Testing for structural breaks in the long-run growth rate of the Russian economy

Andrey Polbin[1], Anton Skrobotov[2]

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[1] The Gaidar Institute for Economic Policy, and The Russian Presidential Academy of National Economy and Public Administration, e-mail: apolbin@gmail.com

[2] The Russian Presidential Academy of National Economy and Public Administration, e-mail: antonskrobotov@gmail.com

The paper is devoted to testing for and dating structural breaks in the long-run growth rate of the structural component of the Russian GDP. To solve this problem we use the methodology of cointegrating regression in which we allow the long-run dependence of the logarithm of the Russian real GDP on the logarithm of the real oil prices. Also, cointegrating regression equation includes the deterministic linear trend in which breaks in the slope are allowed (without any level shifts). This deterministic trend is interpreted as long run level of the structural component of the Russian GDP. The empirical results are in favor of the existence of two structural breaks in the long-run growth rate of the structural component in the period from 1995: in the 3rd quarter of 1998 and in the 3rd quarter of 2007. The point estimate of the second break three quarters early than the corresponding estimates from the univariate statistical tests. This result could indicate that the structural problems of the Russian economy started before the crisis of 2008-2009 and the relatively high growth rate immediately before this crisis was due to sharp oil prices increase.

The empirical results also show that in the cointegrating regression with piecewise continuous linear trend, the long-run elasticity of oil prices decreases approximately by 2 in comparison to estimates obtained in the literature with similar models without allowing existence of structural breaks. Our estimate of the elasticity is about 0.1. The estimate of the long-run growth rate of the structural component is about 5.3% per year until the 3rd quarter of 2007 and about 1.3% per year in subsequent periods. We haven't found evidences for the presence of the third break in the vicinity of the current economic crisis.

Keywords: structural breaks; long-run growth; oil prices; unit roots; Russian economy.

JEL classification: C12, C18, C22, E32, F43.

1 Introduction

The recent trends in the Russian GDP don't cause any optimism, especially given the very rapid economic development before the crisis of 2008-2009 (GDP grew on average by 7% per year). Many studies associate observed economic slowdown with the domestic factors of economic development and with the exhaustion of recovery growth factors after the huge drop in the real GDP due to the collapse of the Soviet Union (see, e.g., (Drobyshevskiy, Polbin 2015; Idrisov, Sinelnikov-Murylev 2014; Kudrin, Gurvich, 2014)). The other explanation of the observed low growth rates in the last seven years could be in the external factors of economic development. In particular rising oil prices before 2008 could be the predominant factor of the growth of the Russian economy. The period of rapid and huge growth in the oil prices is ended, thus we could not observe any significant economic growth of the Russian economy during the last seven years.

In this paper we make an attempt to identify the nature of the changes in the economic growth of the Russian Federation. We try to answer the question whether the observed economic slowdown in the recent years is due to purely foreign economic conditions, or changes in the internal long-term growth factors also occurred. In the paper we try to remove long-run oil price influence from the Russian real GDP and to test the hypothesis of the existence breaks in the long-run growth in the remaining component of the Russian GDP, which we define as a structural component of GDP.

The answer to the question whether changes in the long-run growth of the structural component of the Russian GDP occurred is not obvious and requires a formal statistical testing. For illustration in Figure 1 we compared the time series of the logarithm of the level of the real Russian GDP in constant 2003 prices with artificially simulated time series $\log GDP_t^*$, constructed according to the following stochastic process without any changes in the model parameters:

(1) $$\log GDP_t^* = 8.3 + 0.005t + 0.2\log p_t^{oil} + 0.01\varepsilon_t,$$

where $\log p_t^{oil}$ is logarithm of the real Brent oil prices (deflated by the seasonally adjusted index of US consumer prices)[1], t is the trend (X axis unit - 1 quarter), $\varepsilon_t \sim N(0,1)$ is a white noise.

In equation (1) we assume long-run dependence of the real GDP on the real oil prices with the elasticity equals to 0.2. Approximately the same values of the elasticity are obtained in the econometric studies (Beck et al., 2007; Kuboniwa, 2014; Rautava, 2013). We also assume a moderate 2% per year (0.5% per quarter) long-run growth rate of the structural component of the real GDP. As shown in the Figure 1, artificially simulated time series demonstrate similar trends to the actual dynamics of the real GDP of the Russian Federation. Accordingly the hypothesis that the observed breaks in the real Russian GDP are due to purely external economic factors appear to be realistic. On the other hand, if we assume that the dependence of the Russian GDP on the real oil prices is close to zero, then the observed breaks in the trend function of the Russian GDP should be attributed to changes in the long-run growth rate of its structural component. Thus causes of the recent economic slowdown are unclear.

[1] Data source: Federal Reserve Economic Data (FRED)

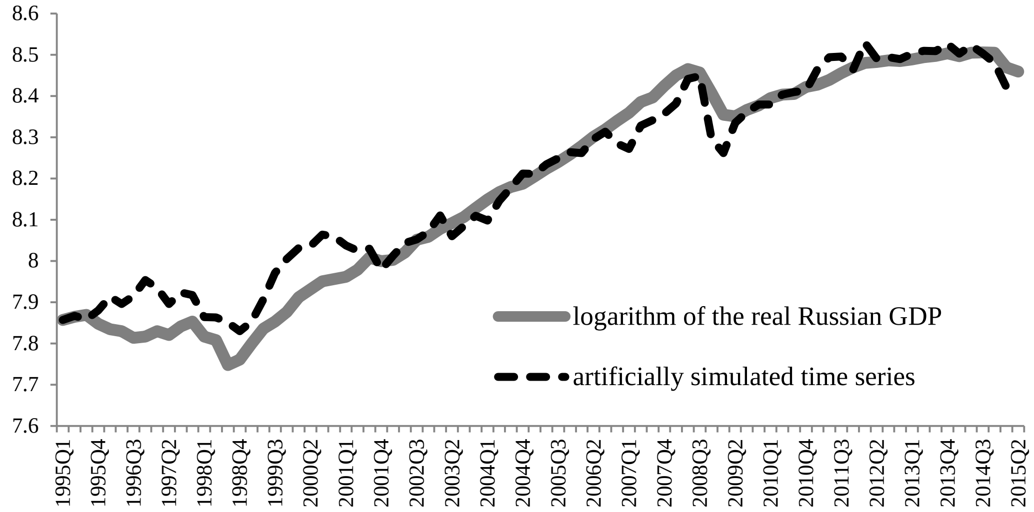

Figure 1. Russian real GDP and artificially simulated time series

The solution of the identification of structural changes problem in long-run economic growth can have a number of important practical applications. Firstly, the presence of structural changes needs to be taken into account in the forecasting, especially in long-run forecasting. Because the standard econometric methods without taking into account structural changes could produce highly biased and inconsistent parameter estimates of the data generating process. Secondly, the relevant bias in the estimates of the parameters could lead to a misidentification of the phase of the business cycle (Perron, Wada, 2009) and incorrect recommendations for economic policy.

The logarithm of the real Russian GDP could be trend stationary (around segmented linear trend). And in this case it is difficult to discuss any long-run dependence of the GDP on real oil prices, which are potentially random walk process (Alquist et al., 2013). Thus Section 2 proceeds with classical univariate tests for the presence of the unit root and structural breaks in the real Russian GDP. Section 3 lays out our cointegrating regression model with the dependence of the real Russian GDP on the real oil prices, presents results of corresponding statistical tests for the presence of cointegration and structural breaks in the long-run growth rate of the structural component of the Russian GDP. Section 4 summarizes and concludes.

2 Univariate analysis

Classical papers on testing of existences of structural breaks in the long-run economic growth rates are based on univariate representation of the investigated time series (see, e.g., (Perron, 2006; Aue, Horvath, 2012; Jandhyala et al., 2016)). In this section we apply the basic univariate statistical tests as the starting point of the study. However, the inclusion of additional covariates in the model could significantly improve the quality of inference (see, for example: (Hansen, 1995)). Thus in the next section we try to incorporate the dynamics of the real oil prices in econometric model.

In empirical analysis we use Russian GDP from 1995Q1 to 2015Q2 in constant 2003 year prices. We seasonally adjust the series by X-12-ARIMA filter in Eviews and take the log of the obtained series. First, we want to detect the number of structural breaks. We use the method proposed by Sobreira and Nunes, 2016. They developed the tests that are robust to the order of integration in the following regression with, say, m breaks:

$$\begin{aligned} &\log GDP_t = \mu_0 + \beta_0 t + \mu_1 DU_t\left(T_1^0\right) + \beta_1 DT_t\left(T_1^0\right) + \ldots + \mu_m DU_t\left(T_m^0\right) + \beta_m DT_t\left(T_m^0\right) + u_t, \\ &u_t = \alpha u_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

where T_j^0, $j = 1,\ldots,m$, are the break dates, $DU_t(T_j^0) = I(t > T_j^0)$ is the shift dummy variable, $DT_t(T_j^0) = (t - T_j^0)I(t > T_j^0)$ is the trend break dummy variable, $I(\bullet)$ is the indicator function, and ε_t is stationary process. The $F_\lambda^*\left(l+1|l\right)$ test for testing the null that the series contain l breaks against the alternative that the series contain $l+1$ breaks is constructed, following Sobreira and Nunes, 2016, as weighting average from the two F-statistics, one for the testing for additional break in regression (2), the second for the testing for additional break in first-differences regression

$$\Delta \log GDP_t = \beta_0 + \mu_1 D_t\left(T_1^0\right) + \beta_1 DU_t\left(T_1^0\right) + \ldots + \mu_m D_t\left(T_m^0\right) + \beta_m DU_t\left(T_m^0\right) + \Delta u_t, \tag{3}$$

where $D_t(T_j^0) = I(t = T_j^0)$, $j = 1,\ldots,m$. See Sobreira and Nunes, 2016 for details.

The results for Russian GDP are provided in Table 1. As Table 1 show, the F(1|0) test rejects the null that there is no break, then we move to the F(2|1) test that rejects the null of one break against the alternative of two breaks. At the third stage the F(3|2) test fails to reject the null of two breaks.

Table 1.

The sequential testing results for detecting the number of breaks

	$F_\lambda^*\left(1\|0\right)$	$F_\lambda^*\left(2\|1\right)$	$F_\lambda^*\left(3\|2\right)$
Test statistic	11.39**	13.05**	9.12
1% critical value	12.91	15.16	16.16
5% critical value	9.41	10.97	11.80
10% critical value	7.68	9.33	10.38

After the estimation of the number of breaks, we need to test the series for a unit root. For unit root testing, we use approach proposed by Skrobotov (2015). First we obtain estimates of break dates proposed by Harvey and Leybourne (2013). After that, we detrend the GDP series and test the residuals for a unit root. We denote this test as $ADF-OLS(\hat{T}_1^D,\hat{T}_2^D)$. In addition, we use GLS-based unit root test $MDF-GLS_2$ with two structural breaks proposed by Harvey et al. (2013). For stationarity testing we use the approach of Carrion-i-Silvestre and Sanso-i-Rossello (2005) (the KPSS test with two breaks). For long-run variance estimation for KPSS test statistic we use two approaches, Sul et al. (2005) ($KPSS_2^{SPC}$ test) and Kurozumi (2002) ($KPSS_2^K$ test).

The results are provided in Table 2. The estimated break dates are 1998Q2 and 2008Q3. The both $ADF-OLS(\hat{T}_1^D,\hat{T}_2^D)$ and $MDF-GLS_2$ tests fail to reject the null of unit root.

The $KPSS_2^{SPC}$ test with estimation of long-run variance as in Sul et al. (2005) fails to reject the null of stationarity, but the $KPSS_2^{K}$ test with long-run variance estimation as in Kurozumi (2002) rejects the null of stationarity at 1% significance level. As one of the tests reject the null of stationarity at 1% significance level, we focus on this result. Therefore, the null of unit root is failed to reject and the null of stationarity is rejected.

Table 2

Unit root and stationarity tests

	$MDF-GLS_2$	$ADF-OLS(\hat{T}_1^D,\hat{T}_2^D)$	$KPSS_2^{SPC}$	$KPSS_2^{K}$
Test statistic	-3.59	-2.59	0.014	0.060**
1% critical value	-5.04	-5.91	0.057	0.057
5% critical value	-4.56	-5.37	0.044	0.044
10% critical value	-4.29	-5.12	0.038	0.038

After unit root testing we move to the first difference model and detect the number of breaks by Bai and Perron (1998, 2003) sequential tests to update the results. Table 3 shows that we fail to reject the null of no breaks against the alternative of one break by $\sup F(1|0)$ test, but we reject the null against the alternative of two breaks by $\sup F(2|0)$ test. The $\sup F(3|2)$ fails to reject the null of two breaks, so that we detect two breaks in first differenced model. The estimated break dates are 1998Q3 and 2008Q2.

Table 3

The sequential testing results for the number of breaks in first differenced model

	$\sup F(1|0)$	$\sup F(2|0)$	$\sup F(3|2)$
Test statistic	4.62	10.34***	1.53
1% critical value	12.29	9.36	13.89
5% critical value	8.58	7.22	10.13
10% critical value	7.04	6.28	8.51

We also use information criteria BIC and LWZ (Liu et al.,1997) for detecting the number of breaks and also detect two breaks by both criteria (see Table 4, minimum value of each criteria is denoted by star).

Table 4

The values of information criteria for different number of breaks

The number of breaks	0	1	2	3	4	5
BIC	-7.98	-8.03	-8.20*	-8.10	-8.00	-7.90
LWZ	-7.97	-7.93	-8.02*	-7.84	-7.66	-7.47

Thus, the univariate testing results indicate that the series of log real Russian GDP is integrated of order one with two breaks. In the next section, we extend our analysis to the cointegrating regression because two breaks could be detected only due to a specific pattern of oil price series in finite sample.

3 Testing for breaks in cointegrating regression

In the present section, we test the presence of breaks in the long-run growth rates of the structural component of the real Russian GDP. We assume that the level of oil prices affects the potential level of the Russian real GDP. This assumption can be formalized as the following long-run cointegration relation:

(4) $\log GDP_t = \mu + \beta t + \gamma \log p_t^{oil} + u_t$,

where γ is the long-run oil price elasticity of real GDP and u_t is the stationary process.

Similar kind of long-run dependence with deterministic trend and log of oil price in cointegration relation of real GDP is used in the econometric analysis of the Russian economy in Kuboniwa (2014) and Rautava (2013).

In general, the stationary process u_t can contain the both oil price shocks and structural component shocks that do not depend on oil prices. But the effect of u_t on GDP vanishes over time and, respectively, β represents long-run growth rates of structural component of real GDP.

From theoretical point of view the positive dependence (4) of the GDP level of an oil exporting country on the real oil prices could be rationalized through the mechanism of capital accumulation. For example, Esfahani et al. (2014) developed modification of the Solow model where some share of oil revenues invested in accumulation of the physical capital. Under this assumption a permanent oil price increase lead to more investments, the higher level of the physical capital and the higher level of the GDP. In Ramsey type models, when saving and investment decisions are results from agents' optimization problems, the level of the capital in the economy could be increased due to increased relative prices in oil exporting sector and nontradable sector (see, e.g., Idrisov et al., 2015). The higher level of the relative prices increases returns on capital and stimulate investments.

Of course there could also be negative dependence of the level of the GDP of an oil exporting country on the real oil prices due to the diversion of the factors of production from non-energy tradable sector, which could have higher productivity growth rate in comparison with other sectors, due to the deterioration of the institutional environment and other channels the negative impact on the GDP in the context of the Dutch disease (see, e.g., Mehlum et al., 2006; Sachs and Warner, 1997).

The presence of a deterministic trend in equation (4) indicates that under a fixed level of the real oil prices and under no random shocks the economy is growing at constant rate β (possibly with structural breaks in this term). We will build on the neoclassical models with exogenous growth, so we will interpret the deterministic trend in (4) as long-run growth of labor efficiency in all sectors of economy, which ensures long-run balanced growth path of the economy.

With this interpretation we allow only smooth changes in deterministic component of the real GDP during structural breaks. It is assumed that only slope of the deterministic trend could be changed without any changes in the level. However in our model discontinuous changes of the potential GDP may be due to sharp changes in the oil prices. We can rewrite model (4) with *m* breaks in long-run growth rates of the structural component of the real GDP in a following form:

(5) $\log GDP_t = \mu + \beta_0 t + \beta_1 DT_t(\hat{T}_1) + ... + \beta_m DT_t(\hat{T}_m) + \gamma \log p_t^{oil} + u_t$,
where $DT_t(T_i) = (t - T_i) I(t > T_i)$ for $i = 1, \dots, m$.

3.1 Testing for breaks in cointegrating regression

We now turn to the formal statistical tests. In the present section we test for the presence of breaks in cointegrating regression. However, as we know, the econometric literature contains no procedures for detecting number of breaks in deterministic trend in cointegrating regression. Bai et al. (1998) considered the construction of confidence interval for the date of break in trend in cointegrating regression but did not analyze the problem of testing for these breaks. Kejriwal and Perron (2010) developed tests for the breaks and sequential testing procedure for the number of breaks in cointegrating regression but they considered only breaks in constant.

Following Kejriwal (2008), at the first stage of detecting the number of breaks in long-run growth rate of structural component of Russian GDP we use information criteria BIC and LWZ. We apply the same criteria for $\log GDP_t^*$ series that is generated according (1) and under construction has no any breaks in long-run growth rate of structural component but visually demonstrates the two breaks in slope. The results are provided in Table 5.

Table 5.

The values of information criteria for different number of breaks

Количество сдвигов		0	1	2	3	4	5
BIC	$\log GDP_t$	-6.32	-6.75	-8.25*	-8.20	-8.18	-8.08
	$\log GDP_t^*$	-9.15*	-9.10	-8.99	-8.86	-8.72	-8.58
LWZ	$\log GDP_t$	-6.29	-6.60	-7.98*	-7.80	-7.65	-7.43
	$\log GDP_t^*$	-9.13*	-8.96	-8.71	-8.47	-8.19	-7.92

Table 5 show that the both criteria indicate two breaks in long-run growth rate of the structural component of the Russian GDP for contegrating regression with $\log GDP_t$ and no breaks for artificially generated $\log GDP_t^*$.

However, although the information criteria consistently estimate the number of breaks we want formal tests and significance level at which we detect the breaks. We will use Kejriwal and Perron (2010b) approach by allowing breaks in trend with simulated critical values based on Monte-Carlo simulations. The approach of Kejriwal and Perron (2010) is similar to Bai and Perron (1998) in the context of cointegrating regression. The test statistics are constructed in the following way. For testing the null of no breaks against the alternative of *k* breaks we construct the test statistic:

$$\sup F(k \mid 0) = \sup_{\boldsymbol{\lambda} \in \Lambda} \frac{SSR_0 - SSR_k}{\hat{\omega}^2},$$

where $\boldsymbol{\lambda}$ is the vector of break fractions, Λ is the admissible set of break fractions, SSR_0 is the sum of squared residuals under the null hypothesis of no breaks, SSR_k is the sum of squared residuals under the alternative hypothesis of k breaks, $\hat{\omega}^2$ is the long-run variance estimator of u_t in the cointegrating regression.

The sequential tests $F(l+1|l)$ are constructed as $F(l+1|l)=\max_{1\le i\le l+1}F^{(i)}$, where $F^{(i)}$ is the F-statistic for additional break in cointegrating regression[2]. For each step, the break date estimates based on minimizing the sum of squared residuals for all possible break dates are used (the consistence of these estimates are proved in Kejriwal and Perron, 2008). Asymptotic critical values for $\sup F(k|0)$ and $F(l+1|l)$ are obtained by simulations using the sample size 1,000 based on DGP under the null hypothesis with 20,000 Monte-Carlo replications.

The results are provided in Table 6[3]. The null of no breaks in long-run growth rate of the structural component of the Russian real GDP against the alternative of one break is failed to reject but is rejected against the alternative of two break at 10% significance level. The nonrejection of the null of no breaks against the alternative of one break and rejection of no breaks against the alternative of two breaks may be due to the different signs in changes of slope of long-run growth. Further, we test the null of two breaks against the alternative of three breaks and the test fails to reject the null. Under the conditions that the two breaks are selected by the both information criteria and that 10% significance level is reasonable under the small number of observations we conclude that there are two breaks in long-run growth rate of the structural component of the Russian real GDP. We perform a similar procedure for artificially generated $\log GDP_t^*$ series and conclude that it has no any breaks.

Table 6.

The sequential testing results for detecting of number of breaks

	$\sup F(1\|0)$	$\sup F(2\|0)$	$\sup F(3\|2)$
Test statistic for $\log GDP_t$	4.86	4.42*	6.92
Test statistic for $\log GDP_t^*$	4.83	3.62	-
1% critical value	9.22	6.83	11.88
5% critical value	6.21	5.04	8.60
10% critical value	4.95	4.14	7.13

3.2 Testing for cointegration and estimation of parameters

Note that while we detected two breaks the Kejriwal and Perron (2010) tests are based on the assumption that the series are cointegrated and the error term is stationary. However, in case of no cointegration the number of breaks is overestimated. Therefore, we need to test the hypothesis

[2] These tests use long-run variance estimator based on residuals under both the null and alternative hypothesis. I.e. the residuals under the null are used for long-run variance estimator with quadratic spectral kernel, but the residuals under the alternative hypothesis are used for bandwidth selection (according Andrews, 1991 method).

[3] The number of leads and lags for cointegrating regressions for those we calculate *F*-statistics is selected by BIC (see Section 3.2).

that the variables are indeed cointegrated provided that we use the estimated number of breaks. Then if we find evidence of cointegration, the estimated number of breaks is correct.

For cointegration testing the typical approach is to estimate cointegrating regression and then to test the obtained residuals for stationarity (the presence of cointegration) and/or unit root (the absence of cointegraton), see Engle and Granger (1987) and MacKinnon (2010).

The presence of structural breaks also affects the results of the tests for cointegration or no cointegration. For example, if we test the null of no cointegration, this hypothesis will be rarely rejected if there are breaks in cointegrating regression (see, e.g., Gregory and Hansen, 1996). On the other hand, the null of cointegration without breaks will be often rejected if the breaks are actually present in the data (see, e.g., Arai and Kurozumi, 2007 and Carrion-i-Silvestre and Sanso-i-Rossello, 2006). Here the limiting distributions depend not only on the number of time series but on the number of structural breaks and the type of them.

For cointegration testing we need to estimate the break dates. Based on minimizing the sum of squared residuals (assuming that there are two breaks) we obtain the following estimates of the break dates: 1998Q3 and 2007Q3. The first break date is coincides to the univariate case break date, but the second break date is shifted to the left to 2007Q3.

After estimation of the break dates we construct the regression

(6) $$\log GDP_t = \mu + \beta_0 t + \beta_1 DT_t(\hat{T}_1) + \beta_2 DT_t(\hat{T}_2) + \gamma \log p_t^{oil} + u_t,$$

and test the residuals $\hat{u}_t$ for a unit root.

Similar to Gregory and Hansen (1996), the unit root test is the conventional ADF test with appropriate critical values. Stationarity test is the conventional KPSS test (with long-run variance correction as in Sul et al., 2005) also with appropriate critical values. Asymptotic critical values are obtained by Monte-Carlo simulations with sample size 1,000 and 20,000 replications. The results are presented in Table 7. Along with tests for cointegration with two breaks we also presents the tests for cointegration with no breaks and with only one break. In the latter case, the break date was estimated by minimizing sum of squared residuals over all possible break dates.

Table 7.

Results for cointegration testing

	No cointegration	cointegration
	No breaks	
Test statistic	-2.64	0.078
10% critical value	-3.49	0.099
5% critical value	-3.77	0.123
1% critical value	-4.30	0.181
	One break (2008Q1)	
Test statistic	-3.95*	0.108**
10% critical value	-3.88	0.064
5% critical value	-4.15	0.079
1% critical value	-4.67	0.113
	Two breaks (1998Q3 and 2007Q3)	
Test statistic	-4.43**	0.033
10% critical value	-4.15	0.048
5% critical value	-4.42	0.056

1% critical value	-4.97	0.081

As Table 7 shows, under the assumption of no breaks in long-run growth rate in the Russian real GDP the null of no cointegration is failed to reject and as well as the null of cointegration is failed to reject. Nonrejection of the first hypothesis can be due to the low power due to the neglecting breaks. And nonrejection of the second one can be due to the breaks in trend have different signs in data generating process. In the case of one break the null of no cointegration is rejected at 10% significance level and the null of cointegration is rejected at 5% significance level. Thus the testing results were inconsistent with each other which reflecting in favor of our assumptions about the low power of the stationarity test with different signs of trend breaks. If we allow two breaks then the results becomes consistent with each other. So the null of no cointegration is rejected at 5% significance level and the null of cointegration is failed to reject at any reasonable significance level. Therefore, the formal statistical results allow us to classify the GDP and oil prices to be cointegrated.

After the cointegration testing we proceed to the estimation of the parameters of cointegrating regression (6). Note that although the estimator of cointegrating vector $(\mu, \beta_0, \beta_1, \beta_2, \gamma)$ obtained by estimating a reduced rank regression as in Johansen (1991) is consistent and asymptotically normal, we can obtain the estimates of cointegrating vector based on regression (6) by OLS. However, in contrast to the Johansen reduced rank regression, the limiting distribution will be non-pivotal due to the correlation between regressors and error term. So we cannot use standard inference.

For obtaining pivotal t-statistics alternative methods were developed. The most popular of them are Dynamic OLS (DOLS) proposed by Saikkonen (1991) and Stock and Watson (1993), fully-modified OLS (FMOLS) proposed by Phillips and Hansen (1990) and Canonical Cointegrating Regressions (CCR) proposed by Park (1992)[4]. Based on these methods we can obtain standard normal t-tests for cointegrating vector. Although all three methods are asymptotically equivalent the DOLS is preferred in finite samples (see Carrion-i-Silvestre and Sanso-i-Rossello, 2006). The method consists in adding the leads and lags of first differences of repressors and the first differences of regressors.

We estimate parameters of (6) by using DOLS. For lead and lag length selection we use BIC[5], which select the number of leads and lags equal to zero. Thus, it is sufficient to include only first difference of log oil prices in cointegrating regression. For long-run variance estimation, we use quadratic spectral kernel with automatic bandwidth selection as in Andrews (1991). The estimation results are presented in Table 8. It should be noted that the high statistical significance of the coefficients β_1 and β_2 that reflect breaks in slopes of trend in the transition from one regime to the next is the additional evidence of at least two breaks in cointegration regression model. For coefficients β_i we make the linear transformation in order to find estimates of growth rates for particular sample periods in % per year terms (see Table 9).

[4] For analytical comparison of these three methods see Kurozumi and Hayakawa (2009).

[5] As Choi and Kurozumi (2012) show the BIC is preferable for reducing of mean squared error of cointegrating vector.

Table 8.

Cointegrating regression parameters estimates

Parameter	Estimate	Std. error
μ	8.045***	0.047
β_0	-0.003***	0.001
β_1	0.016***	0.001
β_2	-0.010***	0.001
γ	0.088***	0.017

Table 9.

Estimates of the long-run growth rates (% per year) of the structural component of the real GDP

Period	Estimate	Std. error
1995Q1 г. –1998Q3	-1.19***	0.44
1998Q4 г. –2007Q3	5.28***	0.33
2007Q4 г. –2015Q2	1.33***	0.30

As Table 9 shows the estimates of long-run growth rate of the structural component of the real GDP are statistically significant for all three regimes. The estimation results indicate that in the period from 1995Q1 to 1998Q3 we observe the transformational recession with approximately -1.2% growth rate. The estimate of long-run growth rate of the structural component on the recovery growth period (1998Q4 –2007Q3) is approximately 5.3% per year and this is 2% lower than actual growth rate of the real Russian GDP on the considered sample period (approximately 7% per year). These 7% growth rates have been achieved due to huge growth in world oil prices during that period of time. Also, the cointegrating regression give positive and statistically significant estimate of long-run growth rate after the second structural break (2007Q4 –2015Q2). Thus the structural component showed translational motion but the growth rates were low (approximately 1.3% per year).

The estimate of the value of the long-run elasticity of the real GDP on the real oil prices in cointegrating regression with two structural breaks is 0.088 with standard error 0.017, i.e. under 10% increase of oil prices the real GDP in the long-run increases approximately by 1%. This estimate indicates economically significant dependence of the Russian economy on the oil prices. If the oil price fall twice the fall of real GDP would be approximately 6% ($0.88\log\{0.5\}\approx-0.06$). However, the estimate of long-run elasticity in cointegrating regression with two structural breaks is moderate enough in comparison with the specification of the model without breaks, in which the long-run elasticity is approximately 0.2 (this value is obtained based on our calculations; similar estimates of long-run elasticity of the Russian GDP on oil prices are obtained by Beck et al., 2007, Kuboniwa, 2014, Rautava, 2013).

In similar econometric specifications in Kuboniwa (2014) and Rautava (2013) the estimates of trend slope were equal to 2.9% and 2%, respectively. Thus, the estimates based on cointegrating regression with breaks in long-run growth rates of the structural component of the

GDP during the recovery growth period assign a greater role for the structural component of economic growth and a less role for the external component.

4 Conclusions

This paper tests existence of structural breaks in the long-run growth rate of the structural component of the Russian GDP. By the structural component we mean the purified GDP from the influence of the most important factor of foreign economic conditions of the Russian economy - oil prices. To solve this problem we use the methodology of cointegrating regression in which we allow the long-run dependence of the logarithm of the Russian real GDP on the logarithm of the real oil prices. Also, cointegrating regression equation includes the deterministic linear trend in which breaks in the slope are allowed (without any level shifts). We treat this term in regression as the long-run level of the structural component of the GDP.

The empirical results are in favor of the existence of two structural breaks in the long-run growth rate of the structural component: in the 3rd quarter of 1998 and in the 3rd quarter of 2007. This is evidenced by information criteria and formal statistical tests. According to the estimation results the long-run growth rate of the structural component is about 5.3% per year during the recovery growth period (1998Q4 –2007Q3) and about 1.3% per year in subsequent periods. The output drop in Russia during current economic crisis is in line with the projected reduction due to the observable oil price decrease. The estimated long-run oil price elasticity of the Russian GDP is 0.088. Thus twofold permanent oil price drop would produce 6% ($0.88\log\{0.5\}\approx-0.06$) decline of the potential level the Russian GDP.

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