1}) + \widehat{\eta}_t^Q, \tag{5}$$

where τ is the depreciation rate and $\bar{r}^k$ stands for the rental rate of capital so that $\beta = 1/(1-\tau+\overline{r}^k)$.The current value of the capital stock depends negatively on the ex ante real interest rate, and positively on its expected future value and the expected rental rate. The introduction of a shock to the required rate of return on equity investment, $\widehat{\eta}_t^Q$, is a shortcut to capture changes in the cost of capital that may be due to stochastic variations in the external finance premium. The equity premium shock follows an i.i.d. normal process. The *capital accumulation equation* is:

$$\widehat{K}_t = (1-\tau)\widehat{K}_{t-1} + \tau \widehat{I}_{t-1}. \tag{6}$$

With partial indexation, the *New Keynesian Phillips curve* is given by:

$$\begin{aligned} \widehat{\pi}_t &= \frac{\beta}{1+\beta\gamma_p} E_t \widehat{\pi}_{t+1} + \frac{\gamma_p}{1+\beta\gamma_p} \widehat{\pi}_{t-1} + \\ &+ \frac{1}{1+\beta\gamma_p} \frac{(1-\beta\xi_p)(1-\xi_p)}{\xi_p} [\alpha \widehat{r}_t^k + (1-\alpha)\widehat{w}_t - \widehat{\varepsilon}_t^a - \widehat{\eta}_t^p]. \end{aligned} \tag{7}$$

Inflation depends on past and expected future inflation and the current marginal cost, which itself is a function of the rental rate on capital, the real wage, and the productivity parameter. When $\gamma_p = 0$, this equation reverts to the standard purely forward-looking Phillips curve. In other words, the degree of indexation determines how backward looking the inflation process is. The elasticity of inflation with respect to changes in the marginal cost depends mainly on the degree of price stickiness. When all prices are flexible ($\xi_p = 0$) and the price-markup shock is zero, this equation reduces to the normal condition that in a flexible price economy the real marginal cost should equal one. The productivity shock is assumed to follow an autoregressive process:

$$\widehat{\varepsilon}_t^a = \rho^a \widehat{\varepsilon}_{t-1}^a + \eta_t^a, \tag{8}$$

whereas $\widehat{\eta}_t^p$ is an i.i.d. normal price mark-up shock.
Similarly, partial indexation of nominal wages results in the following real wage equation:

$$\begin{aligned} \widehat{w}_t &= \frac{\beta}{1+\beta} E_t \widehat{w}_{t+1} + \frac{1}{1+\beta} \widehat{w}_{t-1} + \frac{\beta}{1+\beta} E_t \widehat{\pi}_{t+1} - \frac{1+\beta\gamma_w}{1+\beta} \widehat{\pi}_t + \\ &+ \frac{\gamma_w}{1+\beta} \widehat{\pi}_{t-1} + \frac{1}{1+\beta} \frac{(1-\beta\xi_w)(1-\xi_w)}{\xi_w (1 + \frac{(1+\lambda_w)\sigma_L}{\lambda_w})} * \\ &* [\widehat{w}_t - \sigma_L \widehat{L}_t - \frac{\sigma_c}{(1-h)} (\widehat{C}_t - h\widehat{C}_{t-1}) + \widehat{\varepsilon}_t^L] + \widehat{\eta}_t^w]. \end{aligned} \tag{9}$$

The real wage $\widehat{w}_t$ is a function of expected and past real wages and the expected, current and past inflation rate where the relative weight depends on the degree of indexation (γ_w) to lagged inflation of the non-optimized wages. When $\gamma_w = 0$, real wages do not depend on the lagged inflation rate. There is a negative effect of the deviation of the actual real wage from the wage that would prevail in a flexible labour market. The size of this effect will be greater, the smaller the degree of wage stickiness (ξ_w), the lower the demand elasticity for labour (higher mark-up λ_w) and the lower the inverse elasticity of labour supply σ_L or the flatter the labour supply curve. $\widehat{\varepsilon}_t^L$ is a preference shock representing a shock to the labour supply and is assumed to follow a first-order autoregressive process with an i.i.d. normal error term:

$$\widehat{\varepsilon}_t^L = \rho^L \widehat{\varepsilon}_{t-1}^L + \eta_t^L. \tag{10}$$

In contrast, $\widehat{\eta}_t^w$ is assumed to be an i.i.d. normal wage mark-up shock.

The equalization of marginal cost implies that, for a given installed capital stock, *labor demand* depends negatively on the real wage (with a unit elasticity) and positively on the rental rate of capital:

$$\widehat{L}_t = -\widehat{w}_t + (1+\psi)\widehat{r}_t^k + \widehat{K}_{t-1}, \tag{11}$$

where $\psi = \psi(1)'/\ \psi(1)''$ is the inverse of the elasticity of the capital utilization cost function. The *goods market equilibrium condition* can be written as:

$$\widehat{Y}_t = (1-\tau k_y - g_y)\widehat{C}_t + \tau k_y \widehat{I}_t + \varepsilon_t^g = \phi\widehat{\varepsilon}_t^a + \phi\alpha\widehat{K}_{t-1} + \phi\alpha\psi\widehat{r}_t^k + \phi(1-\alpha)\widehat{L}_t, \tag{12}$$

where k_y is the steady state capital-output ratio, g_y the steady-state government spending-output ratio, ϕ is 1 plus the share of the fixed cost in production. The government spending shock follows a first-order autoregressive process with an i.i.d.-normal error term:

$$\widehat{\varepsilon}_t^G = \rho^G \widehat{\varepsilon}_{t-1}^G + \eta_t^G. \tag{13}$$

The monetary reaction function is given by:

$$\begin{aligned} \widehat{R}_t \quad = \quad & \rho\widehat{R}_{t-1} + (1-\rho)\{\overline{\pi}_t + r_\pi(\widehat{\pi}_{t-1} - \overline{\pi}_t) + r_Y(\widehat{Y}_t - \widehat{Y}_t^p)\} + \\ & + r_{\Delta\pi}(\widehat{\pi}_t - \widehat{\pi}_{t-1}) + r_{\Delta y}(\widehat{Y}_t - \widehat{Y}_t^p - (\widehat{Y}_t - \widehat{Y}_{t-1}^p)) + \eta_t^R. \end{aligned} \tag{14}$$

The monetary authorities follow a generalized Taylor rule by gradually responding to deviations of lagged inflation from an inflation objective (normalized to be zero) and the lagged output gap defined as the difference between actual and potential output (Taylor 1993). The parameter ρ captures the degree of interest rate smoothing. In addition, there is a short-run feedback from the current changes in inflation and in the output gap. Finally, there are two monetary policy shocks: one is a persistent shock to the inflation objective ($\overline{\pi}_t$), the other is a temporary i.i.d.-normal interest rate shock (η_t^R).

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