Detrending Time Series and Business Cycles. The Romanian Case

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Abstract: Detrending time series trend is a very important research topic for the economics of economic cycles, yet up to this moment no consensus has been reached on the methods used, which makes it a controversial topic. The papers made on the comparative analysis of time series exclusion trend are based on relatively large samples as to what we have available in Romania. The initiation of the passage to a market economy starting with 1989 meant for Romania changes in statistical records at that time and afterwards, therefore the samples we have available for the study are relatively limited as to samples from developed countries. Moreover, while the analysis for USA is made on values of the gross domestic product at a monthly rate, for Romania the values for the gross domestic product we have available are at most at a quarterly rate since 1998. Our analysis was conducted on the business cycles of variables representing fundamental indicators of the evolution of an economy on a quarterly basis during 1998.1 – 2011.3: gross domestic product, the final consumption, the working hours, the real wages, the productivity and the capital stock. To estimate the business cycles of variables we took into consideration the polynomial functions of time, the first order differences, the Beveridge-Nelson decomposition and Hodrick-Prescott filter. The results obtained are in compliance with the previous research performed on the economies of other countries.

Keywords: business cycles; stationarity; asimetry; Beveridge-Nelson decomposition.

JEL Classification: E 32; C 18; C22

1 Introduction

Detrending time series is a controversial research topic because a universally valid method has not been agreed upon so far. Detrending the time series also represents a very important research theme as it is at the basis of the estimation of variables' business cycles. Since the developed countries have large data samples of macroeconomic variables and are frequently (monthly) registered, most of the studies regarding the effect of the methods used in detrending time series are performed on these countries. The Central and East European countries, among which Romania as well, have changed their economic system starting with 1990 and the adherence to the European Union imposed the harmonization of the national statistical

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registration system with the European one, determining in the case of Romania the existence of small comparable data sets starting with 1996 or even 1998 with a quarterly frequency at the most.

This paper undertakes to analyze the effect of the estimations methods of the macroeconomic variable trend over the cyclic composition of some macroeconomic series in Romania.

The importance of detrending the macroeconomic series may be considered from several perspectives. On the one hand, the univariate exclusion methods of the macroeconomic series trend enable their cyclic component to be obtained (without considering the random component of time series). On the other hand, the cyclic component of the gross domestic product is the output gap that may indicate its position in the cyclic evolution of the economy and its weakness. The information on the position in the cyclic evolution of the economy is relevant as it affects the inflationist pressure on the economy that at its turn determine the monetary policy.

The estimated trend of the gross domestic product of a country is its potential gross domestic product and the shifts from the trend are the output gap. The potential gross domestic product "reflects the optimum potential supply of an economy and facilitates an estimate of non-inflationary growth" (Altăr et al., 2009).

The issue of detrending the macroeconomic series has been always drawing attention. Canova (1998) makes a synthesis of the exclusion methods used in time series trend. He classifies them into two large groups: statistical procedures, in which he includes polynomial functions of time, first order differences, Beveridge and Nelson's procedure (), unobserved components model, frequency domain methods and economic procedure, in which he includes a model of common deterministic trends, a model of common stochastic trends, the Hodrick and Prescott's filter (1997). Of the methods critically presented by Canova (1998), few are the methods commonly used in specialized literature.

The identification and the exclusion of the trend from macroeconomic variables plays the part of transforming the initial data in a process characterized by mean zero, stochastic and stationary in covariance. Such a process has the second order moment invariant in time. The discharge of the trend is not enough, as seen later, to induce stationarity in covariance, but it is a first stage.

Before describing the trend estimation methods, let it reminded that usually the logarithmic values of variables are used, which express the level of macroeconomic indicators. The logarithm of a variable recorded in time is actually the growth rate of the variable.

This paper deals with the exclusion methods of macroeconomic variable trends analyzed by linear trend, quadratic trend, first difference, Beveridge-Nelson decomposition and the Hodrick-Prescott Filter. We did not consider the Baxter-King, Khristiano-Fitzgerald filters because we obtain a cyclic composition with few values.

2. Methods

The first research conducted on the cyclic behavior of industrialized countries was faced with the issue of separating the fluctuations of long-term variables, the trend from the cyclic fluctuations. In order to ease the calculus, without taking into account the properties of the analyzed time series, the traditional methods were considered. According to those, a time series observed during a certain period is additively decomposed in a trend component and a cyclic component that are supposed to be independent from one another hence:

$y_t = \tau_t + c_t$, $E(\tau_t, \varepsilon_s) = 0$, for all *t,s*

where: y_t - the values of the registered variable

τ_t - the trend component

c_t - the cyclic component

$t = \overline{1.T}$, the registration period

The variable y_t is considered the logarithm of the registered economic variable and the data are observed on a yearly basis. İn case we have monthly or quarterly observations, y_t results after the exclusion of the seasonal component and logarithmation.

2.1. Polynomial functions of time

The linear trend. The trend and cycle components of a time series are not observable and therefore they need to be estimated. The easiest model is the linear trend model.

$\mu_t = \beta_0 + \beta_1 t$

where, if y_t is logarithmated, it implies a constant increase of the variable.

The estimation of the regression model

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t$$

can be done using the least square method. If $\hat{\beta}_0, \hat{\beta}_1$ are the estimators of the parameters of the regression model, the trend component is determined using the relation:

$$\hat{\mu}_t = \hat{\beta}_0 + \hat{\beta}_1 t$$

and the cyclic component is obtained as a residual variable of the estimated equation hence:

$$\hat{c}_t = \hat{\varepsilon}_t = y_t - \left(\hat{\beta}_0 + \hat{\beta}_1 t\right)$$

The non-linear trend. The linear trend model implies that the variable ha a constant growth rate which, in reality, is hardly achieved. In order to exclude this supposition, we may consider that the trend is a polynomial time function of the form:

$$\tau_t = f\left(t\right)$$

or:

$$\tau_t = \beta_0 + \sum_{i=1}^{k} \beta_i t^i .$$

The variable can be decomposed as follows $y_t = \beta_0 + \sum_{i=1}^{k} \beta_i t^i + \varepsilon_t$

It can be observed that when i=1 we have a first order polynomial and it is a linear function, when i=2 we have a second order polynomial, that is a quadratic trend, etc.

2.2. First Order Differences

First-order differences rely on the presupposition that the time series trend is a random walk with no drift, meaning a stochastic trend, while the cyclic component is stationary. If the series follows a random walk, this implies that it is integrated of first order. As a consequence, variable y may be written as follows:

$$y_t = y_{t-1} + \varepsilon_t$$

Therefore

- the residual variable ε_t is the cyclic component and may be obtained by the first order difference of the variable as follows:

$\hat{c}_t = \hat{\varepsilon}_t = y_t - y_{t-1}$

- and the trend is $\tau_t = y_{t-1}$

The cyclic component obtained through the first order differences is not correlated with the trend.

2.3. Beveridge – Nelson Decomposition

Beveridge and Nelson (1981) identified a possibility to decompose a non-stationary time series in a permanent component, the trend, and a cyclic component, by using the ARMA modeling. The Beveridge-Nelson decomposition is applied to non-stationary, first order integrated series that can be stationarized by difference. The decomposition leads to obtaining a trend component that is not stationary and to a stationary cyclic component, both of them being correlated. The trend is considered as a prediction of future values of the series.

The main critics of this decomposition is determined by the fact that Christiano and Eichenbaum (1990) proved that there may be several ARMA models which fit the sample autocorrelations of data set fairly well.

The Wald theorem specifies that each stationary process in co-variance has a MA(∞) representation which is also consistent with an ARMA(p,q) representation. In order to truncate the infinite sum and to obtain thus the trend and the cycle, different methods were proposed by Newbold (1990), Cuddington and Winters (1987), Miller (1988) and Morley et al. (2001).

The cyclic component using the Beveridge-Nelson decomposition can be obtained from the relation:

$$c_t = \sum_{j=1}^{q}\left[\hat{z}_t(j) - \mu\right] + \left(1 - \phi_1 - ... - \phi_p\right)^{-1} \sum_{j=1}^{p}\sum_{i=j}^{p}\phi_i\left[\hat{z}_t(q-j+1) - \mu\right]$$

where: $\hat{z}_t(k)$ - represents k periods before the forecast of $z = \Delta y$ performed during the period t,

ϕ_j - is the AR coefficient for the lag j

μ - is the mean of the process z_t

We will identify the ARMA model of each analyzed time series by taking into account the least values of Akaike (AIC) and Schwarz (SIC) information criteria obtained from the estimation of ARMA models.

2.4. The Hodrick and Prescott's filter

The Hodrick-Prescott filter is one of the most frequently used procedures in the estimation of business cycles. Its use in the macroeconomic field is justified by the fact that it succeeds to estimate the long-term component of time series, the trend, adding flexibility and adjustment to registered values so that the resulted trend corresponds to the line one would draw on the graphical representation of data. The smooth trend resulted following the application of the Hodrick-Prescott filter is ensured so as the imposition as the square of second order difference of τ_t is small. The trend component is obtained by minimizing the expression:

$$min\left[\sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=2}^{T}\left(\left(\tau_{t+1} - \tau_t\right) - \left(\tau_t - \tau_{t-1}\right)\right)\right]^2$$

where: T – the sample size,

λ - a parameter that fines the variability of the trend.

The most used values of the parameter λ are 1600 for quarterly data and 14400 for monthly data.

By applying the Hodrick-Prescott filter the resulted stochastic trend and the cyclic component are not correlated.

3. Data

In our analysis we took into consideration which the most used variables in the study of the business cycles are: the gross domestic product (GDP), the final consumption (CONS), the working hours (HOURS), the real wages (WAGE), the productivity (PROD) and the capital stock (STOCK). The variables are registered on a quarterly basis during the period 1998.1-2011.3.

The values of the gross domestic product in current prices (GDP) and the final consumption were taken from the Eurostat database.

The real values of the gross domestic product were computed by means of the harmonized index of consumption prices that was also taken from the Eurostat database.

İn order to obtain the total working hours in non-agricultural activities, we multiplied the employees' number paid from non-agricultural activities by the average number of weekly hours and the number of weeks within a term (52 weeks per year / 4 terms=13 weeks). The values for the time series of these variables for the analyzed period 1998.1-2011.3 were taken from the Laborsta site of International Labour Organisation. The data concerning the nominal wages were also taken from this database and then they were turned into real wages by means of the harmonized index of consumption prices.

The wages in non-agricultural activities with a quarterly frequency were obtained as a mean of the monthly wages also taken from the Laborsta site of International Labour Organisation. The real values of the wages in non-agricultural activities were the computed.

The productivity series was obtained as a difference between log (GDP) şi log(hours) (Canova, 1998).

Since the variable capital stock is not performed within the official statistics we estimated it by means of the method Perpetual Inventory Method as it was minutely presented by Altar M. Necula C. and Bobeică G (2009). The computing formula is:

$$K_t = K_{t-1}\left(1-\delta\right) + I_t = K_0\left(1-\delta\right)^t + \sum_{j=1}^{t} I_j \left(1-\delta\right)^{t-j}$$

where: K_t - the capital stock at the moment t

K_0 - the initial capital stock

δ - the yearly depreciation rate

I_j - the gross fix capital formation

Values for the gross fix capital formation are available on a quarterly basis in the Eurostat database. We consider the depreciation rate to be 5 percent each year (Denis şi al. 2006). The initial capital stock is considered as being twice the GDP value (Denis et al. 2006) in 1998.1, the start of the period under analysis.

Therefore we will have: $K_t / GDP = 2$

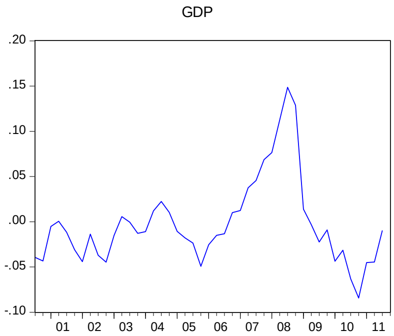
$$K_{t+1}^Q = K_t^Q\left(1-\delta_Q\right) + I_t^Q$$

where: δ_Q - the quarterly depreciation rate, $\left(1-\delta_Q\right)^4 = 1-\delta$

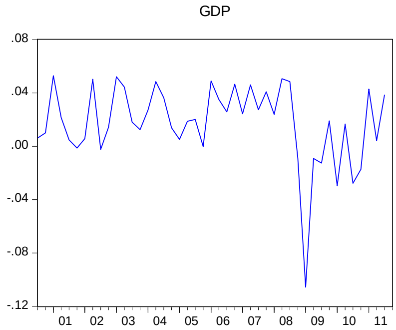
$\delta = 0.05$

4. Empirical Analysis

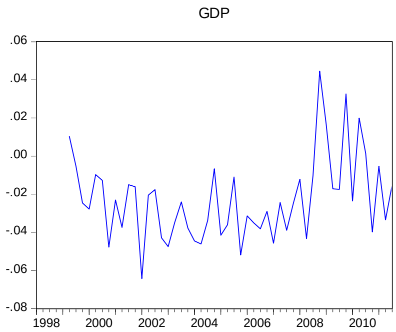
The figure above shows the cyclic components of the gross domestic products estimated by the considered methods. Graphical representations provide us some information on the characteristics of cycles induced by the estimation methods. The cyclic components of GDP estimated by the first difference, the Beveridge-Nelson decomposition and the Hodrick-Prescott 4 filter show little variability in time while the cyclic components estimated by Hodrick-Prescott 1600, the linear trend and the quadratic trend have a high variability.



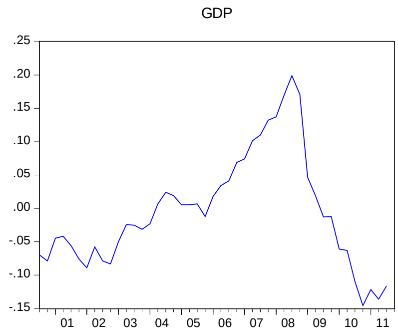
HP 1600



First difference



Beveridge – Nelson decomposition



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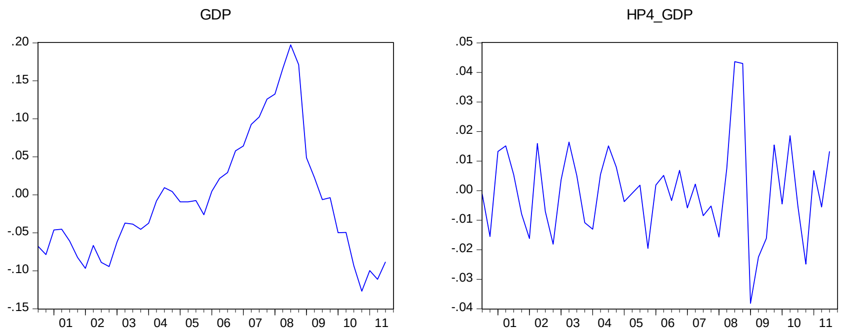

QT HP4

Figure 1. The cyclic component of GDP estimated by means of different methods

Moreover, the evolution stages of the cyclic components achieved by the first group of methods (expansion, crisis, recession, recovery) are difficult to identify because they show little and frequent fluctuations. The second group of estimation methods of cyclic components of GDP make much easier the identification of the cycle evolution stages.

From the same graphical representation we anticipate the cyclic components achieved by the first group of methods are stationary in time, while the cyclic components achieved by the second group of methods are not stationary.

Table 1 The asymmetry indicators of cyclic components of macroeconomic variables under analysis

	CONS	STOCK	GDP	HOURS	PROD	WAGE
HP 1600	1.115781	-0.13645	1.445870	-0.00649	0.852827	0.367259
DF	-0.379253	-1.23429	-0.3128	0.147891	0.300603	0.361547
HP4	-0.032177	0.262512	0.454561	-0.47767	0.116518	-0.54997
TRL	0.405248	-0.19074	0.898270	0.408112	0.714777	0.468802
TRQ	0.604220	0.344252	0.621145	0.352273	-0.11875	0.843889
BN	0.179710	0.829899	0.961670	0.087324	-0.25145	0.039892

To check the stationarity of generated cyclic components, the Augmented Dickey-Fuller test was employed. The achieved results are presented in Annex 1. The results show, as in existing studies, that the use of the linear and quadratic trend does not help in getting stationary cyclic components. Therefore, these methods are hardly ever used. Also, the cyclic component of the achieved GDP by the best used method HP 1600 is not stationary. Although the HP 1600 filter is one of the most used filters for the estimation of cyclic components of macroeconomic variables, in the case of macroeconomic variables in Romania it proves to be inefficient. The cyclic component obtained by means of the HP filter does not meet the stationarity condition. The main reason of the lack of stationarity of the cyclic component is caused, in our opinion, by the very small data sample.

Table 2 The kurtosis indicators of cyclic components of macroeconomic variables under analysis

	CONS	STOCK	GDP	HOURS	PROD	WAGE
HP 1600	4.058915	2.389346	5.192623	2.199105	3.702091	2.579045
DF	3.318798	4.179849	1.674968	3.032075	3.706701	3.473553
HP4	3.486195	3.406133	4.070277	3.185193	2.206635	
TRL	2.088395	1.995279	3.096239	2.073369	3.155096	2.699398
TRQ	2.303150	1.764892	2.812622	2.364457	2.685818	2.498580
BN	4.097854	2.762608	4.108272	2.588209	2.566009	2.428263

The analysis of the asymmetry indicators of cyclic components of analyzed variables shows contradictory results. Therefore for the same variable, different methods of estimating cyclic components show both negative asymmetry and positive asymmetry.

As for the kurtosis, the cyclic components of variables show an excess of kurtosis, HP 1600, BN and DF reaching the highest peaks as shown in the table below.

5. Conclusions

The analysis of the economic cycles of several macroeconomic variables in Romania estimated by various methods shows that the methods employed have a huge impact over their statistical characteristics. The use of the linear or quadratic trend determines the achievement of cyclic components that are non-stationary and therefore cannot be used in statistical prognosis or inference. It is surprising that the best used method of estimating business cycles, the Hodrick-Prescott filter 1600, determines the achievement of economic cycles of GDP, also non-stationary. This result is mainly determined by a very small sample of data.

6. Acknowledgement

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ANNEX Testing the stationarity of cyclic components of the variables under analysis

Table 1 Testing the stationarity of business cycles of Final Consumption (CONS)

	Model with intercept	Model with trend and intercept	Model without trend and intercept
HP 1600	-2.385917	-2.311861	-2.425766
	(0.1513)	(0.4192)	(0.0163)
DF	-5.806976	-6.021015	-5.199069
	(0.0000)	(0.0000)	(0.0000)
HP4	-15.22701	-15.39086	-15.12193
	(0.0000)	(0.0000)	(0.0000)
TRL	-1.187264	-0.617991	-1.186212
	(0.6719)	(0.9730)	(0.2119)
TRQ	-1.350559	-0.907050	-1.348074
	(0.5978)	(0.9462)	(0.1622)
BN	-9.368061	-9.257156	-9.416447
	(0.0000)	(0.0000)	(0.0000)

The results of the Augmented Dickey Fuller test are obtained by means of the Eviews statistical software.
Between brackets there are the probabilities associated to the ADF test.

Table 2 Testing the stationarity of business cycles of Capital Stock (STOCK)

	Model with intercept	Model with trend and intercept	Model without trend and intercept
HP 1600	-1.183990	0.340238	-1.134697
	(0.6733)	(0.9983)	(0.2296)
DF	-2.255409	-2.498532	-0.653436
	(0.1905)	(0.3274)	(0.4286)
HP4	-11.31536	-12.79654	-10.92529
	(0.0000)	(0.0000)	(0.0000)
TRL	-1.139860	0.044755	-1.031709
	(0.6918)	(0.9957)	(0.2677)
TRQ	-0.779490	1.915104	-0.721830
	(0.8152)	(1.0000)	(0.3984)
BN	-28.70771	-29.16187	-29.31551
	(0.0001)	(0.0000)	(0.0000)

The results of the Augmented Dickey Fuller test are obtained by means of the Eviews statistical software.
Between brackets there are the probabilities associated to the ADF test.

Table 3 Testing the stationarity of business cycles of Gross Domestic Product (GDP)

	Model with intercept	Model with trend and intercept	Model without trend and intercept
HP 1600	-1.989472	-1.933748	-2.016845
	0.2903	0.6205	0.0430
DF	-66.35568	-70.80916	-44.91386
	0.0001	0.0000	0.0000
HP4	-9.481144	-9.220988	-9.723982
	0.0000	0.0000	0.0000
TRL	-1.229201	-0.820396	-1.226323
	0.6537	0.9559	0.1987
TRQ	-1.376289	-1.027206	-1.364827
	0.5855	0.9297	0.1575
BN	-5.695239	-6.004495	-3.092263
	0.0000	0.0000	0.0027

The results of the Augmented Dickey Fuller test are obtained by means of the Eviews statistical software.
Between brackets there are the probabilities associated to the ADF test.

Table 4 Testing the stationarity of business cycles of working hours (HOURS)

	Model with intercept	Model with trend and intercept	Model without trend and intercept
HP 1600	-3.412898	-3.326062	-3.455117
	0.0156	0.0751	0.0009
DF	-7.493158	-7.491849	-7.492314
	0.0000	0.0000	0.0000
HP4	-11.21484	-10.95977	-11.45412
	0.0000	0.0000	0.0000
TRL	-2.175803	-2.042655	-2.178098
	0.2176	0.5627	0.0297
TRQ	-1.993158	-1.684425	-2.002667
	0.2887	0.7418	0.0444
BN	-7.792994	-7.826030	-7.772136
	0.0000	0.0000	0.0000

The results of the Augmented Dickey Fuller test are obtained by means of the Eviews statistical software.
Between brackets there are the probabilities associated to the ADF test.

Table 5 Testing the stationarity of productivity business cycles (PROD)

	Model with intercept	Model with trend and intercept	Model without trend and intercept
HP 1600	-2.629021	-2.591290	-2.656518
	0.0948	0.2860	0.0090
DF	-6.162775	-6.385855	-4.896991
	0.0000	0.0000	0.0000
HP4	-14.70887	-14.30323	-15.08278
	0.0000	0.0000	0.0000
TRL	-1.254981	-1.009195	-1.285185
	0.6422	0.9324	0.1804
TRQ	-1.811788	-1.599618	-1.810818
	0.3702	0.7775	0.0671
BN	-7.082570	-7.201655	-7.141381
	0.0000	0.0000	0.0000

The results of the Augmented Dickey Fuller test are obtained by means of the Eviews statistical software.
Between brackets there are the probabilities associated to the ADF test.

Table 6 Testing the stationarity of real wage business cycles (WAGE)

	Model with intercept	Model with trend and intercept	Model without trend and intercept
HP 1600	-2.085990 (0.2511)	-1.933566 (0.6206)	-2.105081 (0.0352)
DF	-7.213524 (0.0000)	-7.304897 (0.0000)	-5.850522 (0.0000)
HP4	-17.51904 (0.0000)	-17.01204 (0.0000)	-17.72242 (0.0000)
TRL	-1.503322 (0.5229)	-1.182166 (0.9022)	-1.476745 (0.1290)
TRQ	-1.339199 (0.6032)	-0.858151 (0.9519)	-1.336665 (0.1654)
BN	-8.338623 (0.0000)	-8.275054 (0.0000)	-8.065585 (0.0000)

The results of the Augmented Dickey Fuller test are obtained by means of the Eviews statistical software.
Between brackets there are the probabilities associated to the ADF test.