7. INVESTIGATING THE IMPACT OF UNEMPLOYMENT RATE ON THE ROMANIAN SHADOW ECONOMY. A COMPLEX APPROACH BASED ON ARDL AND SVAR ANALYSIS

Adriana Anamaria DAVIDESCU(ALEXANDRU)[1]

Abstract

The paper aims to investigate the potential impact of unemployment rates (both recorded and ILO) on the Romanian shadow economy (SE) for quarterly data covering the period 2000-2013, using ARDL cointegration method in conjunction with the structural VAR (SVAR) analysis in order to provide evidence for both the long and short-run dynamics between the variables.

The size of the shadow economy as % of official GDP was estimated previously using a special case of the structural equation models - the MIMIC model, recording the value of 40% at the beginning of 2000 and following a downward trend over the analyzed period.

The results of ARDL approach pointed out that there is no long-run relation between unemployment rates and the Romanian shadow economy. The relationship between the two variables is further tested by imposing a long-run restriction in the Structural VAR model to analyze the effect in the size of the Romanian shadow economy to a temporary shock in unemployment rates. The impulse response function generated by the Structural VAR confirms that in the short run, a rise in the recorded unemployment rate will lead to an increase in the size of the shadow economy, meanwhile an increase in the ILO unemployment rate highlighted a decrease in the size of the shadow economy.

Keywords: shadow economy, unemployment rates, cointegration; ARDL Bounds Testing, SVAR model, impulse response function

JEL Classification: C32, E41, O17

[1] *Department of Statistics and Econometrics, Academy of Economic Studies, Bucharest, e-mail:* adrianaalexandru@yahoo.com.

I. Introduction

Shadow economy is a controversial topic that has aroused the interest of the specialists since the 60's, when the phenomenon took a great extent. Formulated in the literature under various names, the shadow economy exists to a larger or less extent in all countries, regardless of their level of development, enjoying a long-lasting existence, although as area of research is a new "young" area.

The concept of shadow economy is a generic notion including all market-based legal production of goods and services that are deliberately concealed from public authorities for the following reasons: to avoid payment of income, value added or other taxes; to avoid payment of social security contributions; to avoid certain legal labor market standards, such as minimum wages, maximum working hours, safety standards; to avoid complying with certain administrative procedures, such as completing statistical questionnaires or other administrative forms.

Hence, the subject of the paper does not deal with typical underground, economic (classic crime) activities, which are all illegal actions that fit the characteristics of classic crimes like burglary, robbery, drug dealing, and also exclude the informal household economy, which consists of all household services and production.

According to Giles and Tedds (2002), two opposing forces determine the relationship between unemployment and the informal economy. On the one hand, an increase in the unemployment rate may involve a decrease in the informal economy because it is positively related to the growth rate of GDP and eventually negatively correlated with unemployment (Okun's law). On the other hand, increase in unemployment leads to an increase in people working in the informal economy because they have more time for such activities.

Dell'Anno and Solomon (2007) stated that there is a positive relationship in the short-run between unemployment rate and U.S. shadow economy for the period 1970-2004. Using SVAR analysis, they investigate the response of the shadow economy to an aggregate supply shock (impact of the shadow economy on a temporary shock in unemployment). The empirical results show that in the short-run, a positive aggregate supply shock causes the shadow economy to rise by about 8% above the baseline.

The paper aims to investigate if the presence of the shadow economy acts as a buffer as it absorbs some of the unemployed workers from the official economy into the shadow economy and it is important to analyse the potential impact of unemployment rates on the size of the Romanian shadow economy (SE) using ARDL cointegration method in conjunction with the structural VAR (SVAR) analysis.

II. Data and Methodology

The data used in the research covers the period 2000:Q1-2013Q4. The variables used are as follows: the size of the Romanian shadow economy expressed as % of official GDP (SE) obtained from MIMIC model; ILO unemployment rate (ILO_UR) and registered unemployment rate (R_UR). The unemployment rates were seasonally by means of tramo seats method. The main source of the data for unemployment rates is the National Institute of Statistics (Tempo database) and the National Bank of Romania.

The size of the Romanian shadow economy (SE) has been estimated using a special case of the structural equation models the MIMIC model in which the shadow economy is modelled like a latent variable linked, on the one hand, to a number of observable indicators (reflecting changes in the size of the SE) and on the other hand, to a set of observed causal variables, which are regarded as some of the most important determinants of the unreported economic activity (Dell'Anno, 2003).

This type of models is composed by two sorts of equations, the structural one and the measurement equation system. The equation that captures the relationships between the latent variable (η) and the causes (Xq) is named "structural model" and the equations that link indicators (Yp) with the latent variable (non-observed economy) is called the "measurement model". A MIMIC model of the hidden economy is formulated mathematically as follows:

$$Y = \lambda\eta + \varepsilon \quad (1)$$

$$\eta = \gamma' X + \xi \quad (2)$$

where:

η is the scalar latent variable(the size of shadow economy);

$Y' = (Y_1,....Y_p)$ is the vector of indicators;

$X' = (X_1,...X_q)$ is the vector of causes;

$\lambda_{(p\times1)}$ and $\gamma_{(q\times1)}$ vectors of parameters;

$\varepsilon_{(p\times1)}$ and $\xi_{(p\times1)}$ vectors of scalar random errors;

The $\varepsilon' s$ and ξ are assumed to be mutually uncorrelated.

Substituting (2) into (1), the MIMIC model can be written as: $y = \Pi X + z$ (3)

where: $\Pi = \lambda Y'$, $z = \lambda\xi + \varepsilon$, $\text{cov(z)} = \lambda\lambda'\psi + \Theta_\varepsilon$, $\text{cov}(\xi) = \psi$, $\text{cov}(\varepsilon) = \Theta_\varepsilon$

The multi-equation model was estimated by restricted Maximum Likelihood estimation testing if the data follow a multivariate normal distribution.

For the econometrical estimation of the size of shadow economy, the causal variables considered in the model are: tax burden, total and decomposed into indirect taxes, direct taxes and social contributions, subsidies, unemployment rate, self-employment, government employment[2], real unit labour cost index, 12 months real interest rate.

The indicator variables incorporated in the model are: real gross domestic product index, M_1/M_2 currency ratio and also an equivalent, C/M_1, and labour force participation rate. The main elements of tax burden and subsidies are expressed as percentages of gross domestic product while government employment, self-

[2] Government employment in labour force is called bureaucracy index.

employment, unemployment rate and labour force participation rate are calculated like percentages of labour force (active population). The index of real GDP and the real unit labour cost index are expressed in % (base year 2005=100).

The identification procedure of the best model starts with the most general model specification (MIMIC 10-1-3) and continues removing the variables which have not statistically significant structural parameters.

As the data has been differentiated for the achievement of the stationarity and the assumption of a multivariate normal data distribution is confirmed, we used MLE (maximum likelihood estimator).

Because in order to estimate the model, Giles and Tedds (2000) mentioned that it needs to constain one element of some pre-assigned value, the coefficient of the index of real GDP[3] is normalised to -1 to sufficiently identify the model ($\lambda_1 = -1$).This indicates an inverse relationship between the official and shadow economy.

The best model for the estimation of the size of the Romanian shadow economy was a MIMIC 4-1-2 model with four causal variables (unemployment rate, self-employment, government employment and 12 months real interest rate) and two indicators (index of real GDP and currency ratio M1/M2). The shadow economy measured as percentage of official GDP records 40% in the first quarter of 2000 and follows a descendent trend to 27% in the third quarter of 2008. The size of the shadow economy begins to increase slowly, reaching the value of 32.8% of the official GDP in the third quarter of 2010. In the last years, the size of the unreported economy oscillates around 28%-29% of the official GDP. The results are in line with the studies of Schneider *et al*. (2010) and Albu (2010).

It is important to note that the results drawn of these estimates should be interpreted with due reserve, given the limitations of the method.

A detailed presentation of the estimation process is presented in the working paper "Estimating the size of the Romanian shadow economy using the MIMIC approach" presented at the Conference of European Statistics Stakeholders, Sapienza-University of Rome, Rome, 24-25 November 2014.

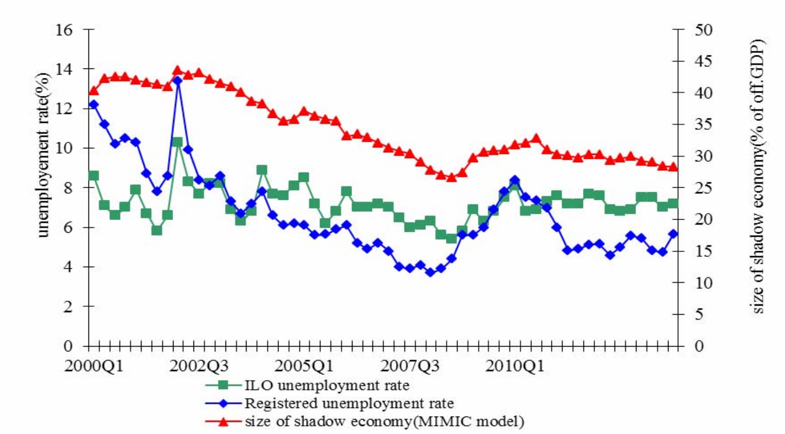
Regarding the Romanian unemployment data, there are two measures available for unemployed persons: the first is the registered unemployment rate, calculated by the National Agency for Employment (NAE) and based on statements of people who pass by employment agencies and said that they are unemployed and the ILO unemployment rate, published quarterly by the National Institute of Statistics and is based on labour force survey (LFS).The figures are hardly identical.

The graphic evolution of the shadow economy versus unemployment rates reveal the existence of a positive relationship between variables, low for ILO unemployment rate, quantified by a value of about 0.41 of correlation coefficient and strong for the registered unemployment rate, quantified by a value of 0.81 of correlation coefficient.

[3] $Index\ real\ GDP = \mathrm{Re}\,al\ GDP_t \big/ \mathrm{Re}\,al\ GDP_{2005Q3}$

Figure 1

Shadow Economy vs. Unemployment Rates in Romania



Source: Size of the shadow economy (% of official GDP); Tempo database, National Institute of Statistics, Monthly Bulletins 2000-2010, National Bank of Romania.

The following models describe the relationship between shadow economy and unemployment rates:

$$SE_t = \alpha_1 + \beta_1 \cdot R\_UR_t + \varepsilon_{1t} \tag{4}$$

$$SE_t = \alpha_2 + \beta_2 \cdot ILO\_UR_t + \varepsilon_{2t} \tag{5}$$

where: SE_t is the size of Romanian shadow economy as % of the official GDP obtained through MIMIC model; R_UR_t is the registered unemployment rate; ILO_UR_t is the ILO unemployment rate; α_1, α_2 are constants; $\varepsilon_{1t}, \varepsilon_{2t}$ are the disturbance terms.

The ARDL bounds testing approach to cointegration (Pesaran (1997), Pesaran and Shin (1999), and Pesaran *et al*. (2001)) is used.

The first step in the ARDL approach to cointegration is to estimate the following relationship using the OLS estimation technique:

$$\Delta SE_t = a_0 + \sum_{i=1}^{m} a_{1i}\Delta SE_{t-i} + \sum_{i=0}^{m} a_{2i}\Delta UR_{t-i} + a_3 \cdot SE_{t-1} + a_4 \cdot UR_{t-1} + \varepsilon_{1t} \tag{6}$$

$$\Delta SE_t = b_0 + \sum_{i=1}^{m} b_{1i}\Delta SE_{t-i} + \sum_{i=0}^{m} b_{2i}\Delta ILO\_UR_{t-i} + b_3 \cdot SE_{t-1} + b_4 \cdot ILO\_UR_{t-1} + \varepsilon_{2t} \tag{7}$$

where: Δ is the difference operator; SE_t is the size of Romanian shadow economy as % of official GDP; R_UR_t is the registered unemployment rate, ILO_UR_t is the ILO unemployment rate; ε_{1t} and ε_{2t} are serially independent random errors with a mean value of zero and a finite covariance matrix; "m" represents number of lags.

The first part of both equations with a_{1i}, a_{2i} and b_{1i}, b_{2i} represents the short-run dynamic of the models whereas the second part with a_3, a_4 and b_3, b_4 represent the long-run phenomenon.

The null hypothesis in the first equation (15) is $H_0 : a_3 = a_4 = 0$, which means the non-existence of a long-run relationship against the alternative $H_1 : a_3 \neq a_4 \neq 0$ meaning that there is a long-run relationship. In the second equation (16), the null is $H_0 : b_3 = b_4 = 0$ against the alternative $H_1 : b_3 \neq b_4 \neq 0$ which states that we have cointegration.

The F-statistic tests checking for the joint significance of the coefficients on the one period lagged levels of the variables. The asymptotic distributions of the F-statistics are non-standard under the null hypothesis of no cointegration relationship between the examined variables, irrespective of whether the variables are purely *I*(0) or *I*(1), or mutually co-integrated. The F-test depends upon (i) whether variables included in the ARDL model are I(0) or I(1), (ii) the number of regressors, and (iii) whether the ARDL model contains an intercept and/or a trend.

The computed F-statistics is compared with the critical values tabulated by Pesaran[4] (2001) or Narayan[5] (2005) for limited samples (40-45 observations).

Two sets of asymptotic critical values are provided by Pesaran and Pesaran (1997). The first set, the lower bound critical values, assumes that the explanatory variables x_t are integrated of order zero, while the second set, the upper bound critical values, assumes that x_t are integrated of order one, or I(1).

If the computed F-statistics is greater than the upper bound critical value, then we reject the null hypothesis of no cointegration (no long-run relationship) and conclude that there is steady state equilibrium between the variables. If the computed F-statistics is less than the lower bound critical value, then we cannot reject the null of no cointegration. If the computed F-statistics falls within the lower and upper bound critical values, then the result is inconclusive.

Once cointegration is confirmed, we move to *the second stage* and estimate the long-run coefficients of the level equations (4)-(5) and the short-run dynamic coefficients via the following ARDL error correction models[6]:

$$\Delta SE_t = \gamma_0 + \sum_{i=1}^{m} \gamma_{1i} \Delta SE_{t-i} + \sum_{i=0}^{n} \gamma_{2i} \Delta R\_UR_{t-i} + \gamma_3 ECT_{t-1} + \varepsilon_{1t} \qquad (8)$$

[4] *Pesaran* et al*. (2001) have generated critical values using samples of 500 and 1000 observations.*

[5] *Narayan (2005) argued that these critical values are inappropriate in small samples which are the usual case with annual macroeconomic variables. For this reason, Narayan (2005) provides a set of critical values for samples ranging from 30 to 80 observations for the usual levels of significance.*

[6] *The Optimal ARDL models are specified on a basis of a set of criteria (Schwarz, Akaike).*

$$\Delta SE_t = \lambda_0 + \sum_{i=1}^{m} \lambda_{1i} \Delta SE_{t-i} + \sum_{i=0}^{n} \lambda_{2i} \Delta ILO\_UR_{t-i} + \lambda_3 ECT_{t-1} + \varepsilon_{2t} \tag{9}$$

where: SE_t, UR_t are the variables described above; Δ is the difference operator and ECT_{t-1} is the one-period lagged error correction term, γ_3, λ_3 indicate the speed of adjustement to the equilibrium level after a shock. The expected sign of ECT is negative. The coefficients $\gamma_{1i}, \gamma_{2i}, \lambda_{1i}, \lambda_{2i}$ are the coefficients for the short-run dynamic of the model convergence to equilibrium, and $\varepsilon_{1t}, \varepsilon_{2t}$ are the error terms.

To ascertain the goodness-of-fit of the ARDL models, diagnostic and stability tests are conducted. The commonly used tests for this purpose are the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMQ), both introduced by Brown *et al*. (1975).

The third stage includes conducting standard Granger causality tests augmented with a lagged error-correction term. The advantage of using an error correction specification to test for causality is that, on the one hand, it allows testing for short-run causality through the lagged differenced explanatory variables and, on the other hand, for long-run causality through the lagged ECT term. A statistically significant ECT term implies long-run causality running from all the explanatory variables towards the dependent variable.

Furthermore, the VAR and SVAR approaches are used in the study to analyse te relationship between Romanian shadow economy and unemployment rates.

We define a vector of variables in the SVAR as follows:

$$\mathrm{X_t} = \begin{bmatrix} \Delta \mathrm{SE_t} \\ \Delta \mathrm{UR_t} \end{bmatrix} \tag{10}$$

where the variables are first differences of the shadow economy (SE), and unemployment rates (R_UR and ILO_UR), respectively (we have considered both registered unemployment rate and ILO unemployment rate).

The VAR model can be re-written using vector moving average (VMA) as follows:

$$\begin{bmatrix} \Delta SE_t \\ \Delta UR_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} \Delta SE_{t-1} \\ \Delta UR_t \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{11}$$

where:

$\mathrm{X_t} = \begin{bmatrix} \Delta \mathrm{SE_t} \\ \Delta \mathrm{UR_t} \end{bmatrix}; e_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}; A(L) =$ the 2×2 matrix with elements equal to the polynomials $A_{ij}(L)$ and the coefficients of $A_{ij}(L)$ are denoted by $a_{ij}(k)$.

There is a linear relation between $e_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$ and $\varepsilon_t = \begin{bmatrix} \varepsilon_{dt} \\ \varepsilon_{st} \end{bmatrix}$ as follows:

$$e_t = B_0 \varepsilon_t \tag{12}$$

where: B0 is a 2 x 2 matrix that defines the contemporaneous structural relation between the variables. Additionally, we have to identify for the vector of the structure shocks so that it can be recovered from the estimated disturbance vector. We require four parameters to convert the residual from the estimated VAR into the original shocks that drive the behavior of the endogenous variables.

If we ignore the intercept terms, in the particular bivariate moving average form, the VAR can be written:

$$\Delta SE_t = \sum_{k=0}^{\infty} b_{11}(k)\varepsilon_{dt-k} + \sum_{k=0}^{\infty} b_{12}(k)\varepsilon_{st-k} \tag{13}$$

$$\Delta UR_t = \sum_{k=0}^{\infty} b_{21}(k)\varepsilon_{dt-k} + \sum_{k=0}^{\infty} b_{22}(k)\varepsilon_{st-k} \tag{14}$$

or

$$\begin{bmatrix} \Delta \mathrm{SE}_t \\ \Delta \mathrm{UR}_t \end{bmatrix} = \sum_{i=0}^{\infty} L^i \begin{bmatrix} b_{11i} & b_{12i} \\ b_{21i} & b_{22i} \end{bmatrix} \begin{bmatrix} \varepsilon_{dt} \\ \varepsilon_{st} \end{bmatrix} \tag{15}$$

The vector $\varepsilon_t = \begin{bmatrix} \varepsilon_{dt} \\ \varepsilon_{st} \end{bmatrix}$ contains the two structural shocks, the demand one and the supply one. The elements b_{11i} and b_{21i} are the impulse responses of an aggregate demand shock on the time path of the shadow economy and unemployment rate. The coefficients b_{12i} and b_{22i} are the impulse responses of an aggregate supply shock on the time path of shadow economy and unemployment rate, respectively.

According to Blanchard and Quah, the key is to assume that one of the structural shocks has a temporary effect on ΔSE_t. We assume that an aggregate supply (unemployment rate) shock has no long-run effect on shadow economy. In the long-run, if the shadow economy is to be unaffected by the supply shock, it must be the case that the cumulated effect of a ε_{st} shock on the ΔSE_t sequence must be equal to zero. In other words, we impose a long-run restriction on the relationship between the observed data (SE) and the unobserved structural shock (ε_{st}) such that:

$$\sum_{k=0}^{\infty} b_{12}(k)\varepsilon_{st-k} = 0 \tag{16}$$

Equation (16) is an Aggregate Supply Shock stating that the second structural shock (aggregate supply) has no long-run effect on shadow economy.

II. Empirical Results

The main goal of the study is to investigate the potential impact of unemployment rates (both registered and ILO) on the Romanian shadow economy (SE) for quarterly data covering the period 2000-2013, using ARDL cointegration method in conjunction with the structural VAR (SVAR) analysis in order to provide evidence for both the long and short run dynamics between the variables.

The analysis of non-stationarity realised using ADF and PP tests revealed that all series are integrated on the same order, I(1).

Forthmore, we investigated the possibility of cointegration between the shadow economy and the unemployment rates using the bounds tests within the ARDL modeling approach. The optimal lag length[7] required in the bound cointegration test has been selected on the both SBC and AIC Information Criteria.

For the model describing the relationship between shadow economy and registered unemployment rate, the lag order selected by AIC and SBC is $p = 1$ irrespective of the inclusion of a trend term. For the ILO unemployment rate shadow economy relationship, the lag order selected by AIC is $p = 2$ if a trend is included and $p = 7$ if not.The lag length selected by SBC is $p = 2$ irrespective of the inclusion of a trend term. In view of the importance of the assumption of serially uncorrelated errors for the validity of the bounds tests, it seems prudent to select p to be 2.

Table 1

Bounds F and t-Statistics for the Existence of a Levels Relationship between Shadow Economy and Registered Unemployment Rate

Without Determintic Trends						
p	F_iii	p-val F_iii*	t_iii	p-val t_iii*		
1*			-3.876663c			
2			-3.076983c			
3			-2.712440b			
4			-2.707638b			
With Determintic Trends						
p	F_iv	p-val F_iv*	F_v	p-val F_v*	t_v	p-val t_v*
1*					-3.766593c	
2					-3.023787a	
3					-2.603645a	
4					-2.594874a	

[7] *The maximum duration of lags for both models has been taken as 8.*

Bounds F and t-Statistics for the Existence of a Levels Relationship between Shadow Economy and ILO Unemployment Rate

Without Determintic Trends						
p	F_iii	p-val F_iii*	t_iii	p-val t_iii*		
2*			-1.436187a			
3			-0.992433a			
4			-0.987800a			
5			-0.175602a			
With Determintic Trends						
p	F_iv	p-val F_iv*	F_v	p-val F_v*	t_v	p-val t_v*
2*					-2.412434a	
3					-1.983443a	
4					-2.031228a	
5					-0.539625a	

*Note: Akaike Information Criterion (AIC) and Schwartz Criteria (SC) were used to select the number of lags required in the co-integration test. The term p shows lag levels and * denotes the optimum lag selection in each model, as suggested by AIC. F_{IV} represents the F statistic of the model with unrestricted intercept and restricted trend. F_V represents the F statistic of the model with unrestricted intercept and trend, and F_{III} represents the F statistic of the model with unrestricted intercept and no trend. t_V and t_{III} are the t ratios to test $a_3 = 0$ and $b_3 = 0$ in equations(6)-(7) with and without a deterministic linear trend.[a] indicates that the statistic lies below the lower bound, [b] that it falls within the lower and upper bounds, and [c] that it lies above the upper bound (Katircioglu(2009)).*

The cointegration test under the bounds framework involved the comparison of the F and t statistics with the critical values of F and t for ARDL approach, presented in Table 2 for the three different scenarios.

Table 2

Critical Values for ARDL Modeling Approach

	90% level		95% level		99% level	
k = 1	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
F_{IV}	4.23	4.73	5.01	5.54	6.89	7.53
F_V	5.80	6.51	6.93	7.78	9.8	10.67
F_{III}	4.15	4.92	5.12	6.04	7.43	8.46
t_V	-3.13	-3.40	-3.41	-3.69	-3.96	-4.26
t_{III}	-2.57	-2.91	-2.86	-3.22	-3.43	-3.82

Source: Narayan(2005) for F-statistics(n=55 observations) pg.1988-1990 and Pesaran(2001) for t-ratios pg.303-304.

Note: (1) k[8] is the number of independent variables in ARDL models (Erbaykal, 2008), F_{IV} represents the F statistic of the model with unrestricted intercept and restricted trend, F_V represents the F statistic of the model with unrestricted intercept and trend, and F_{III} represents the F statistic of the model with unrestricted intercept and no trend. (2) t_V and t_{III} are the t ratios for testing $a_3 = 0$ and $b_3 = 0$ in equations(6)-(7) with and without a deterministic linear trend.

[8] *k is the number of regressors for the dependent variable in the ARDL models.*

The empirical results do not support the existence of a level relationship between shadow economy and registered unemployment rate or ILO unemployment rate. The existence of a cointegration between shadow economy and unemployment rates is rejected.

Due to the fact that unemployment rates do not have a significant impact on the size of the shadow economy on the long run, it is important to quantify the impact on short term using SVAR analsyis.

The first step in applying the SVAR analysis is to determine the level of integration of the variables and the optimal number of lags in order to estimate a bivariate VAR model and to identify the supply and demand shocks.

The unit root analysis using ADF and PP test point out the variables are non-stationary at their levels but stationary at their first differences, being integrated of order one, I(1), and I have differenced the variables in order to estimate de model.

For the recorded unemployment rate model, the optimal number of lags is found to be 1 according to SBC, AIC, HQ, LR and FPE criterions. The estimated VAR model verifies the stability condition and the non-autocorrelation homoskedasticity and normality hypothesis of the residuals were verified by estimated VAR.

Furthermore, we impose on this VAR a long-run restriction which specifies that the long-run effect of the supply shock (registered unemployment rates) on the shadow economy is null. The restriction in (16) implies that the ***cumulative effect*** of ε_{st} on ΔSE_t is zero and consequently the long-run effect[9] of ε_{st} on the level of SE_t itself is zero. The supply shock (ε_{st}) has only short-run effects on the shadow economy.

Table 3

Empirical Results of SVAR Model for Registered Unemployment Rate

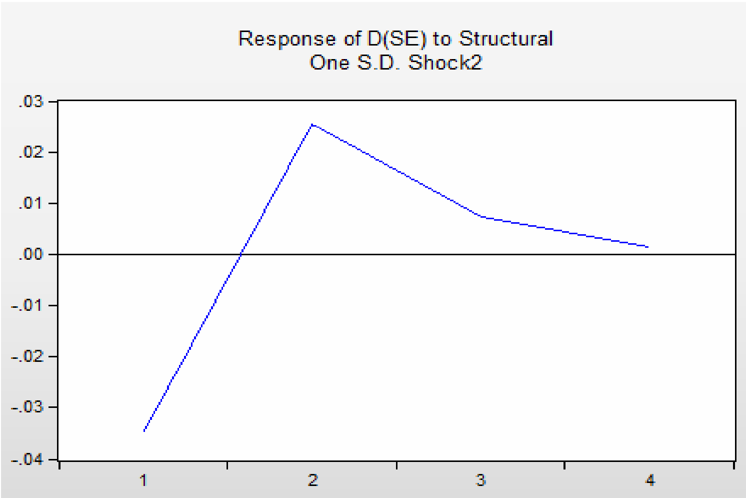
Structural VAR Estimates				
Sample (adjusted): 2000Q3 2013Q4				
Included observations: 54 after adjustments				
Estimation method: method of scoring (analytic derivatives)				
Model: Ae = Bu where E[uu']=I				
	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.103705	0.106204	10.39230	0.0000
C(2)	0.360981	0.092791	3.890272	0.0001
C(3)	0.632292	0.060842	10.39230	0.0000
Log likelihood	-118.7421			

Starting from this model, we analyze the impulse response function for the structural version of the model. Finally, we estimate a Structural VAR model to examine the response of shadow economy to an aggregate supply shock.

[9] *In Eviews I specify the restriction such as: @lr1(@u2)=0 "zero LR response of 1st variable to 2nd shock".*

Figure 2

The Effect of an Aggregate Supply Shock (Registered Unemployment Rate) on the Size of the Shadow Economy



The impulse response functions shows that the Romanian shadow economy increases following an aggregate supply shock (a shock in registered unemployment rate) but this steadily declines after the second quarter. This strengthens the evidence of a structural relationship between the shadow economy and unemployment.

The variance decomposition using the actual ε_{st} and ε_{dt} sequence allow assessing the relative contributions of demand and supply shocks to forecast error variance of the shadow economy.

Table 4

Variance Decomposition of D(SE) Due to Supply-Side Shock (Registered Unemployment Rate)

Period	S.E.	Shock1	Shock2
1	0.879716	99.84503	0.154971
2	0.899397	99.77081	0.229194
3	0.900031	99.76457	0.235432
4	0.900048	99.76432	0.235685
Factorization: Structural			

For the ILO unemployment rate model, the optimal number of lags is found to be 1 according to SBC, AIC, HQ, LR an FPE criterions The estimated VAR model verifies

the stability condition and the non-autocorrelation homoskedasticity and normality hypothesis of the residuals were verified by estimated VAR.
Furthermore, we impose on this VAR a long-run restriction which specifies that the long run effect of the supply shock (ILO unemployment rates) on the shadow economy is null. The restriction in (16) implies that the ***cumulative effect*** of ε_{st} on ΔSE_t is zero and consequently the long-run effect[10] of ε_{st} on the level of SE_t itself is zero. The supply shock (ε_{st}) has only short-run effects on the shadow economy.

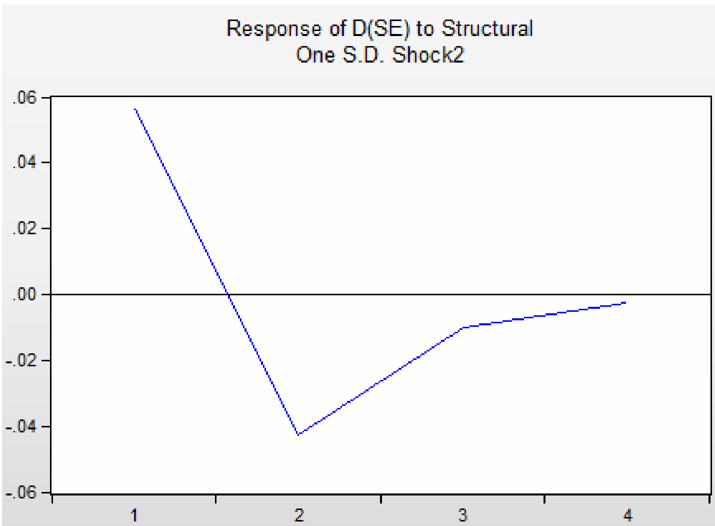
Table 5

Empirical Results of SVAR Model for ILO Unemployment Rate

Structural VAR Estimates				
Sample (adjusted): 2000Q3 2013Q4				
Model: Ae = Bu where E[uu']=I				
Restriction Type: long-run text form				
	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.113409	0.107138	10.39230	0.0000
C(2)	0.158378	0.069733	2.271208	0.0231
C(3)	0.500044	0.048117	10.39230	0.0000
Log likelihood	-106.5493			

Figure 3

The Effect of an Aggregate Supply Shock (ILO Unemployment Rate) on the Size of the Shadow Economy



[10] *In Eviews I specify the restriction such as: @lr1(@u2)=0 "zero LR response of 1st variable to 2nd shock"*

The impulse response functions show that the Romanian shadow economy decreases following a shock in ILO unemployment rate but this steadily increases after the second quarter.

The variance decomposition using the actual ε_{st} and ε_{dt} sequence allows assessing the relative contributions of demand and supply shocks to forecast error variance of the shadow economy.

Table 6

Variance Decomposition of D(SE) Due to Supply-Side Shock (ILO Unemployment Rate)

Period	S.E.	Shock1	Shock2
1	0.878573	99.59228	0.407725
2	0.897221	99.38393	0.616068
3	0.898393	99.37281	0.627186
4	0.898466	99.37211	0.627885

Factorization: Structural

Concluding, the empirical results of SVAR analysis confirms that in the short run a rise in the recorded unemployment rate will lead to an increase in the size of the shadow economy, and meanwhile an increase in the ILO unemployment rate highlighted a decrease in the size of the shadow economy.

One possible explanation for the positive short-run relantionship between registered unemployment rate and the size of the Romanian shadow economy is that some of those who declare themselves as unemployed participate in economic activities in the informal economy. So, an increase in unemployment in the formal sector causes an increase in the number of people working in the informal economy, causing an expansion of the informal sector.

However, the results provide an interesting analysis as to the role of the shadow economy in acting as a buffer to the official economy in the presence of changes in the unemployment rate (Dell'Anno, 2007).

One possible motivation for the negative short-run relationship between ILO unemployment rate and the size of the shadow economy is represented by the fact that opportunities to work in the informal economy can be limited when the unemployment level is excessively high, fewer businesses offering jobs; either they are official or underground.

IV. Policy İmplications

Investigation of the magnitude by which unemployment affects work in the informal economy is important to know the extent to which countries win or lose by neglecting the impact of the informal economy on macroeconomic indicators.

According to Giles and Tedds (2002), two opposing forces determine the relationship between unemployment and the informal economy. On the one hand, an increase in the unemployment rate may involve a decrease in the informal economy because it is positively related to the growth rate of GDP and eventually negatively correlated with unemployment (Okun's law). On the other hand, increase in unemployment leads to an increase in the number of people working in the informal economy because they have more time for such activities.

Tanzi (1999) considers that the relationship between unemployment and the informal economy is ambiguous. The greater the number of unemployed, the more individuals will seek a job in the informal economy. However, it is likely that opportunities to work in the informal economy should be limited when unemployment is high; businesses provide fewer jobs whether they are official or clandestine.

Concluding, the empirical results of SVAR analysis confirms that in the short run, a rise in the recorded unemployment rate will lead to an increase in the size of the shadow economy, and meanwhile an increase in the ILO unemployment rate highlighted a decrease in the size of the shadow economy.

One possible explanation for the positive short-run relantionship between registered unemployment rate and the size of the Romanian shadow economy is that some of those who declare themselves as unemployed participate in economic activities in the informal economy. Here I refer to a fraction of the unemployed that can participate in unofficial activities in order to supplement their earnings and also to those who leave the unemployment without finding officially a job and are expelled from official statistics after the expiration of unemployment aid, being forced to work temporarily or permanently in the informal economy and also to those who declared thwmselves to be unemployed, who are interested to work but cannot find a job.

Thus, the existing institutional framework at a particular time can influence the market behavior of individuals and businesses, prompting them to resort to informal activities. Therefore, it is possible that in certain periods the evolution of the informal economy be directly related to the various changes/developments of the institutional framework regarding the unemployment phenomenon.

The impact of the ILO unemployment on the size of the informal economy was estimated to be negative in the short run, caused by the inability of the labor market to provide more jobs whether they are official or 'hidden' / unregistered (clandestine in some extent of course) in the event of rising unemployment, underlining a limitation of opportunities to work in the informal economy.

On long term, the state has a role in either inhibiting mechanisms of the informal economy or in their stimulation. State action is the only one that can indeed be long-term oriented when it is subordinated to pro-cyclical action, only when the relationship between formal and informal sectors becomes reversed. In other words, the individual is left noting that "state", state power or that it began to act as if it were an individual competition with other individuals, only then, informality appears as an "economic place of" refuge, in bloom all the opportunities denied by one way or another, whether express or implied in "formal". It should be noted that pro-cyclical action of the state, repeated, long-term or otherwise "irresponsible" state entity, to push the "informal" in a systematic and continuous manner, to justify recourse to this as sui generis rule of coexistence and economic and social action.

In this context, the legitimate and justified restricting action of "informal sphere" and "continuous expansion of formality" (without support through this that could ever be eradicated informal sector) can only be done by creating the necessary space in which individuals and corporations exercise fully the action of pro-cyclical, which, among others, will lead essentially to strengthen the state space to be able to exercise fully and continuously as possible, the anti- cyclical. Effective combination of these two types of actions may lead to a de-legitimization of the informal and appeal to it. It creates the premises for training a movement lasting character irreversibility potential in terms of reducing the scope of the informal economy, with subsequent consequences for the life of that society that a particular national economy sustains at a time.

V. Conclusions

The paper aims to investigate the impact of recorded and ILO unemployment rates on the Romanian shadow economy (SE) for quarterly data covering the period 2000-2013, using ARDL cointegration method in conjunction with the structural VAR (SVAR) analysis in order to provide evidence for both the long and short-run dynamics between the variables.

The size of the shadow economy as % of official GDP was estimated previously using a special case of the structural equation models- 4-1-2 MIMIC model, recording the value of 40% at the beginning of 2000 and following a descendent trend over the analyzed period.

The results of ARDL approach pinted out that there is no long-run relation between unemployment rates and the Romanian shadow economy.

The relationship between the two variables is further tested by imposing a long-run restriction in the Structural VAR model to analyze the effect in the size of Romanian shadow economy to a temporary shock in unemployment rates.

The impulse response function generated by the Structural VAR confirms that in the short run a rise in the recorded unemployment rate will lead to an increase in the size of the shadow economy, and meanwhile an increase in the ILO unemployment rate highlighted a decrease in the size of the shadow economy.

One possible explanation for the positive short-run relantionship between registered unemployment rate and the size of the Romanian shadow economy is that some of those who declare themselves as unemployed participate in economic activities in the informal economy. So, an increase in unemployment in the formal sector causes an increase in the number of people working in the informal economy, leading to an expansion of the informal sector.

However, the results provide an interesting analysis as to the role of the shadow economy in acting as a buffer to the official economy in the presence of changes in the unemployment rate (Dell'Anno, 2007).

One possible motivation for the negative short-run relationship between ILO unemployment rate and the size of the shadow economy can be the inability of the labor market to provide more jobs, either they are official or 'hidden'/unregistered (clandestine to some extent, of course) in case of rising unemployment, underlining a limitation of opportunities to work in the informal economy.

Acknowledgement

This work was supported from the European Social Fund through Sectoral Operational Programme Human Resources Development 2007–2013, project number POSDRU/ 159/1.5/S/142115, project title "Performance and Excellence in Postdoctoral Research in Romanian Economics Science Domain".

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