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LABOUR MARKET ANALYSIS USING TIME SERIES MODELS: RUSSIA 1999-2011

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Abstract [2]

We investigate the relationship between the main indicators of the labour market in Russia. We try to construct a model of the Russian labour market and identify key relationships. Our special attention is drawn to the impact of the crisis on the Russian labour market and influence of oil price on labor market indicators. We estimated two types of models. They are systems of simultaneous equations model (SEM) and VECM. We received that real wage in Russia are more flexible than employment. During the crisis period real wage was decreasing. SEM model shows that real wage positively depends on real oil price. While the number of employed and unemployment don't depend on real oil price.

J.E.L. classification: J20, J40.

Keywords: labour market, time series models, Russia.

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1. Introduction

In this paper we investigate the relationship between the main indicators of the labour market in Russia. We try to construct a model of the labour market and identify key relationships. The Russian labour market isn't like the labour markets of Western countries. This is indicated by the Russian experts (Kapelyushnikov, 2003). In this research we'd like to test the hypotheses that are discussed by experts in the field.

Usually labour markets are analyzed at the micro level using data on firms. Because it is rather difficult to understand and to model the labour market at the country level. The situation with the Human Resources develops differently for different industries of the economy. It seems that analyze the interaction of employers and employees have to do separately for each industry as it was done in many papers on labour market analysis [(Akhmedov A. et al., 2003), (Addison J.T., Teixeira P., 2001), (Nakanishi Y., 2001)]. However, this analysis also has its weaknesses. The situation in individual industries and sectors depends on the overall economy conjecture. It is impossible to study industrial market apart from all other sectors, because they are all interrelated with each other. Therefore, we chose for the analysis macro data of the Russian labour market.

The aim of this work is to build a model of the Russian labour market at the macro level. One of the objectives of the study is to investigate the effect of the crisis on the labour market. For these purposes the macro data also is required.

In the study we verify the following hypotheses:

1) According to common opinion of experts in Russia the adjustment in the labour market is through wages, but not through the number of employees. In times of crisis (2008-2011) monthly salary was reduced and the number of employed didn't change. Therefore real wage is more flexible than the number of employed.
2) The price of oil (macro economic situation) affects the main characteristics of the labour market. When the oil price is increased, the number of employees and wages are also increased, because the Russian economy is an economic recovery.

2. Literature

The labour market relationship is interesting for government and researchers in different countries. The authors from Chili Central Bank (Albagli E. et al., 2003) investigated labor market flexibility and structural shocks for Chili, OECD and emerging economies. They rank Chili in terms of labor market flexibility among these countries. To do that, they built an indicator of labor-market flexibility which allows international comparisons. Such indicator was obtained by estimating a structural VAR (SVAR). The authors found that Korea, HongKong, Chile, US and Mexico are the most flexible economies. Germany, Sweden, Spain and Colombia are the most rigid labor markets.

Bachmann R., Balleer A. (2010) explored the differences in labor market volatilities between Germany and the U.S. Employing a structural VAR with long-run restrictions, they analyzed the role of different sources of these dynamics: technology and demand shocks. They received, that unemployment increased after positive technology shocks in both countries, but for strikingly different reasons.

The authors (Braun H. et al., 2009) use SVAR to analyze the responses of worker flows, job flows, vacancies, and hours to demand and supply shocks. They received, that demand and supply shocks are equally important in driving business cycle fluctuations of labor market variables.

Corsini L. and Guerrazzi M. (2004) analyzed long run relationships in the Italian labour market and assessed the role that institutional factors, such as the presence of unions in the wage bargaining process, played in it. They consider New Keynesian model as theoretical background. The authors chose the cointegrated VAR approach as estimation technique.

Carstensen K. and Hansen G. (2000) analyzed the West German labour market by means of a cointegrated structural VAR model. They found sensible stable long-run relationships that are interpreted as a labour demand, a wage setting and goods market equilibrium.

Summers P. (2000) provides an overview of how labour market analysis can be conducted in the context of VAR-based models. The various techniques are illustrated in models which examine the dynamics of gross job flows; assess the relationship between real wages and unemployment; quantify the contribution of sectoral shocks to the number of people unemployed by duration of unemployment; examine the relative contributions of discouraged worker effects, insider effects, etc. on the persistence of unemployment; and analyze the effects of labour market shocks in the OECD countries.

Therefore, such short literature review shows that there are a lot of papers about labour market analysis with VAR, SVAR, VECM models for different countries. In this paper we try to construct similar model for the Russian labour market in order to test our hypothesis.

3. Data and Variables

For the analysis we used monthly data of Rosstat[3] from January 1999 to October 2011. This period wasn't selected randomly. As for the beginning of the period, it was decided to take the figures after 1998, post-crisis period.

In this paper we analyze monthly data of number of employed in the economy, average monthly wages, unemployment rate, consumer price index (CPI). For the analysis we also use the index of physical volume of GDP (data from Ministry of Finance) and the price of crude oil Brent[4]. All monetary figures were deflated to a single accounting base. In particular we calculated real wage, which has been deflated by the CPI (in prices in January 1999). Oil prices in dollar equivalent transferred to the ruble using the monthly average exchange rates which have been taken from the site of the Central Bank of Russia[5] and have been deflated by the CPI. You can see all the variables in the table 1.

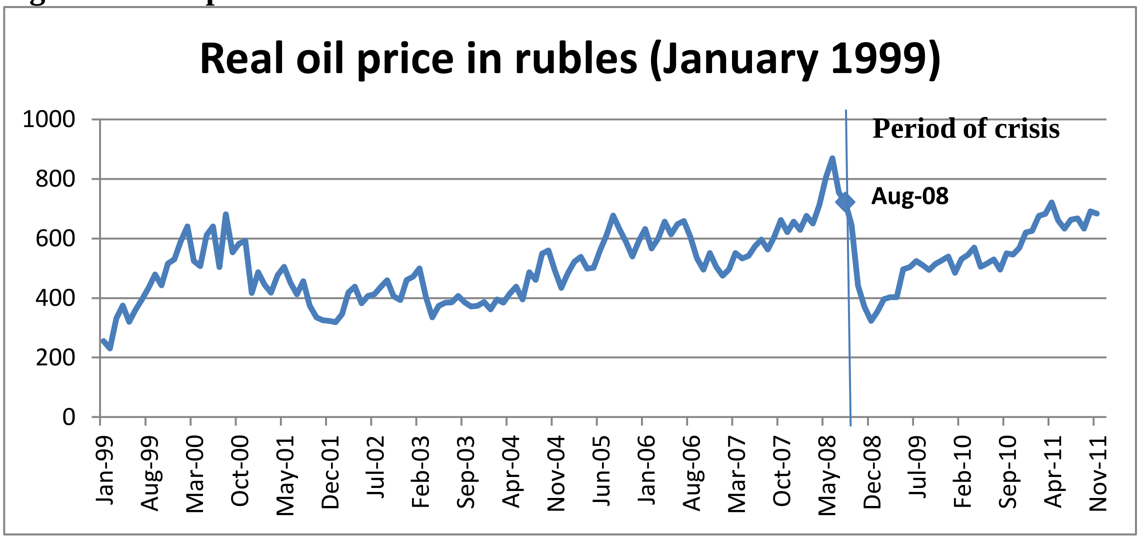
Table 1. Description of the variables

Variables	Description	Units
Labour	Number of employed	Million
unemp	Number of unemployed	Million
u	Unemployment rate	%
Aktiv_labour	Number of active labour force	Million
Rwage	Real wage	Rubles January 1999
Phis_99	Index of physical volume of GDP	Base January 1999
phis_labour_99	Labour productivity	Base January 1999
Oil_real	Oil price in ruble	Rubles January 1999
Ipc_99	CPI	Base January 1999

[3] http://gks.ru/
[4] Data from http://www.finam.ru/
[5] http://cbr.ru/

In order to understand how the crisis has affected the basic characteristics of the labour market, a dummy variable “crisis” was introduced in the model. This variable divides the reviewed period on two parts. They are pre-crisis and post crisis periods. To determine these periods, it was decided to analyze the behavior of oil prices, because the Russian economy is highly dependent on oil price (Gurvich, Vakulenko, Krivenko, 2009). In Fig. 1 you can see that throughout the period the oil price had rising trend, and in August 2008 a sharp decline began. Therefore we decided to define the period before August 2008 as the pre-crisis, and after the crisis period. In all models the dummy variable "crisis" was introduced only in the constant in the regression equation. Thus, we studied the effect of the crisis on main indicators of labour market.

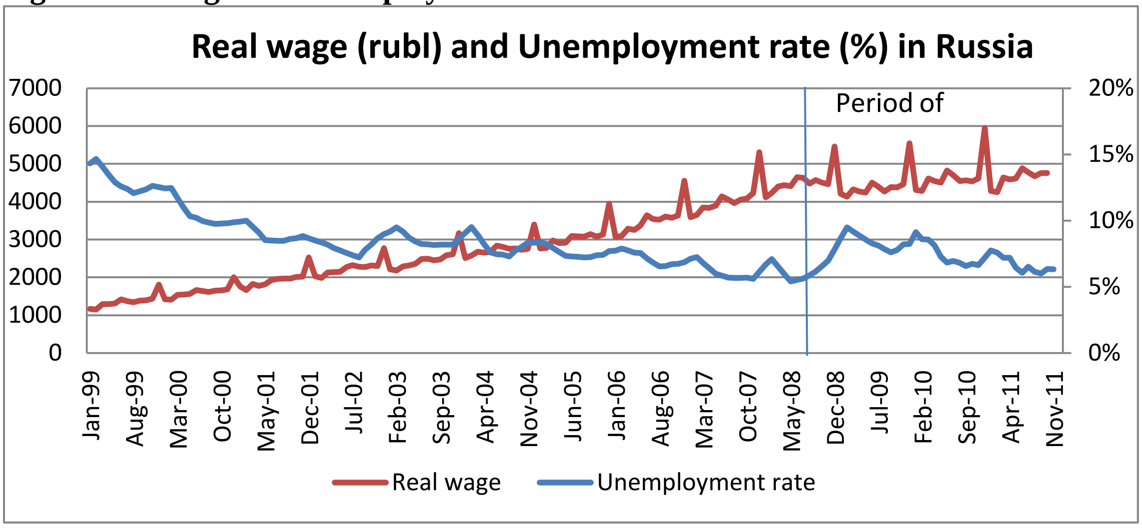
Fig. 1. Real oil price in rubles



Graphics of all the analyzed variables are presented in the appendix (Fig. 2 Appendix A). The correlation matrix of the variables is in the Table 2(Appendix A). Descriptive statistics of the variables are presented in Table 3 (Appendix A).The graphs (Fig. 2 Appendix A) show that the index of physical volume of GDP, the real labour productivity (the ratio of the volume index of GDP by the index number of employees) and real wage had an increasing trend throughout the observation period. However in the mid-2008 the dynamics of these variables declined. If we turn to the graph of oil prices (Fig. 1), we can see that since January 2009 oil prices began to rise. Note that in 2009 the index of physical volume of GDP began to rise. This fact also confirms the strong dependence of the Russian economy on oil prices.

The dynamics of employment in the economy throughout the period had an increasing dynamics. This variable is very volatile, which is mainly due to seasonal changes (Fig. 2 Appendix A). In early 2009, the number of employees has decreased. The unemployment rate has the opposite trend (Fig. 3). Throughout the period under review, the dynamics of unemployment were decreasing, and at the beginning of the 2009 the unemployment rate rose vice versa. It would be incorrect to say that unemployment increased in the crisis. The number of employees exposed to strong seasonality. Decline in employment is happened in the first quarter of the year.

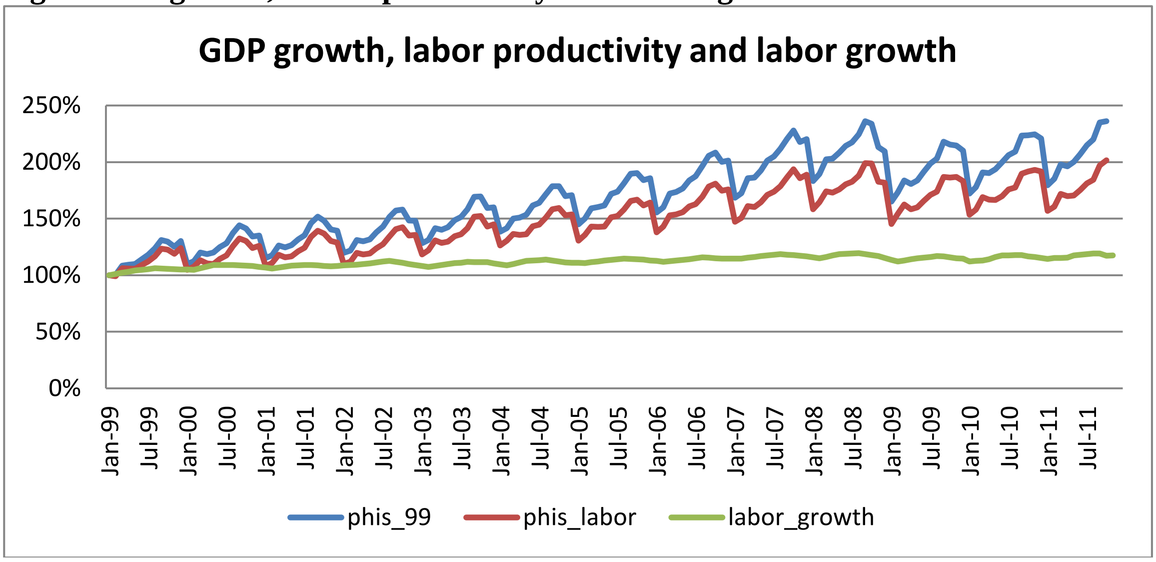
Fig. 3. Real wage and Unemployment



One of our hypotheses is about relationship between real wage and unemployment in crisis period of time. In Fig.3 you can see the dynamics of real wage and unemployment rate.

In Fig. 4 you can see the relationship between index of physical volume GDP, labour productivity and labour growth. It is difficult to say about trends of the dynamics of this variable in crisis.

Fig. 4. GDP growth, labour productivity and labour growth



All of the available time series were checked for stationarity. We test the order of integration of the variables using the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) unit root test. In Table 2 the results of KPSS unit root tests are presented. As expected, the studied series are not stationary. We reject the null hypothesis of (trend) stationarity. Only for oil price we can't reject the null hypothesis of (trend) stationarity when we use an intercept and trend in the test. However, we can't reject the null hypothesis of (trend) stationarity for the first differences of our series. Therefore all variables are integrated of order one I(1).

Table 2. Unit root tests Kwiatkowski–Phillips–Schmidt–Shin (KPSS)

Variables	**KPSS (constant)**[6]	**KPSS (constant, trend)**[7]
Labour	1.419090	0.229072
unemp	0.916685	0.253364
Aktiv_labour	1.431873	0.140859
Rwage	1.489614	0.162350
Phis_99	1.476727	0.167770
phis_labour_99	1.613720	0.166299
Oil_real	0.690597	0.070306
Ipc_99	1.500157	0.337138
Critical value (5%)	**0.463**	**0.146**

[6] KPSS (constant) uses an intercept in the test.
[7] KPSS (constant, trend) uses an intercept and trend in the test.

4. Labour market models

As it is mentioned above all time series are I(1). In this case we can analyze the differences, but it means the study of short-terme effects of the interaction, or look for cointegrating relations of the variables. However there is a question of causality, which variable is exogenous and which is endogenous. To solve such problems, there are special econometric methods. There are method of instrumental variables, estimation of systems of simultaneous equations model (SEM) and the construction of vector autoregression model (VAR). These methods allow us to evaluate multiple simultaneous equations related to each other, i.e. estimate the system of equations or evaluate a single model, but with instrumental variables. In this paper we estimate both SEM and VAR models. We built a lot of different models with different combinations of factors. The selection of the best models was carried out on the basis of information criteria Akaike and Schwartz, diagnostic of model's residuals, comparison of predicted and actual values, i.e. predicted power.

4,1. System of simultaneous equations

In the theory a classic example of simultaneous equations is the equilibrium in the goods market. Knowing the equilibrium price and quantity of goods we'd like to separate the demand and supply of goods (Johnston J., DiNardo J., 2007). In our case, we'd like to construct such system to equilibrium in the labour market. We estimate a system of two equations. The first equation describes a number of people employed in the economy and the second equation is wage setting. Therefore the endogenous variables in the system of equations are the number of employees and real monthly wage.

1) **The equation of number of employed in the economy**. The independent variables in this equation are the real wage, the lags of employment, the index of physical volume of GDP, real oil price, dummy variable "crisis" and the seasonal dummy variables (dummy variables for months).
2) **The equation of wage setting.** In this equation regressors are the number of unemployment, the lag of real wage, real labour productivity, crude oil prices, the seasonal dummy variables, dummy variable "crisis", CPI.

Thus, these two equations present a system of equations. In both equations we included the lag of dependent variable. This was done in order to take into account the inertia of the variables. In the equation of wage setting we included the number of unemployed, which is related to the number of employed by the following identity:

$$unemp_t = aktiv\_labor_t - labor_t \tag{0.1}$$

Unemployment, by definition, is the difference between the number of active population and the number of employed in the economy.

Thus, the system of equation is:

$$\begin{cases} labor_t = c + \beta_1 labor_{t-1} + \beta_2 rwage_t + \beta_3 phis\_99_t + \beta_4 oil\_real_t + \beta_5 crisis + \sum_{i=2}^{12} \gamma_i dum_i + \varepsilon_t \\ rwage_t = c' + \beta_1' rwage_{t-1} + \beta_2' unemp_t + \beta_3' phis\_labor\_99_t + \beta_4' oil\_real_t + \beta_5' crisis + \beta_6' ipc\_99_t + \sum_{i=2}^{12} \gamma_i' dum_i + \eta_t \\ unemp_t = aktiv\_labor_t - labor_t \end{cases}$$

(0.2)

Where ε_t and η_t are random normal distributed error term.

Thus the system in this case consists of two equations and equality. To evaluate system (1.2), it is necessary to impose restrictions on the coefficients. We substitute the relation for the number of unemployed in the second equation (1.2). Then we obtain system (1.3).

$$\begin{cases} labor_t = c + \beta_1 labor_{t-1} + \beta_2 rwage_t + \beta_3 phis\_99_t + \beta_4 oil\_real_t + \beta_5 crisis + \sum_{i=2}^{12} \gamma_i dum_i + \varepsilon_t \\ rwage_t = c' + \beta_1' rwage_{t-1} + \beta_2' \left(aktiv\_labor_t - labor_t \right) + \beta_3' phis\_labor\_99_t + \beta_4' oil\_real_t + \beta_5' crisis + \beta_6' ipc\_99_t + \sum_{i=2}^{12} \gamma_i' dum_i + \eta_t \end{cases}$$

(0.3)

Therefore, we have to take into account the restriction that in the second equation the coefficients for the number of active population and number of employed equal with opposite sign. We also include other lags of endogenous variables (i.e. 2 and 12th lag) in the system.

There are some comments on the estimation of system (1.3):

- We checked the order condition for each equation of the system which is a necessary condition for identifiability of the system. In our case, they are made.
- We also checked the rank condition. The system is fully identified.

- We checked for the presence of cointegration of the variables in the model for each of the equations in the system.
- The system was estimated by three-step method of least squares (3sls). We selected such method because we suggested that random errors of equations may be correlated.

4.2. Results

Results of estimation SEM for different specification presents in Table 5 below. Only significant seasonal dummies are presented.

Table 5. Results of estimation SEM.

	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(4)
VARIABLES	**labour[8]**	**rwage[9]**	**labour**	**rwage**	**labour**	**rwage**	**labour**	**rwage**
L.labour	0.937***		0.937***		0.954***		0.967***	
	(0.076)		(0.076)		(0.076)		(0.076)	
L2.labour	-0.258***		-0.253***		-0.239***		-0.234***	
	(0.071)		(0.071)		(0.071)		(0.072)	
rwage	0.001***		0.001***		0.001**		0.000***	
	(0.000)		(0.000)		(0.000)		(0.000)	
L12.rwage	-0.001***	0.739***	-0.001***	0.739***	-0.000	0.811***		0.815***
	(0.000)	(0.042)	(0.000)	(0.042)	(0.000)	(0.052)		(0.052)
phis_99	0.855***		0.825***		0.846***		0.842***	
	(0.268)		(0.266)		(0.262)		(0.261)	
oil_real	-0.000	0.211**		0.189**		0.299***		0.312***
	(0.000)	(0.090)		(0.088)		(0.096)		(0.097)
crisis	-0.057	-142.184***	-0.049	-142.766***	-0.192	-40.864	-0.311***	-31.072
	(0.134)	(48.048)	(0.134)	(48.047)	(0.130)	(62.181)	(0.085)	(62.283)
dum3	0.412***	112.470***	0.416***	112.847***	0.456***	134.920***	0.476***	136.971***
	(0.101)	(31.752)	(0.101)	(31.754)	(0.100)	(32.027)	(0.099)	(32.030)
dum4	0.514***		0.513***		0.529***		0.530***	
	(0.106)		(0.107)		(0.107)		(0.107)	
dum5	0.760***		0.756***		0.765***		0.763***	
	(0.101)		(0.101)		(0.101)		(0.102)	
dum6	0.485***		0.480***		0.466***		0.455***	
	(0.105)		(0.105)		(0.106)		(0.106)	
dum7	0.529***		0.524***		0.512***		0.504***	
	(0.087)		(0.087)		(0.088)		(0.088)	
dum8	0.623***		0.616***		0.607***		0.600***	
	(0.084)		(0.084)		(0.085)		(0.084)	
dum12	-0.514***	297.861***	-0.487***	297.033***	-0.422***	256.519***	-0.389***	254.649***
	(0.120)	(43.348)	(0.117)	(43.322)	(0.115)	(45.511)	(0.113)	(45.594)

[8] Estimation of labour equation of system (1.3).
[9] Estimation of wage setting equation of system (1.3).

L.rwage		0.160***		0.161***		0.199***		0.203***
		(0.027)		(0.027)		(0.029)		(0.029)
labour		89.869***		90.933***		111.792***		113.614***
		(18.584)		(18.620)		(20.797)		(20.858)
aktiv_labour		-89.869***		-90.933***		-111.792***		-113.614***
		(18.584)		(18.620)		(20.797)		(20.858)
phis_labour_99		339.808***		341.499***		321.880***		322.415***
		(95.100)		(95.139)		(93.954)		(94.044)
dum2		103.345***		103.307***		134.662***		135.779***
		(31.083)		(31.161)		(33.497)		(33.619)
ipc_99						-156.409**		-168.684***
						(61.560)		(61.877)
Constant	18.860***	436.433**	18.522***	450.602**	16.632***	640.542***	15.529***	654.233***
	(2.895)	(200.604)	(2.888)	(200.775)	(2.884)	(219.558)	(2.827)	(220.208)
Observations	142	142	142	142	142	142	142	142
R-squared	0.986	0.992	0.986	0.992	0.987	0.993	0.987	0.993

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Engle-Granger procedure shows that the series are cointegrated in each of the equations of the system. Residuals are stationary for both equations. Therefore we can analyze the series in levels, despite the fact that they are non stationary. System of equations is not divided on the supply and demand. The number of employed in the economy positively depends on real wages. Therefore it is labor supply. However, the coefficient is very small. The average elasticity of employment to real wage is only 0,046%. The number of employees also positively depends on index of physical volume of GDP. The oil price isn't effect the number of employees.

Real wage negatively correlates with the number of unemployed. The oil price and labour productivity positively affect real wage. Consumer price index is significant. The coefficient for CPI is negative.

Both variables, real wage and number of employees, have inertia. Lags of the dependent variable are significant in both equations. Seasonal dummy variables are significant for both equations. Dummy variable for the crisis are significant only for real wage. The coefficient is negative. However, dummy crisis is significant for labour in 4th specification (see Table 5). Therefore, it appears that in times of crisis adjustment of the labour market has been through the real wage, which was reduced. In Russia real wage is more flexible than the number of employees.

4.3. VECM

The analyzed time series are not stationary. We can't estimate VAR model for series in levels. Therefore it is necessary to test for cointegration and construct VECM. We consider four time series. They are real crude oil price, real wage, the number of unemployed, real labor productivity. These variables are assumed endogenous. The dummy variable for the crisis and seasonal dummies are exogenous variables. Johansen test for cointegration of these series showed that the series are cointegrated (Table 6, Appendix B). The number of lags we chose using Schwarz, Hannan-Quinn and Akaike information criterion (Table 9, Appendix B). Using TRACE and MAX statistics we chose the specification of the model (with trend, constant, etc.) so that there is one cointegrating relationship. They are a fourth or fifth specifications. We chose fourth specification with intercept and linear trend in cointegrating relationship and with constant in VAR. In general case Vector Error Correction Model (VECM) is presented as (1.4).

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1}\Gamma_i \Delta X_{t-i} + \Phi D_t + \varepsilon_t,\ t = 1,\ldots,T \qquad (0.4)$$

$\Delta = 1 - L$; L is lag operator. $\beta' X_t$ - cointegrating relationship is a **long-term relationship** between analyzed variables. D_t - vector of dummy variables (constant, seasonal dummy variables, a dummy variable for the crisis). ε_t - vector of random errors. It is assumed that it is a vector of normally distributed random variables with zero expectation and covariance matrix Ω.

X_t - vector of time series. Γ_is $(i = 1,...,k-1)$ are **short-term parameters** of the models.

k - the number of lags.

4.4. Results

Wald test shows that first, second and 12^{th} lags are significant in the model (Table 10, Appendix B). Twelfth lag means annual lag, because we use monthly data. Estimation of VECM model for Russia is presented in Table 8 Appendix B.

VECM results are interpreted using impulse response functions (IRF) and Variance Decomposition (VD). However, the result of the impulse response function depends on variables' order in the vector X_t. It is necessary to include variables in the following order. The first variable must be the most exogenous variable. The last variable must be the endogenous variable. We did the division of variables into exogenous and endogenous variables using a test of causality by Granger (Table, Appendix B). This test indicates which variable causes the other. In our case the most exogenous variable is the real price of oil. The most endogenous variable is real wage. This variable must be the last in the system. It isn't clear the order for variables the number of unemployed and real labor productivity. Therefore we decide to estimate model with different orders of the variables. We consider two variants. The first way is the order oil_real→unemp→phis_labor_99→rwage. The second variant is such order oil_real→phis_labor_99→unemp→rwage. It is nessesary to do because correlation between residuals isn't equal zero (Table 12, Appendix B). The IRF for both variants are presented in Appendix B Fig. 7 and 9. The generalized IRF are

Firstly, note that residuals of all the equations fluctuate around a zero horizontal trend (Fig. 6, Appendix B). This is a good indicator of stationarity of the residuals. There is no serial correlation in residuals in the model (Table 11, Appendix B) at 1% significance level. The cointegrating relationship fluctuates around a zero horizontal trend (Fig. 5, Appendix B). However, the cointegrating relationship shifts from the horizontal in crisis period. The long-run relationship shows that real wage positively depends on real labor productivity, negatively depends on unemployment and doesn't depend on real oil.

The cointegrating relationship is significant for three equations of the system. Only in equation for real wage it is insignificant. Therefore it means that it is necessary to estimate these equations jointly. Dummy variable for crisis is insignificant only for real wage equation. Real oil price isn't effect for others endogenous variables.

The equation of real labour productivity. The second and twelfth lags of the dependent variable are significant. Second lag of unemployment has negative effect on real labour productivity. The first and second lags of real wage negatively affect real labour productivity. The same you can see looking at the impulse response function. Unemployment and real wages shocks negatively effect on labour productivity in the first period. However, later the effect of these shocks decreased. Now, let's turn to variance decomposition. Shocks of real labour productivity explain around 90% of its variance (Appendix B, Fig.8). Real wage explains 6% at the end of the period of shocks. Shocks of the unemployment rate explain approximately 5% of variance of real labour productivity.

The equation of the real wage. All lags of real productivity affects real wage. The first and second lags of real labor productivity have a positive effect on real wage, and the twelfth lag has a negative sign (Appendix B, Table 8). Impulse response functions are presented in Fig. 7, 9, 11 Appendix B. Shock of real productivity has a positive effect on real wage in the first period, and then this effect is reduced. The real labour productivity explains a large proportion of variance in real wage from 6 to 22% in different periods. The first and 12th lags of unemployment are significant. The first lag of unemployment negatively affects the real wage and 12th lag positively affects. Real wage decreased in response to shocks of unemployment. However, this effect decreased. The number of unemployed explained from 3 to 8% of the variance of real wage (Appendix B, Fig.8). Seasonal dummy variables are also significant.

The equation of the number of unemployed in the economy.

Seasonal components are significant in the equation. Real wage positively affects the number of unemployed in the economy. The growth of real labour productivity positively effects on the unemployment rate. If we turn to the variance decomposition of unemployment (Figures 8 and 9 Appendix B), the real productivity will explain from 5 to 16% of the variance of unemployment in the different period.

5. Conclusion

In this paper we have attempted to model the relationship of the Russian labor market. We constructed two different types of models. Of course not all results of the models conform to each other. Despite this fact it is possible to identify some conclusions. The main conclusion is that real wage in Russia are more flexible than employment. Wage elasticity of employment is higher than the elasticity of employment to real wage. Another proof of the fact that real wage is more flexible than the number of employees, is the reaction of these variables to the crisis. In most models dummy "crisis" for the number of employees isn't significant. While for real wage this variable is significant and has negative coefficient. It is mean a decline in real wage during the crisis period. Only for fourth specification of SEM dummy for crisis is significant for employment and insignificant for real wage. Also dummy for crisis is insignificant for real wage and significant for the number of unemployment in VECM model when we consider short-term relationship.

The number of employed and unemployment don't depend on real oil price. This result is similar for both types of models. However, such relationship is, for example, in Germany. Using monthly data from 1973 to 2008, Loschel A.and Oberndorfer U. (2009) show that oil price increases induce a rise in unemployment in the German labor market. Nevertheless our SEM model shows that real wage positively depends on real oil price. However this result doesn't confirm in VECM model where there is no significant relationship between real wage and real oil price.

The constructed models (especially VECM) can be used for short-term (and even long-term) forecasting of key labor market indicators. However, for this we must either predict the main explanatory variables or use a scenario projections developed by the ministries. Also the models can be used to estimate the effects of certain public policies related to the labor market.

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Appendix A

Fig. 2. Dynamic of the variables

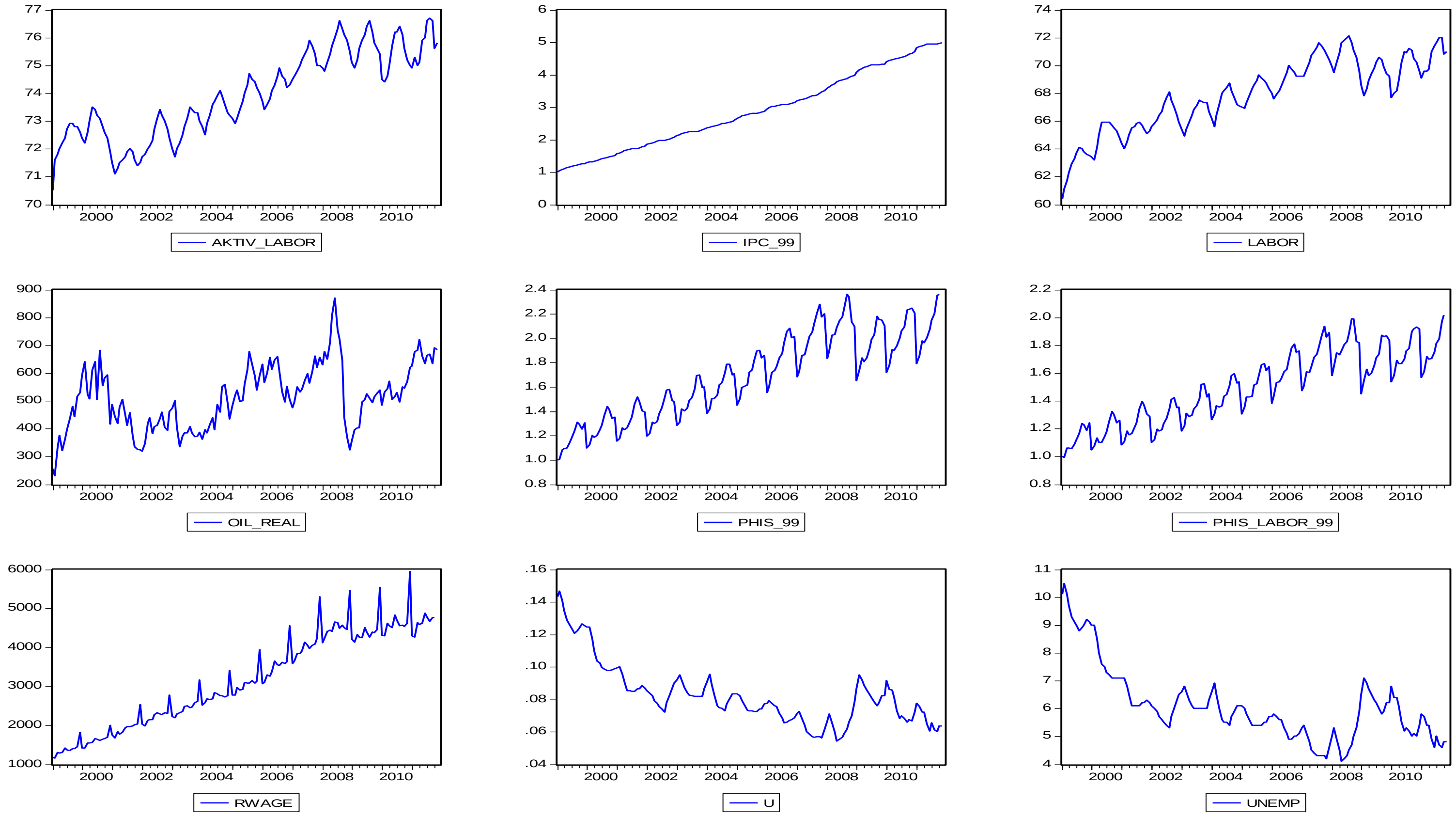


Table 3. Correlation matrix

	AKTIV_LABOR	IPC_99	LABOR	OIL_REAL	PHIS_99	PHIS_LABOR_99	RWAGE	UNEMP
AKTIV_LABOR	1.000000	0.888321	0.915302	0.582302	0.912104	0.896661	0.895853	-0.618634
IPC_99	0.888321	1.000000	0.861480	0.488802	0.878593	0.871699	0.958468	-0.643954
LABOR	0.915302	0.861480	1.000000	0.597276	0.942349	0.921928	0.894892	-0.882684
OIL_REAL	0.582302	0.488802	0.597276	1.000000	0.562576	0.545331	0.500523	-0.485650
PHIS_99	0.912104	0.878593	0.942349	0.562576	1.000000	0.997927	0.927079	-0.773955
PHIS_LABOR_99	0.896661	0.871699	0.921928	0.545331	0.997927	1.000000	0.922544	-0.752140
RWAGE	0.895853	0.958468	0.894892	0.500523	0.927079	0.922544	1.000000	-0.700344
UNEMP	-0.618634	-0.643954	-0.882684	-0.485650	-0.773955	-0.752140	-0.700344	1.000000

Table 4. Descriptive statistics

	AKTIV_LABOR	IPC_99	LABOR	OIL_REAL	PHIS_99	PHIS_LABOR_99	RWAGE	UNEMP
Mean	73.90649	2.862443	67.82013	510.4069	1.688094	1.494262	3155.905	6.086364
Median	73.75000	2.783801	68.05000	504.5587	1.704130	1.514920	3074.831	5.900000
Maximum	76.70000	4.959833	72.10000	869.4489	2.361958	2.015004	5950.208	10.50000
Minimum	70.50000	1.000000	60.40000	230.6405	1.000000	0.990520	1151.777	4.100000
Std. Dev.	1.537151	1.164800	2.569768	115.5374	0.353657	0.263334	1191.063	1.317359
Skewness	0.025899	0.232480	-0.413160	0.204264	0.022735	0.012414	0.069920	1.282778
Kurtosis	1.897952	1.878230	2.567106	2.732334	1.914126	1.934076	1.789296	4.553652
Jarque-Bera	7.810314	9.461723	5.583791	1.530632	7.579295	7.294533	9.531065	57.72376
Probability	0.020138	0.008819	0.061305	0.465187	0.022604	0.026062	0.008518	0.000000
Sum	11381.60	440.8162	10444.30	78602.67	259.9665	230.1164	486009.4	937.3000
Sum Sq. Dev.	361.5135	207.5843	1010.368	2042381.	19.13619	10.60972	2.17E+08	265.5214
Observations	154	154	154	154	154	154	154	154

Appendix B

Table 6. Cointegration test (Johansen)

Sample: 1999:01 2011:12
Included observations: 141
Series: OIL_REAL PHIS_LABOR_99 RWAGE UNEMP
Exogenous series: CRISIS DUM2 DUM3 DUM4 DUM5 DUM6 DUM7 DUM8 DUM9 DUM10 DUM11 DUM12
Warning: Rank Test critical values derived assuming no exogenous series
Lags interval: 1 to 2, 12 to 12

Selected (5% level) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	2	2	2	1	1
Max-Eig	2	2	0	1	1

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-1097.696	-1097.696	-1091.052	-1091.052	-1086.787
1	-1081.292	-1080.331	-1077.665	-1068.170	-1064.712
2	-1071.568	-1067.236	-1066.402	-1056.096	-1055.079
3	-1066.379	-1060.910	-1060.909	-1050.472	-1049.515

4	-1066.121	-1060.541	-1060.541	-1047.594	-1047.594
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	16.25100	16.25100	16.21350	16.21350	16.20975
1	16.13181	16.13236	16.13709	16.01660	16.01010
2	16.10735	16.07426	16.09081	15.97299*	15.98694
3	16.14723	16.11220	16.12637	16.02087	16.02149
4	16.25704	16.23463	16.23463	16.10771	16.10771
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	17.25483*	17.25483*	17.30098	17.30098	17.38088
1	17.30294	17.32441	17.39188	17.29231	17.34854
2	17.44580	17.45453	17.51290	17.43691	17.49269
3	17.65297	17.68069	17.71577	17.67302	17.69454
4	17.93010	17.99133	17.99133	17.94807	17.94807

Table 7. VEC Pairwise Granger Causality/Block Exogeneity Wald Tests

Sample: 1999:01 2011:12
Included observations: 141

Dependent variable: D(OIL_REAL)

Exclude	Chi-sq	df	Prob.
D(PHIS_LABOR_99)	2.406962	3	0.4923
D(RWAGE)	7.517906	3	0.0571
D(UNEMP)	2.405647	3	0.4926
All	12.41470	9	0.1909

Dependent variable: D(PHIS_LABOR_99)

Exclude	Chi-sq	df	Prob.
D(OIL_REAL)	3.820242	3	0.2815
D(RWAGE)	41.90194	3	0.0000
D(UNEMP)	9.673853	3	0.0216
All	51.73712	9	0.0000

Dependent variable: D(RWAGE)

Exclude	Chi-sq	df	Prob.
D(OIL_REAL)	2.567888	3	0.4631
D(PHIS_LABOR_99)	30.54740	3	0.0000
D(UNEMP)	13.51400	3	0.0036
All	48.71520	9	0.0000

Dependent variable: D(UNEMP)

Exclude	Chi-sq	df	Prob.
D(OIL_REAL)	0.257486	3	0.9678
D(PHIS_LABOR_99)	15.47281	3	0.0015

D(RWAGE)	7.272709	3	0.0637
All	24.22557	9	0.0040

Table 8. Vector Error Correction Estimates

Sample(adjusted): 2000:02 2011:10
Included observations: 141 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,4)=1
Convergence achieved after 1 iterations.
Restrictions identify all cointegrating vectors
Restrictions are not binding (LR test not available)

Cointegrating Eq:	CointEq1
OIL_REAL(-1)	-0.105806
	(0.49188)
	[-0.21510]
PHIS_LABOR_99(-1)	-7208.716
	(943.940)
	[-7.63684]
UNEMP(-1)	330.9522
	(90.2342)
	[3.66770]
RWAGE(-1)	1.000000
@TREND(99:01)	30.22396
	(6.12585)
	[4.93384]
C	3300.516

Error Correction:	D(OIL_REAL)	D(PHIS_LABOR_99)	D(UNEMP)	D(RWAGE)
CointEq1	0.076302	2.84E-05	-0.000121	0.010262
	(0.01888)	(7.5E-06)	(5.9E-05)	(0.02336)
	[4.04088]	[3.78928]	[-2.06500]	[0.43927]
D(OIL_REAL(-1))	-0.253004	2.30E-05	9.27E-05	-0.183015
	(0.09597)	(3.8E-05)	(0.00030)	(0.11873)
	[-2.63631]	[0.60489]	[0.31022]	[-1.54144]
D(OIL_REAL(-2))	-0.198544	-4.86E-05	0.000101	-0.002190
	(0.09551)	(3.8E-05)	(0.00030)	(0.11816)
	[-2.07882]	[-1.28224]	[0.33904]	[-0.01853]
D(OIL_REAL(-12))	-0.101514	3.40E-05	-0.000106	0.067101
	(0.08838)	(3.5E-05)	(0.00028)	(0.10935)
	[-1.14855]	[0.97022]	[-0.38477]	[0.61365]
D(PHIS_LABOR_99(-1))	203.2113	0.067769	-1.933534	1339.027
	(218.699)	(0.08677)	(0.68118)	(270.568)
	[0.92918]	[0.78102]	[-2.83850]	[4.94894]
D(PHIS_LABOR_99(-2))	-29.62455	0.359499	-0.730585	436.4284
	(227.997)	(0.09046)	(0.71014)	(282.072)
	[-0.12993]	[3.97418]	[-1.02878]	[1.54722]
D(PHIS_LABOR_99(-12))	-248.2494	0.330715	-1.655855	-676.7776
	(205.536)	(0.08155)	(0.64018)	(254.284)
	[-1.20781]	[4.05551]	[-2.58653]	[-2.66151]
D(UNEMP(-1))	-25.05588	-0.015743	0.165731	-94.50365
	(29.0986)	(0.01154)	(0.09063)	(36.0001)
	[-0.86107]	[-1.36359]	[1.82858]	[-2.62510]

D(UNEMP(-2))	-29.85115	-0.027277	0.154399	-31.03657
	(29.8405)	(0.01184)	(0.09294)	(36.9179)
	[-1.00036]	[-2.30390]	[1.66120]	[-0.84069]
D(UNEMP(-12))	2.735719	0.003191	0.026704	85.91400
	(29.9673)	(0.01189)	(0.09334)	(37.0747)
	[0.09129]	[0.26842]	[0.28610]	[2.31732]
D(RWAGE(-1))	-0.026468	-0.000110	0.000385	-0.428014
	(0.05940)	(2.4E-05)	(0.00019)	(0.07349)
	[-0.44557]	[-4.68853]	[2.08258]	[-5.82408]
D(RWAGE(-2))	-0.016365	-8.48E-05	8.32E-06	-0.156617
	(0.05059)	(2.0E-05)	(0.00016)	(0.06259)
	[-0.32344]	[-4.22536]	[0.05277]	[-2.50209]
D(RWAGE(-12))	0.098255	1.61E-05	0.000132	0.835527
	(0.04896)	(1.9E-05)	(0.00015)	(0.06057)
	[2.00682]	[0.82884]	[0.86671]	[13.7938]
C	65.10203	-0.037918	-0.498098	-29.49065
	(53.8687)	(0.02137)	(0.16778)	(66.6450)
	[1.20853]	[-1.77416]	[-2.96867]	[-0.44250]
CRISIS	-126.0377	-0.049957	0.208281	-36.23485
	(32.0916)	(0.01273)	(0.09996)	(39.7029)
	[-3.92743]	[-3.92359]	[2.08373]	[-0.91265]
DUM2	-36.51207	0.038133	0.508335	155.9460
	(70.8627)	(0.02811)	(0.22072)	(87.6694)
	[-0.51525]	[1.35633]	[2.30312]	[1.77880]
DUM3	-118.8330	0.103505	0.290313	91.44837
	(67.0514)	(0.02660)	(0.20885)	(82.9542)
	[-1.77227]	[3.89074]	[1.39009]	[1.10240]

DUM4	-66.20900	0.026541	0.363698	-33.02647
	(61.4578)	(0.02438)	(0.19142)	(76.0340)
	[-1.07731]	[1.08846]	[1.89998]	[-0.43436]
DUM5	-55.49426	0.017546	0.342318	43.26316
	(66.0839)	(0.02622)	(0.20583)	(81.7572)
	[-0.83975]	[0.66921]	[1.66310]	[0.52917]
DUM6	-62.26189	0.067080	0.520956	84.24535
	(62.0545)	(0.02462)	(0.19328)	(76.7722)
	[-1.00334]	[2.72459]	[2.69533]	[1.09734]
DUM7	-47.43062	0.075951	0.607607	44.05860
	(60.7584)	(0.02411)	(0.18924)	(75.1687)
	[-0.78064]	[3.15068]	[3.21070]	[0.58613]
DUM8	3.685158	0.079328	0.597302	8.348950
	(68.7564)	(0.02728)	(0.21416)	(85.0635)
	[0.05360]	[2.90798]	[2.78911]	[0.09815]
DUM9	0.977184	0.105269	0.696148	-14.46559
	(76.1070)	(0.03020)	(0.23705)	(94.1576)
	[0.01284]	[3.48621]	[2.93671]	[-0.15363]
DUM10	23.41843	0.070415	0.618906	-88.18605
	(73.0281)	(0.02897)	(0.22746)	(90.3485)
	[0.32068]	[2.43028]	[2.72093]	[-0.97607]
DUM11	23.23997	0.019580	0.321847	-30.93868
	(65.7655)	(0.02609)	(0.20484)	(81.3633)
	[0.35338]	[0.75041]	[1.57121]	[-0.38025]
DUM12	-44.60969	0.069694	0.310307	353.0213
	(66.6973)	(0.02646)	(0.20774)	(82.5161)
	[-0.66884]	[2.63369]	[1.49371]	[4.27821]

R-squared	0.270387	0.958744	0.637795	0.975969
Adj. R-squared	0.111775	0.949776	0.559055	0.970745
Sum sq. resids	308946.9	0.048632	2.997205	472873.4
S.E. equation	51.83141	0.020564	0.161439	64.12443
F-statistic	1.704709	106.9000	8.100003	186.8217
Log likelihood	-742.3680	361.9718	71.43079	-772.3768
Akaike AIC	10.89884	-4.765557	-0.644408	11.32449
Schwarz SC	11.44258	-4.221814	-0.100665	11.86824
Mean dependent	0.715936	0.006865	-0.029787	23.68022
S.D. dependent	54.99605	0.091761	0.243118	374.9083

Determinant Residual Covariance	101.0036
Log Likelihood	-1068.170
Log Likelihood (d.f. adjusted)	-1125.650
Akaike Information Criteria	17.51276
Schwarz Criteria	19.79230

Fig. 5. Cointegrating relation

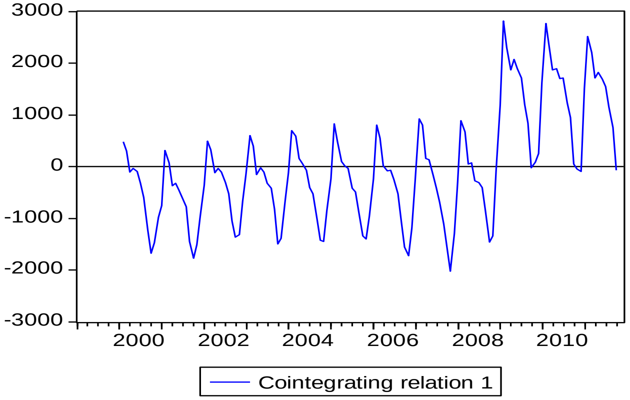


Table 9. VAR Lag Order Selection Criteria

Endogenous variables: D(OIL_REAL) D(UNEMP) D(PHIS_LABOR_99) D(RWAGE)
Exogenous variables: C CRISIS DUM2 DUM3 DUM4 DUM5 DUM6 DUM7 DUM8 DUM9 DUM10 DUM11 DUM12

Sample: 1999:01 2011:12
Included observations: 141

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1287.414	NA	2099.319	18.99878	20.08626	19.44069
1	-1226.177	107.7066	1108.021	18.35712	19.77922*	18.93502
2	-1191.443	59.12254	853.0409	18.09139	19.84809	18.80525*
3	-1176.980	23.79687	877.2869	18.11319	20.20451	18.96303
4	-1161.694	24.28441	893.9206	18.12332	20.54925	19.10913
5	-1150.367	17.35173	966.2772	18.18960	20.95014	19.31139
6	-1135.508	21.92025	996.8033	18.20578	21.30093	19.46354
7	-1122.355	18.65554	1057.617	18.24618	21.67594	19.63991
8	-1103.672	25.44067	1042.122	18.20812	21.97249	19.73783
9	-1079.396	31.67954	953.3858	18.09073	22.18971	19.75641
10	-1062.235	21.42123	970.4306	18.07426	22.50785	19.87592
11	-993.0172	82.47230	475.1556	17.31939	22.08760	19.25703
12	-956.1645	41.81862*	370.9521*	17.02361*	22.12643	19.09722

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 10. VEC Lag Exclusion Wald Tests

Sample: 1999:01 2011:12
Included observations: 141

Chi-squared test statistics for lag exclusion:

Numbers in [ ] are p-values

	D(OIL_REAL)	D(PHIS_LABOR_99)	D(UNEMP)	D(RWAGE)	Joint
DLag 1	8.413105	24.99854	12.21651	48.42436	94.35106
	[0.077565]	[5.03E-05]	[0.015812]	[7.70E-10]	[3.92E-13]
DLag 2	6.466154	22.37523	5.343212	6.265582	42.73008
	[0.166936]	[0.000169]	[0.253859]	[0.180173]	[0.000307]
DLag 12	6.138380	23.20068	7.649611	208.3730	259.0530
	[0.189050]	[0.000115]	[0.105290]	[0.000000]	[0.000000]
df	4	4	4	4	16

Table 11. VEC Residual Serial Correlation LM Tests

H0: no serial correlation at lag order h

Sample: 1999:01 2011:12
Included observations: 141

Lags	LM-Stat	Prob
1	25.31548	0.0645
2	12.74127	0.6916
3	27.65343	0.0348
4	14.21215	0.5829

Probs from chi-square with 16 df.

Fig. 6. Residuals

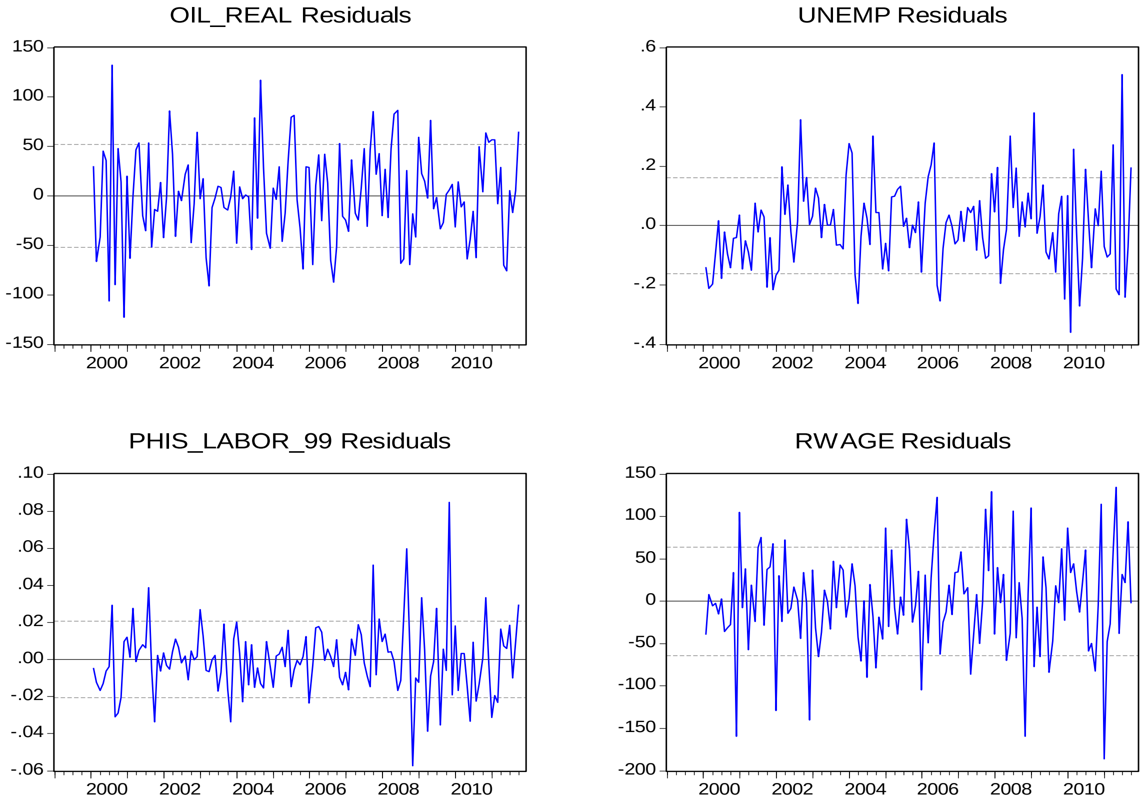


Fig. 7. IRF (oil_real-phis_labor_99-unemp-rwage)

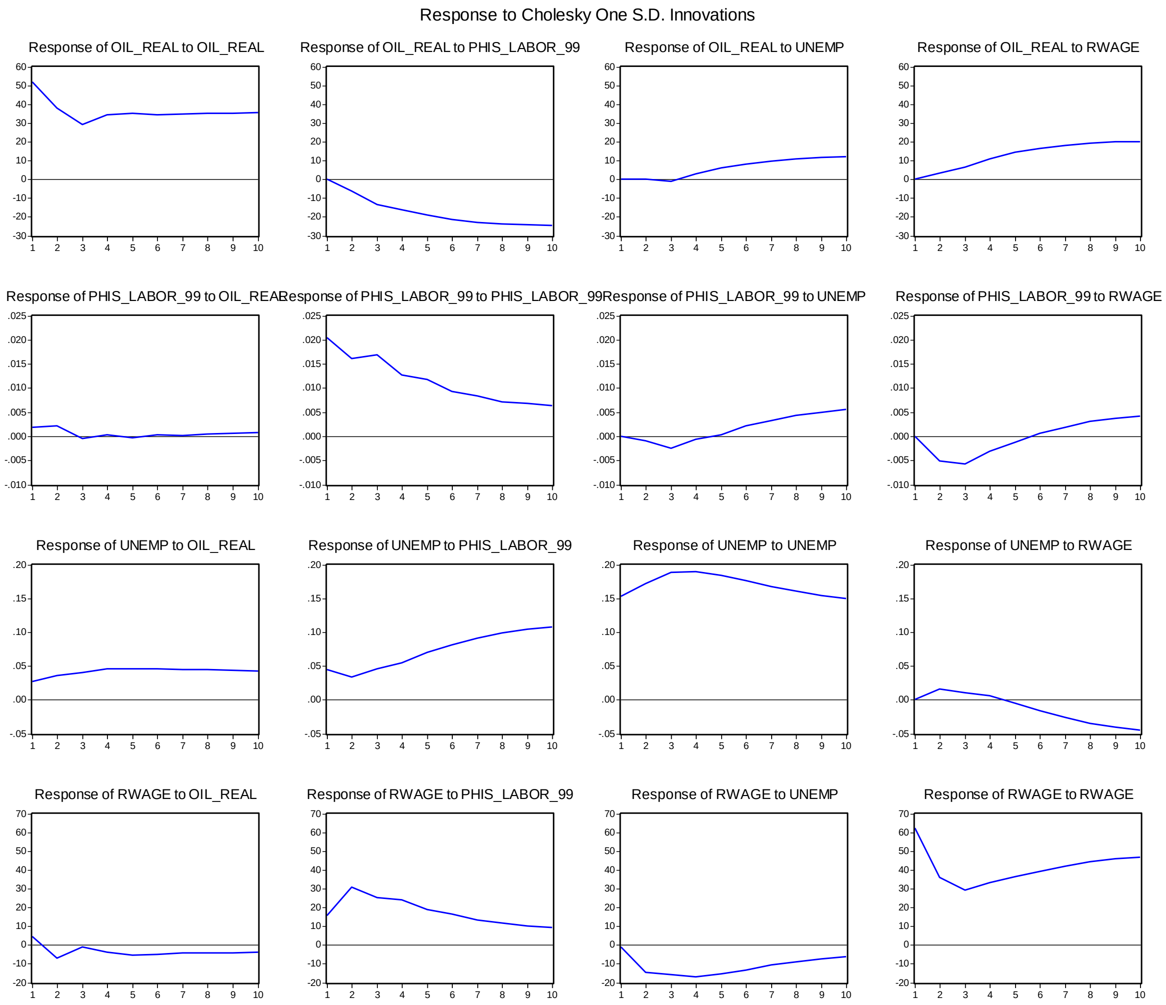
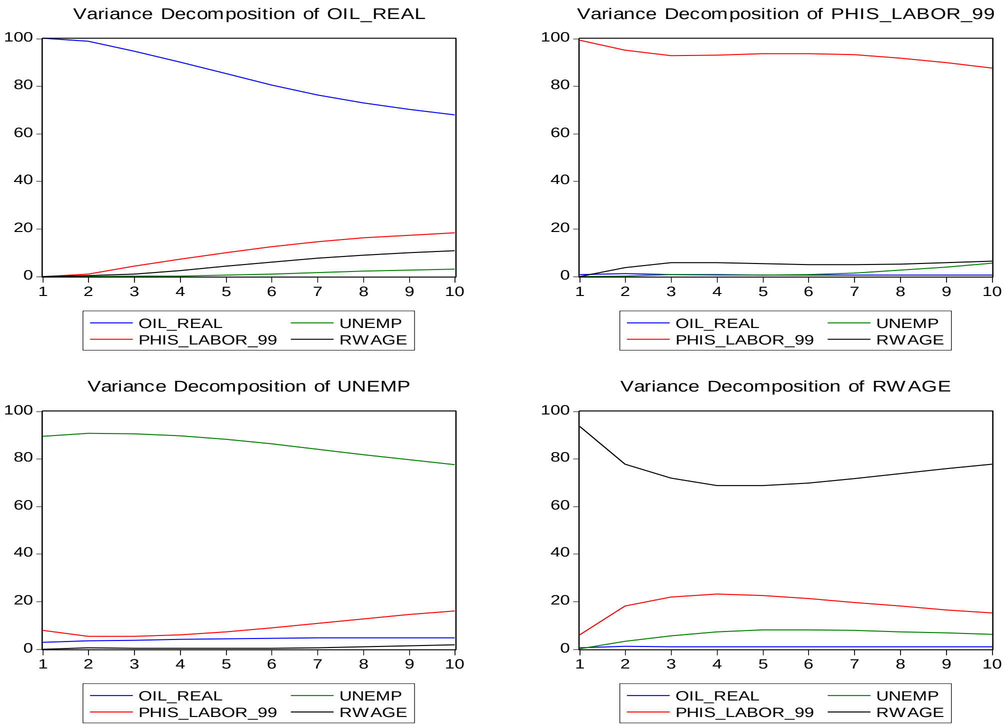
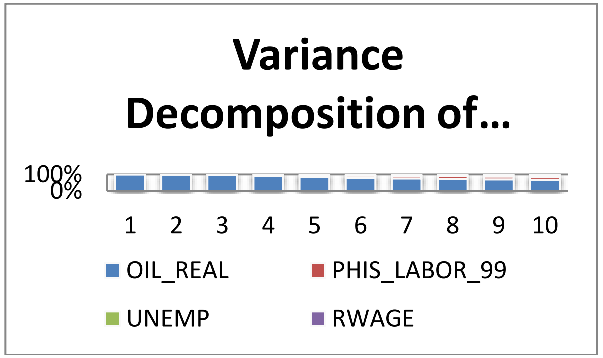
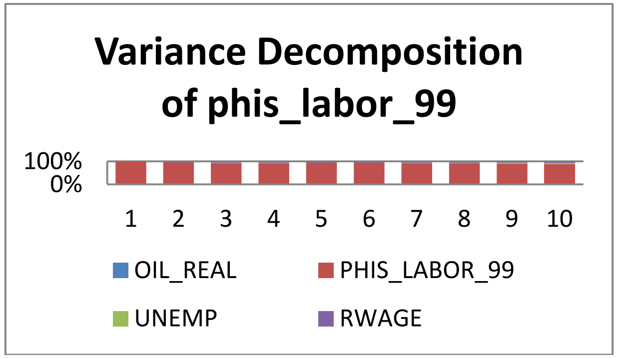
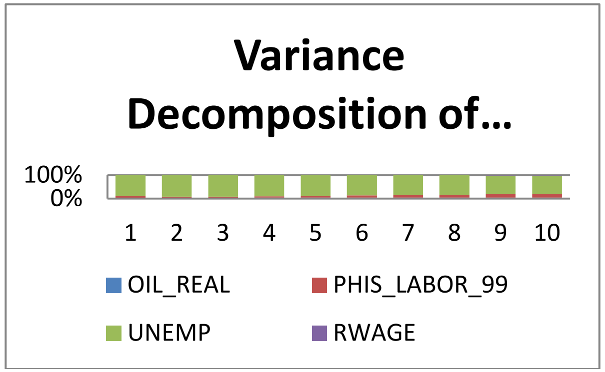


Fig. 8. Variance Decomposition (oil_real-phis_labor_99-unemp-rwage)




Variance Decomposition of...
100%
0%
1 2 3 4 5 6 7 8 9 10
OIL_REAL
PHIS_LABOR_99
UNEMP
RWAGE


Variance Decomposition of phis_labor_99
100%
0%
1 2 3 4 5 6 7 8 9 10
OIL_REAL
PHIS_LABOR_99
UNEMP
RWAGE


Variance Decomposition of...
100%
0%
1 2 3 4 5 6 7 8 9 10
OIL_REAL
PHIS_LABOR_99
UNEMP
RWAGE

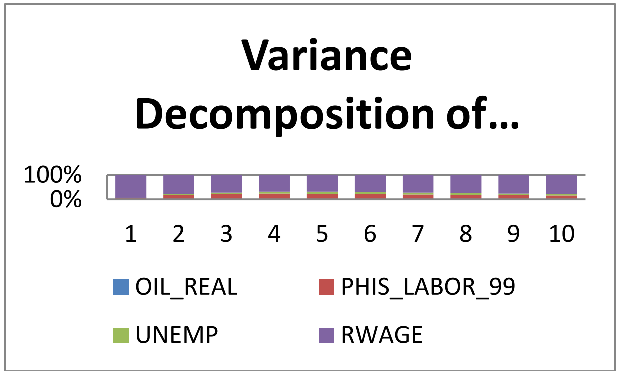

Variance Decomposition of...
100%
0%
1 2 3 4 5 6 7 8 9 10
OIL_REAL
PHIS_LABOR_99
UNEMP
RWAGE

Fig. 9. IRF (oil_real-unemp-phis_labor_99-rwage)

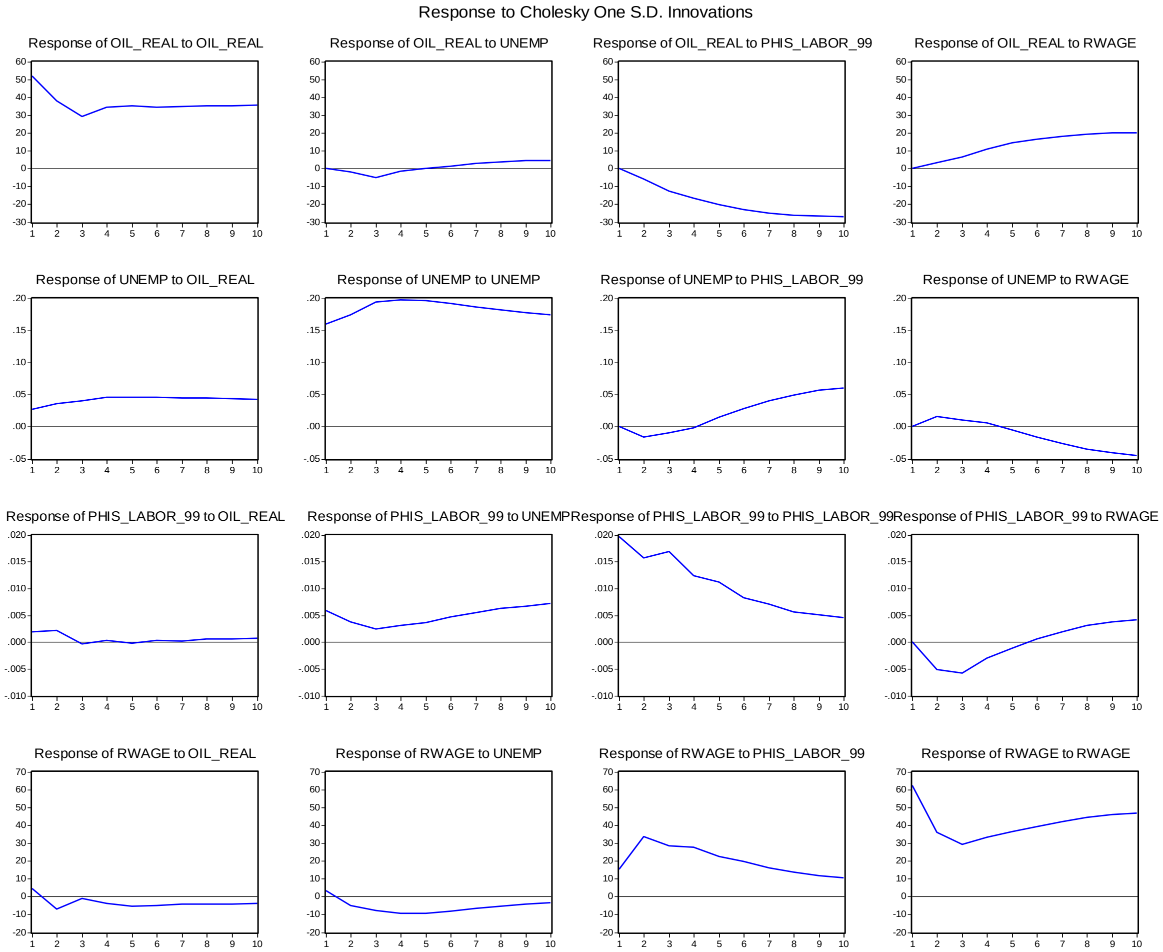
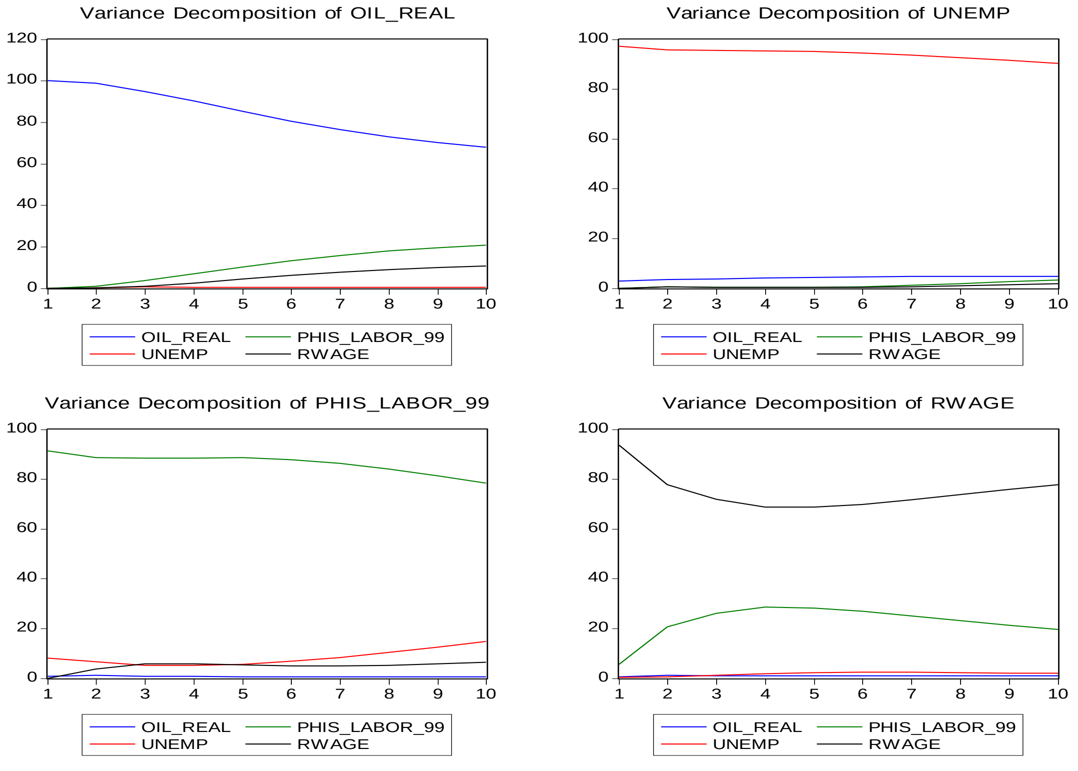
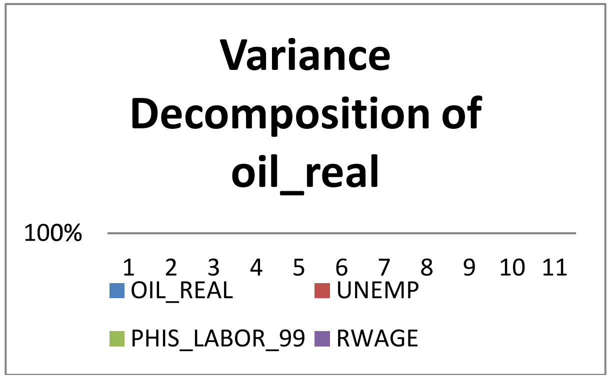
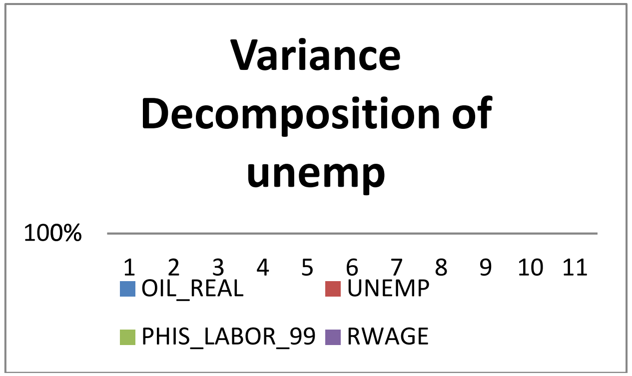
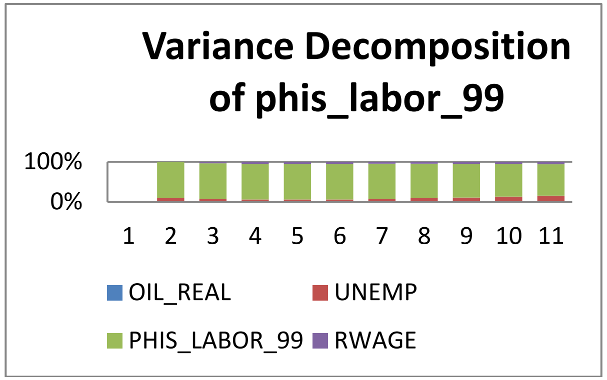


Fig. 10. Variance Decomposition (oil_real-unemp-phis_labor_99-rwage)




Variance Decomposition of oil_real
100%
1 2 3 4 5 6 7 8 9 10 11
OIL_REAL
UNEMP
PHIS_LABOR_99
RWAGE


Variance Decomposition of unemp
100%
1 2 3 4 5 6 7 8 9 10 11
OIL_REAL
UNEMP
PHIS_LABOR_99
RWAGE


Variance Decomposition of phis_labor_99
100%
0%
1 2 3 4 5 6 7 8 9 10 11
OIL_REAL
UNEMP
PHIS_LABOR_99
RWAGE

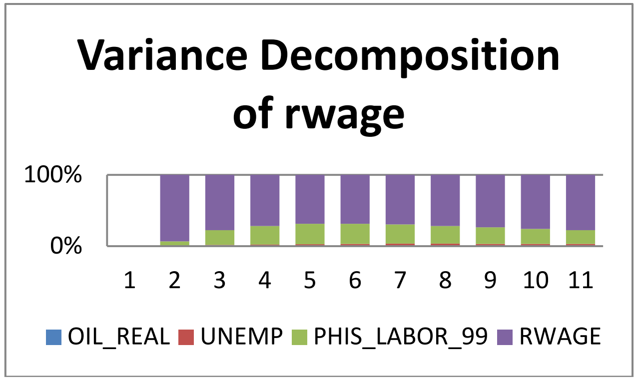

Variance Decomposition of rwage
100%
0%
1 2 3 4 5 6 7 8 9 10 11
OIL_REAL
UNEMP
PHIS_LABOR_99
RWAGE

Fig. 11. Generalized IRF (oil_real-phis_labor_99-unemp-rwage)

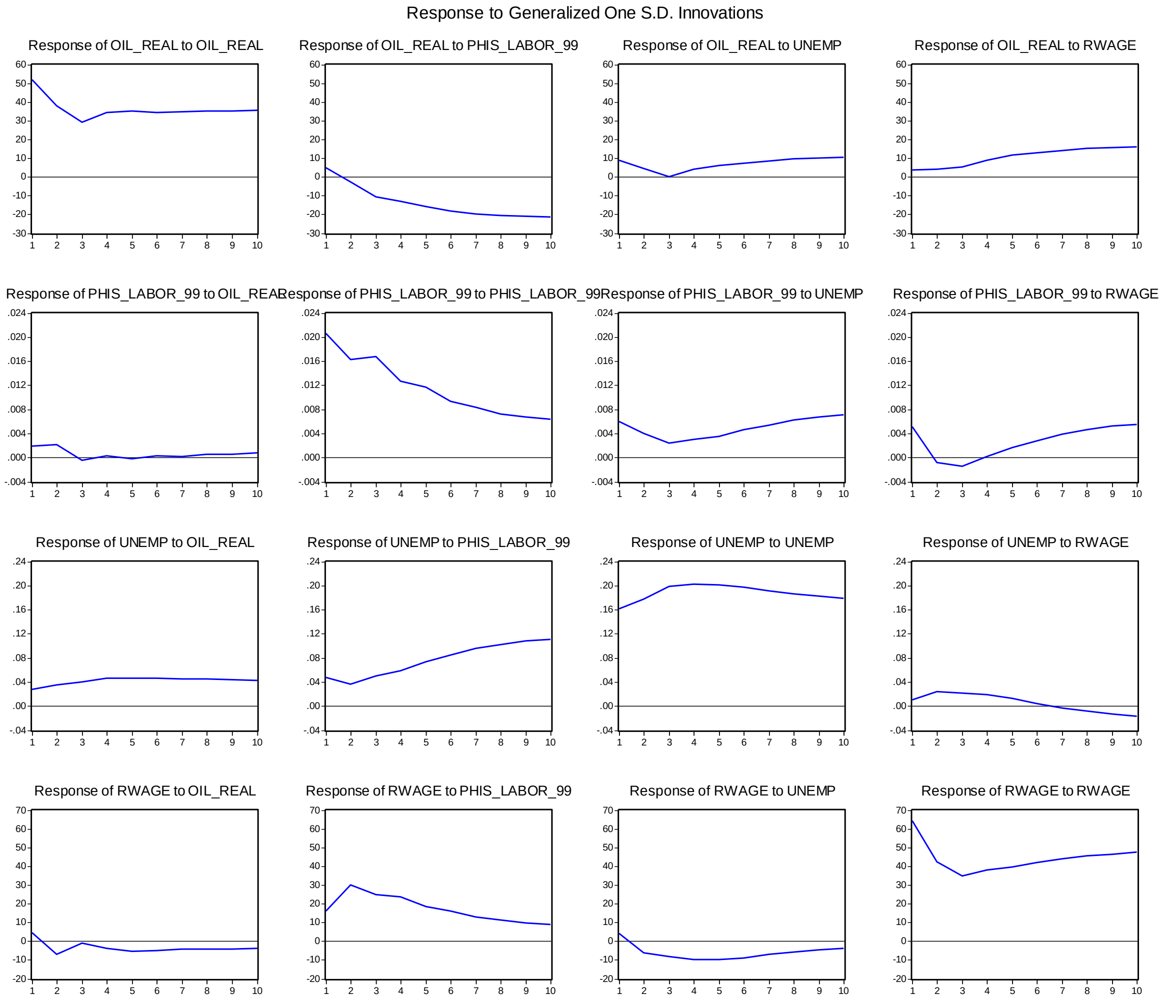


Table 12. Residual correlation matrix

	OIL_REAL	PHIS_LABOR_99	UNEMP	RWAGE
OIL_REAL	1	0.0907269626987	0.168592746621	0.0702137353774
PHIS_LABOR_99	0.0907269626987	1	0.293394944365	0.247779676952
UNEMP	0.168592746621	0.293394944365	1	0.0649041749119
RWAGE	0.0702137353774	0.247779676952	0.0649041749119	1

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