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A SVAR ANALYSIS OF THE RELATIONSHIP BETWEEN ROMANIAN UNEMPLOYMENT RATES AND THE SIZE OF THE SHADOW ECONOMY

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ABSTRACT

The paper analyses the relationship between shadow economy and unemployment rates using a Structural VAR approach for quarterly data during the period 2000-2010. The size of Romanian shadow economy is estimated using the currency demand approach based on VECM models, stating that its size is decreasing over the analyzed period, from 36.5% at the end of 2000 to about 31.5% of real GDP at the middle of 2010.

The relationship between the variables is tested by imposing a long-run restriction in the Structural VAR model to analyze the impact of the shadow economy to a temporary shock in unemployment. The accumulated responses generated by a positive supply shock (unemployment rate) confirms that in the short-run, a rise in both registered and ILO unemployment rates in formal sector will lead to a decrease in the number of people who work in the shadow economy in the second quarter following the initial shock and to an smaller increase in the size of the Romanian shadow economy in the third quarter following the initial shock.

Keywords: *shadow economy, unemployment rates, Structural VAR, Romania*
JEL classification: C32, E41, O17

1. INTRODUCTION

The paper aims to investigate the relationship between the size of the shadow economy (SE) and unemployment rates for the case of Romanian data using SVAR analysis for quarterly data covering the period 2000-2010. The size of Romanian shadow economy is estimated using currency demand approach based on vector error correction models (Davidescu and Dobre (2013)).

The empirical results of currency demand approach based on VECM models emphasizes that there is a general downward trend in the size of the shadow economy as % of official GDP for the period 2000-2010 with an highlight on two low periods, 2003Q1 and 2008Q4.Thus, the size of the shadow economy as % of official GDP measures approximately

36.6% in 2000Q1 and follows a downward trend after registering the value of 31% by 2008. For the past few quarters, there is a slightly upward trend in the size of Romanian shadow economy.

The results are consistent with studies of Schneider (2007) and Albu (2007, 2010, 2011) which show a mainly downward trend of shadow economy in Romania.

It is important to note that because of its undetectable nature and character, it is nearly impossible to measure precisely the size of economic activities taking place in the informal economy of any country in the world, whether developed or less developed. Given this, any theoretical or empirical inference derived from these results should always be regarded as an approximation. In the face of these difficulties, the results drawn from these estimates should be interpreted with due reserve, given the limitations of the methods.

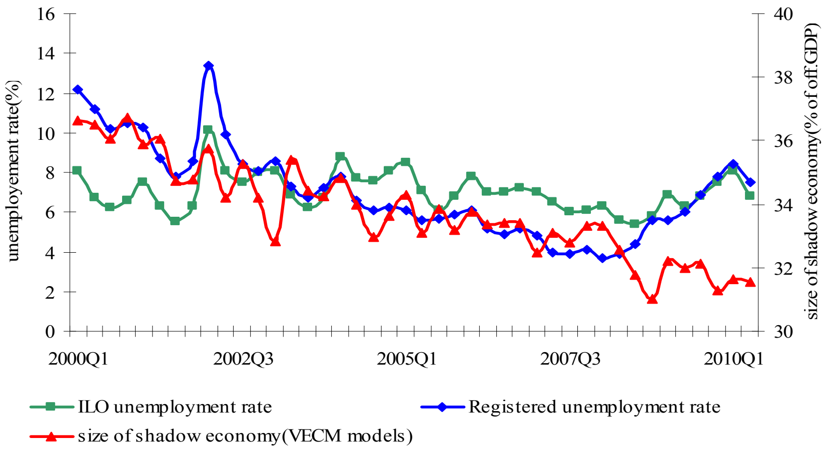
2. THE RELATIONSHIP BETWEEN UNEMPLOYMENT RATES AND SHADOW ECONOMY IN ROMANIA. A SVAR ANALYSIS

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 to 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.

Regarding the Romanian unemployment data, there are two measures available for unemployed persons: the first is the registered unemployment rate, who is calculated by 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, who is published quarterly by the National Institute of Statistics and is based on labour force survey (LFS).

Fig.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 graphical evolution of the shadow economy versus unemployment rates reveal the existence of a positive relationship between variables, low for the case of ILO unemployment rate, quantified by a value of about 0.22 of correlation coefficient and strong for the case of registered unemployment rate, quantified by a value of 0.67 of correlation coefficient.

The aim of the paper is to investigate the nature of the relationship between unemployment rates and the size of the Romanian shadow economy using SVAR approach.

2.1. Methodology and data

The data used in the research covers the period 2000:Q1- 2010Q2; the number of observation is 42. The variables used are as follows: the size of the Romanian shadow economy expressed as % of official GDP (SE) obtained using the VECM approach; 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 SVAR approach (also called the analysis of disturbances) has been developed over the last decade to interpret business cycle fluctuations and to help identify the effects of different economic policies. It is an extension on the traditional theoretic VAR approach in that it combines economic theory with time-series analysis to determine the dynamic response of economic variables to various disturbances. The main advantage with SVAR analysis is that the necessary restrictions on the estimated reduced form model, required for identification of the underlying structural model, can be provided by economic theory. These restrictions can be either contemporaneous or long-run in nature depending on whether the underlying disturbances are considered to be temporary or permanent in nature. Once the identification is achieved it is possible to recover the structural shocks. These shocks can then be used to generate impulse response and variance decomposition functions to assess the dynamic impacts on different economic variables.

In the development of SVAR approach, the contributions of Sims (1986), Bernanke(1986) and Blanchard and Watson(1986) should be remembered, since they use the economic theory to impose restrictions on the observed values of the estimated residuals (et) to recover the underlying structural disturbances (t). Instead of the arbitrary method of restriction imposition used in traditional VARs, the SVAR approach estimates the structural parameters by imposing contemporaneous structural restrictions based on economic theory. These can be considered as short-run restrictions in that the shocks are considered to have temporary effects.

An alternative SVAR approach, advanced by Blanchard and Quah (1989), is to consider the shocks as having permanent effects. This would imply that the variables are non-stationary since the shocks continue to accumulate through time given they are permanent. The presence of unit roots in the variables can give rise to spurious regression if the VAR is estimated in levels. Therefore it is necessary to use first differences[1] to ensure stationarity in the case of shocks that have permanent effects.

Therefore, a Structural VAR is a standard VAR where the restrictions needed for identification of the underlying structural model are provided by economic theory. These can be either contemporaneous or long-run restrictions depending on whether economic theory suggests the shocks are either temporary or permanent in nature (McCoy, 1997).

We aim to investigate the existence of a structural relationship between shadow economy and unemployment rate, in order to extract information on underlying aggregate supply and demand disturbances using VAR decomposition. We recover the underlying demand and supply disturbances using the Structural Vector Autoregression technique developed by Blanchard and Quah[2] (1989).

The basic idea is that an economy is hit by two types of shocks, demand and supply shocks. Demand shocks are identified with the help of the restriction that their long-term impact on output is zero. Only supply shocks can have a permanent effect on output.

The procedure proposed by Blanchard and Quah (1989) decomposes permanent and temporary shocks to a variable using a VAR model. The structural VAR methodology with long-run restrictions proposed by Blanchard and Quah (1989) does not impose restrictions on the short-run dynamics of the permanent component of output, but incorporates a process for permanent shocks that is more general than a random walk.

Blanchard and Quah (1989) provide an alternative way to obtain a structural identification. Instead of associating each disturbance (t) directly with an individual variable, they consider the shocks as having either temporary or permanent effects. The objective is to decompose real GNP into its temporary and permanent components. Economic theory is used to associate aggregate demand shocks as being the temporary shocks and aggregate supply shocks as having permanent effects[3].

So, they develop a macroeconomic model such that real GNP is affected by demand-side and supply-side disturbances. In accordance with the above mentioned theoretical framework, the demand-side disturbances have no long run effect on real GNP. On the supply side, productivity shocks are assumed to have permanent effect on output.

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[1] Alternatively, a cointegrated framework can be used to avoid the loss of information about the equilibrium relationships in the model that can result from first differencing. The stationary linear combinations of the non-stationary variables can be constructed prior to estimation (Keating, 1992). This cointegration constraint can then be imposed using a vector error correction model (VECM).

[2] A detailed presentation of this topic is provided in Enders, W.(1995). Applied Econometric Time Series, Wiley, New York.

[3] Long run restrictions are imposed to identify the aggregate demand and aggregate supply disturbances.

Using a bivariate VAR, Blanchard and Quah show how to decompose real GNP and recover the two pure shocks that cannot otherwise be quantified. They assume that there are two kinds of disturbances, each uncorrelated with the other and that neither has a long run effect on unemployment. They assume however, that the first has a long run effect on output while the second does not. These assumptions are sufficient to just identify the two types of disturbances and their dynamic effects on output and unemployment.

In the same manner, we consider a Vector Autoregression representation of a system composed by two variables that are the first differences of the shadow economy (SE) and unemployment rates (R_UR and ILO_UR)(we have considered both registered unemployment rate and ILO unemployment rate). The Blanchard - Quah technique requires that both variables must be stationary.

Thus, the two variables that compose VAR are:

$$\mathrm{X_t} = \begin{bmatrix} \Delta \mathrm{SE_t} \\ \Delta \mathrm{UR_t} \end{bmatrix} \quad (1)$$

The classical VAR can be writing as:

$$\Delta SE_t = b_{10} - b_{12}\Delta UR_t + \gamma_{11}^1 \Delta SE_{t-1} + \gamma_{12}^1 \Delta UR_{t-1} + ... + \gamma_{11}^p \Delta SE_{t-p} + \gamma_{12}^p \Delta UR_{t-p} + \varepsilon_{dt} \quad (2)$$

$$\Delta UR_t = b_{20} - b_{21}\Delta SE_t + \gamma_{21}^1 \Delta SE_{t-1} + \gamma_{22}^1 \Delta UR_{t-1} + ... + \gamma_{21}^p \Delta SE_{t-p} + \gamma_{22}^p \Delta UR_{t-p} + \varepsilon_{st} \quad (3)$$

We can re-write the above equations in a matrix form:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} \Delta SE_t \\ \Delta UR_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11}^1 & \gamma_{12}^1 \\ \gamma_{21}^1 & \gamma_{22}^1 \end{bmatrix} \begin{bmatrix} \Delta SE_{t-1} \\ \Delta UR_{t-1} \end{bmatrix} + ... + \begin{bmatrix} \gamma_{11}^p & \gamma_{12}^p \\ \gamma_{21}^p & \gamma_{22}^p \end{bmatrix} \begin{bmatrix} \Delta SE_{t-p} \\ \Delta UR_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{dt} \\ \varepsilon_{st} \end{bmatrix} \quad (4)$$

Furthermore, in general form it becomes:

$$\mathrm{BX_t} = \Gamma_0 + \Gamma_1 \mathrm{X_{t-1}} + ... + \Gamma_p \mathrm{X_{t-p}} + \varepsilon_t \quad (5)$$

where:

$\mathrm{X_t}$ is a vector of the two considered variables, Γ_t are the matrices of coefficients, p lags are considered and ε_t is the vector of error terms.

By multiplying with the inversion of B matrix ($1 - \mathrm{b_{12} b_{21}} \neq 0$) we obtain:

$$\mathrm{X_t} = \mathrm{B^{-1}}\Gamma_0 + \mathrm{B^{-1}}\Gamma_1 \mathrm{X_{t-1}} + ... + \mathrm{B^{-1}}\Gamma_p \mathrm{X_{t-p}} + \mathrm{B^{-1}}\varepsilon_t \quad (6)$$

Re-writing the VAR model, we obtain:

$$\mathrm{X_t} = \mathrm{A_0} + \mathrm{A_1 X_{t-1}} + ... + \mathrm{A_p X_{t-p}} + \mathrm{e_t} \quad (7)$$

$$\mathrm{X_t} = \mathrm{A(L)LX_t} + \mathrm{e_t}$$

which can be re-written as follows:

$$\begin{bmatrix} \Delta SE_t \\ \Delta UR_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} \Delta SE_{t-1} \\ \Delta UR_t \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (8)$$

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 $a_{ij}(k)$.

Since the demand-side and supply-side shocks are not observed, the problem is to recover them from VAR estimation. The residuals from this estimated VAR are composites of the structural disturbances ε_{dt} and ε_{st}.

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

$$\Delta SE_t = \sum_{k=0}^{\infty} b_{11}(k)\varepsilon_{dt-k} + \sum_{k=0}^{\infty} b_{12}(k)\varepsilon_{st-k} \quad (9)$$

$$\Delta UR_t = \sum_{k=0}^{\infty} b_{21}(k)\varepsilon_{dt-k} + \sum_{k=0}^{\infty} b_{22}(k)\varepsilon_{st-k} \quad (10)$$

or

$$\begin{bmatrix} \Delta SE_t \\ \Delta UR_t \end{bmatrix} = \sum_{i=0}^{\infty} L^i \begin{bmatrix} b_{11i} & b_{12i} \\ b_{21i} & b_{22i} \end{bmatrix} \begin{bmatrix} \varepsilon_{dt} \\ \varepsilon_{st} \end{bmatrix} \quad (11)$$

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.

The key to decomposing the SE_t sequence into its trend and irregular components is to assume that one of the shocks has a temporary effect (no long-run effect) on the SE_t. 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: $\sum_{k=0}^{\infty} b_{12}(k)\varepsilon_{st-k} = 0$ (12)

Equation (12) is an Aggregate Supply Shock stating that the second structural shock (aggregate supply) has no long-run effect on shadow economy.

2.2. Empirical results

In order to analyze the nature of the relationship between shadow economy and unemployment rate (registered or ILO unemployment rate), we use the Structural VAR approach, for Blanchard and Quah methodology. In order to identify supply and demand shocks, we start by running two bivariate VAR models (first for shadow economy and registered unemployment rate and second for shadow economy and ILO unemployment rate).

The variables included in the VARs are suspected to have a unit root. To verify this, ADF and PP unit root tests were applied revealing that the variables are non-stationary at their levels but stationary at their first differences, being integrated of order one, I(1).

Table 1. ADF and PP Tests for Unit Root

		Shadow economy(SE)			Registered unemployment rate(R_UR)			ILO unemployment rate(ILO_UR)		
		T&C	C	None	T&C	C	None	T&C	C	**None**
Level	ADF	-6.29*	-1.05	-3.28	0.24	-1.58	-0.73	-3.03	-2.70	**-0.36**
	lag	(0)	(6)	(6)	(4)	(4)	(4)	(1)	(0)	**(0)**
	PP	-6.29*	-1.74	-1.38	-0.68	-2.13	-1.34	-2.88	-2.70	**-0.32**
	lag	(1)	(3)	(1)	(3)	(1)	(1)	(1)	(0)	**(5)**
First diff.	ADF	-10.63*	-10.74*	-10.45*	-3.51***	-2.83***	-2.89*	-6.13*	-6.22*	**-6.30***
	lag	(0)	(0)	(0)	(3)	(3)	(3)	(0)	(0)	**(0)**
	PP	-11.34*	-9.90*	-8.86*	-7.14*	-6.17*	-6.19*	-6.59*	-6.72*	**-6.85***
	lag	**(3)**	**(2)**	**(3)**	**(7)**	**(1)**	**(1)**	**(6)**	**(6)**	**(6)**

Note:
T&C represents the most general model with a drift and trend; C is the model with a drift and without trend; None is the most restricted model without a drift and trend. Numbers in brackets are lag lengths used in ADF test (as determined by SCH set to maximum 12) to remove serial correlation in the residuals. When using PP test, numbers in brackets represent Newey-West Bandwith (as determined by Bartlett-Kernel). Both in ADF and PP tests, unit root tests were performed from the most general to the least specific model by eliminating trend and intercept across the. *, ** and *** denote rejection of the null hypothesis at the 1%, 5% and 10% levels respectively. Tests for unit roots have been carried out in E-VIEWS 6.0.

Because the variables are integrated of the same order, I(1) we will difference the variables and we introduce the first difference in the VAR analysis[4]. Including a sufficient number of lags to eliminate serial correlation from the residuals is crucial as using a lag structure that is too parsimonious can significantly bias the estimation of the structural components.

Table 2. Optimal lag length

Models	Sequential LR	AIC	SC	HQ	FPE	Chosen[5]
d(SE) and d(R_UR)	-	1	1	1	1	**1**
d(SE) and d(ILO_UR)	**-**	**1**	**1**	**1**	**1**	**1**

Note: LR is the sequential modified LR test statistic; FPE is the Final Prediction Error; AIC is the Akaike Information Criterion; SBC is the Schwarz Information Criterion; HQ is the Hannan-Quinn Information Criterion.

[4] According Blanchard and Quah(1989), we estimate the VARs models without intercept.
[5] Given the small size of our series, we preferred to choose the optimal lag as 1 based on the discussion of Mills and Prasad, 1992.

Table 2 offers the optimal lag length for each model according to the five criteria. It can be observed that the optimal lag length is found to be one. The number of lags for each VAR was chosen according with the information criteria above and by taking into consideration other information from VAR analysis. At the same time, the autocorrelation of residuals was analyzed to be sure that through the number of chosen lags the residuals do not remain with autocorrelation. Further on, the both VARs verify **the stability condition**. Since each VAR represents a system of linear first-order difference equations, it is stable only if the absolute values of all eigenvalues of the system matrix lie inside the unit circle. This condition is fulfilled by both VARs. Furthermore, we inspect the diagnostic concerning non-autocorrelation[6], homoskedasticity[7] and normality[8] of the residuals. These hypotheses were verified by the residuals of both estimated VARs.

We have estimated the VAR models with one lag who verifies the stability condition[9]. Furthermore, we impose on this VAR a long-run restriction which specifies that the long run effect of the supply shocks on the shadow economy is null.

According to Blanchard and Quah, the key is to assume that one of the structural shocks has a temporary effect on ΔSE. Following Dell'Anno and Solomon[10] (2006) we assume that an aggregate supply (unemployment rate) shock has no long-run effect on shadow economy. The long-run restriction on the relationship between the observed data (SE) and the unobserved structural shock (ε_{st}) is: $\sum_{i=0}^{\infty} b_{12i} = 0$ (13)

The restriction in (13) implies that the cumulative effect of ε_{st} on ΔSE_t is zero and consequently the long-run effect 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. Starting from this model, we analyze the impulse response function for the structural version of the model.

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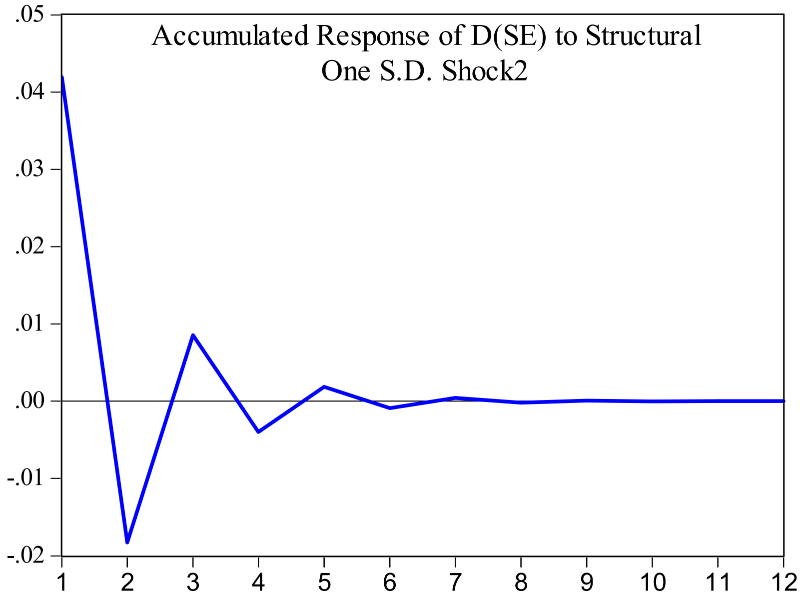
[6] The presence of autocorrelation in the residuals was tested using the LM test.
[7] For the homoskedasticity it was applied the White test.
[8] The normality of the residuals was tested using Cholesky normality test.
[9] Since each VAR represents a system of linear first-order difference equations, it is stable only if the absolute values of all eigenvalues of the system matrix lie inside the unit circle.
[10] Dell'Anno and Solomon (2006) investigate the relationship between shadow economy and unemployment rate for he case of United States using SVAR approach for the period 1970-2004. They that an aggregate supply (unemployment rate) shock has no long-run effect on shadow economy.

Fig 2. Accumulated responses of shadow economy to a positive aggregate supply shock (registered unemployment rate)



In the short-run, a positive aggregate supply shock (registered unemployment rate) causes a decrease in the shadow economy by about 1.8% below the baseline. This occurs in the second quarter following the initial shock. In the third quarter, the size of the shadow economy will begin to increase by about 0.6% above the baseline.

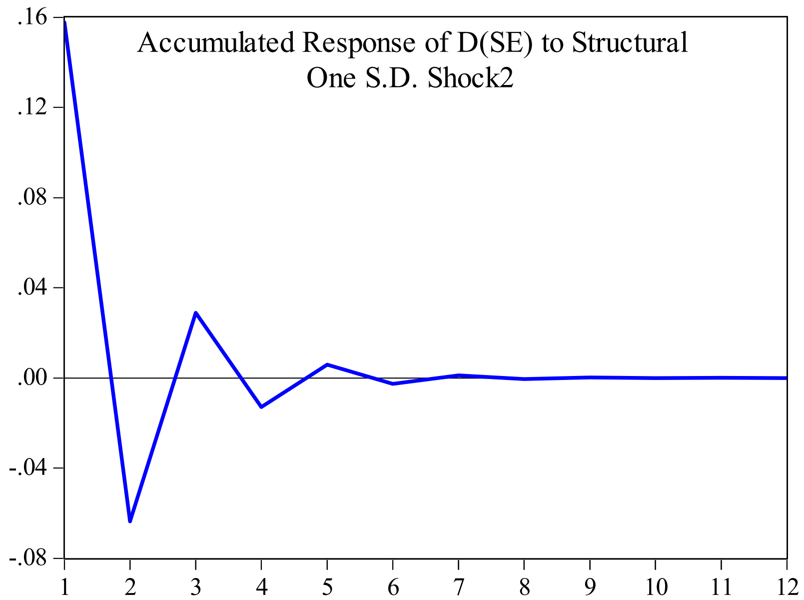
The variance decomposition using the actual ε_{st} and ε_{dt} sequence allow assessing the relative contributions of demand and supply shocks to forecast error variance of the shadow economy.

Table 3. Variance decomposition of D(SE) due to supply-side shock(registered unemployment rate)

	Percent of Forecast Error Variance due to:	
Period	Shock1(demand-side shock)	Shock2(supply-side shock)
1	99.71260	0.287399
3	99.22069	0.779312
6	99.20373	0.796272
9	99.20355	0.796446
12	99.20355	0.796448
Factorization: Structural		

As is immediately evident, demand-side shocks explain almost all the forecast error variance of the shadow economy at any forecast horizon. Hence, the demand shocks are responsible for movements in shadow economy.

Fig 3. Accumulated responses of shadow economy to a positive aggregate supply shock (ILO unemployment rate)



In the short-run, a positive aggregate supply shock (ILO unemployment rate) causes a decrease in the shadow economy by about 6.3% below the baseline. This occurs in the second quarter following the initial shock. In the third quarter, the size of the shadow economy will begin to increase by about 2.8% above the baseline.

Table 4. Variance decomposition of D(SE) due to supply-side shock(ILO unemployment rate)

	Percent of Forecast Error Variance due to:	
Period	Shock1(demand-side shock)	Shock2(supply-side shock)
1	95.79529	4.204706
3	89.48092	10.51908
6	89.31066	10.68934
9	89.30929	10.69071
12	89.30928	10.69072
	Factorization: Structural	

As is immediately evident, demand-side shocks explain almost all the forecast error variance of the shadow economy at any forecast horizon. Hence, the demand shocks are responsible for movements in shadow economy.

CONCLUSIONS

In this paper, the SVAR methodology with long-run restrictions has been applied to analyze to relationship between shadow economy as % of official GDP and unemployment rate for the case of Romania using quarterly data covering the period 2000-2010. The size of the shadow economy as % of official GDP was obtained using the currency demand approach based on VECM models. Its size is estimated to be decreasing over the sample period from 37% to 31% of official GDP.

The relationship between the variables is tested by imposing a long-run restriction in the Structural VAR model to analyze the impact of the shadow economy to a temporary shock in unemployment.

The accumulated responses generated by a positive supply shock (unemployment rate) confirms that in the short-run, a rise in both registered unemployment rate and ILO unemployment rate in formal sector will lead to a decrease in the number of people who work in the shadow economy in the second quarter following the initial shock and to an increase in the size of the Romanian shadow economy in the third quarter following the initial shock.

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