Underground Shocks, Ground Zero Responses.

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Abstract

This paper deals with the relationship between regular and “irregular” components of the Italian official GDP. Results from univariate and VAR models seem to suggest that there are no connections (causal relationships, feedbacks, contemporaneous cyclical movements, common stochastic trends) between these two time series. In this sense, we could correctly refer to the Italian black sector as an independent economy.

1. Introduction

The non-observed sector of the economy has neither a commonly accepted definition, nor a commonly used name. A plethora of terms (underground, subterranean, moonlight, hidden, irregular, shadow, non-observed, black, etc.) have been used to call it. All of them are suggestive of a particular aspect of the phenomenon, which is manifold. I will indifferently use here some of these adjectives but, in the Italian case, the most appropriate one turns out to be “independent”. Since I use elaboration of Italian national institute of statistics (ISTAT) data, the definition of the black economy is the “official” one. That is, the hidden production here studied represents (SNA, 1993) the area of (legal) production activities that are not directly observed due to reasons of economic nature (deliberate desire to avoid taxes and/or to avoid observing the law provisions concerning the labour market) and/or statistical nature (*e.g.* due to the failure to fill out the administrative forms or statistics questionnaires). In the Italian GDP both the irregular (“economic underground”) and the regular component (directly observed *plus* “statistical underground”) are included.

There are several important reasons to analyse the potential links between the regular and the irregular side of the economy. In a highly indebted system, like Italy, may be useful to ask oneself if fiscal policy can go on with a long sequence of surpluses, hoping that the regular sector does not sensitively react. A “mass escape” from the regular sector would dramatically reduce government revenues worsening the public budget situation. The linkages can derive from labour market policies as well. In a paper by Boeri and Garibaldi (2002) it is argued that any unemployment reducing policy will endogenously reduce shadow employment, while it is very difficult to reduce shadow employment without increasing unemployment. On the positive side, in a climate of economic stagnation and decline the underground economy may serve a useful economic and social function providing jobs to many of willing workers. In addition, from firms' point of view, the black workers pool allow increasing the degree of flexibility (Signorelli, 1997; Bovi and Castellucci, 1999), from the public finance point of view, to the extent policymakers can convert irregular incomes into regular ones, the underground economy could be seen as a resource rather than a constraint. The tax amnesties implemented in Italy during the last decades are suggestive episodes as regard to this possibility.

To the best of my knowledge, very few works focusing on this topic with a medium-term perspective are available because of the shortage of reliable time-series data (a relevant exemption is Giles *et al.*, 1999). The present attempt is based on recently published author's estimates of the regular and the irregular component of the Italian real GDP throughout the period 1980-1991, which are self consistent with the ISTAT 1992-2001 series (Bovi, 2004). Starting from this 1980-2001 yearly data set, I examine the relationship between unreported and regular GDP, to point out some stylized facts via a time series analysis. Missing a consolidated economic theory and, above all, to limit the curse of dimensionality, I chose to be as agnostic as possible. In other words, with a proper allowance for the stochastic properties of the data, several bivariate VARs are estimated. Then, impulse response functions with Monte Carlo based bands are computed in order to see if and how the two portions of the market interact. Somewhat puzzling, results show that the regular sector seems to be rather orthogonal to the black side of the Italian economic system and (less univocally) *vice versa*. No Granger causality, no common stochastic trend, no contemporaneous movements, no shocks transfer from one market to another emerge from the data.

The paper is organised as follow. The next section presents univariate statistical analysis, while section 3 deals with estimating the bivariate VARs. Concluding remarks are relegated in the final section.

3. Univariate analysis

The first necessary step before validly estimating and using a VAR model is the univariate analysis of the stochastic properties of the series involved. The attention devoted to this topic is well deserved for several reasons. First, in contrast to stationary or trend stationary time series, models with a stochastic trend have time dependent variances that go to infinity with time, thus they are persistent in the sense that shocks have permanent effects on the values of the process. Second, when a series is used in regressions with other variables the interpretation of the regression results can depend on whether the variables involved are trend (TS) or difference stationary (DS). This phenomenon is related to the “nonsense” and "spurious” regression literature due to Yule (1926) and Granger and Newbold (1974).

It is also well known that unit root tests are based on asymptotic critical values. One expects in finite samples that the use of asymptotic critical values will result in over-rejection, and twenty-two (1980-2001) observations are definitively a finite sample. I address this potential problem by studying the properties of the total real GDP, which is available from 1960 to 2003 (drawn from the OECD online data base). The logic is straightforward. On the one hand, because of ISTAT reconstructions, the GDP series contains the regular and the irregular components even for the period 1960-1979 (ISTAT released only the total GDP for this period). On the other hand, once I know the statistical properties of the total GDP, I can use the algebra of integrated variables to infer the properties of the GDP components. Granger and Hallmann (1991) show that for a pair of independent variables holds (using a widespread notation) [1]:

[1] The result is more general than here reported because it refers to any linear combination of the variables.

$$I(0) + I(0) = I(0);$$

$$I(1) + I(0) = I(1);$$

$$I(1) + I(1) = I(1).$$

If the two series are cointegrated, then I(d)+ I(d) = I(d-1), where d is the order of integration. Even forty-four years may prove insufficient for valid asymptotic inferences so, to assess the robustness of the results I perform three unit root tests. The first (NP) was worked out by Ng and Perron (2001). It yields both substantial power gains and a lower size distortions over the standard unit root tests, maintaining the null of unit root. NP offer four test statistics based on the GLS detrended data y_t^d. Altogether these statistics are enhanced versions of Phillips-Perron Z_α and Z_t statistics (1988), the Bargava (1986) R_1 statistic, and the Elliot *et al.* Point Optimal statistic (1996):

$$MZ_\alpha = \left(T^{-1}(y_t^d)^2 - f_0\right)/2\kappa \qquad [1]$$

$$MSB = \left(\kappa/f_0\right)^{1/2} \qquad [2]$$

$$MZ_t = MZ_\alpha \text{ X } MSB \qquad [3]$$

$$MPT = \bar{c}^2 \kappa - \bar{c}T^{-1} (y_t^d)^2) / f_0 \quad \text{(if exogenous = constant)} \qquad [4]$$

$$MPT = \bar{c}^2 \kappa + (1-\bar{c})T^{-1} (y_t^d)^2) / f_0 \quad \text{(if exogenous = constant, trend)} \qquad [5]$$

where $\kappa = \sum_{t=2}^{T} (y_{t-1}^d)^2)/T^2$ and f_0 is an estimate of the residual spectral density at the zero frequency[2]. The choice of the autoregressive truncation lag, p, is critical for correct calculation of f_0. Here p is chosen using the modified AIC suggested by Ng and Perron (2001).

[2] The frequency zero spectrum method used is the AR-GLS detrended.

The second is the KPSS test (Kwiatkowski *et al.* (1992)), which can be thought as complementing the NP one because it tests the null hypothesis that real GDP is a TS stochastic process. Suppose the NP test fails to reject the unit root null because of low power. The KPSS test which has (trend) stationarity as the null should indicate the data have no unit roots. On the other hand, if the KPSS test rejects the trend stationarity null, then we have stronger evidence for unit root persistence. That is, consistent results from NP and KPSS tests yield more persuasive evidence on data persistence, while conflicting results indicate uncertainty associated with the interpretation of the individual test outcomes. The KPSS test is based upon the residuals from the OLS regression of y_t on the exogenous variables x_t:

$$y_t = x_t'\delta + u_t \qquad [6]$$

The LM statistic is be defined as:

$$\text{LM} = \sum\nolimits_t^n S(t)^2 / (T^2 f_0) \qquad [7]$$

where f_0 is an estimator[3] of the residual spectrum at frequency zero and where S(t) is a cumulative residual function:

$$S(t) = \sum_{r=1}^{t} \hat{u}_r \qquad [8]$$

based on the residuals $\hat{u}$ = yt – x' $\hat{\delta}$(0). I maintain the same lag length selection criterion already used in the NP test.

Finally, I rely on a multivariate method as well. Hansen (1995) shows that incorporating information from related time series has the potential to enormously increase the power of unit

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[3] The frequency zero spectrum method used is the Kernel-Bartlett sum-of-covariances.

root tests (see also Elliott and Jansson, 2003). Basically, the test is a multivariate version of the ADF test (that is why it is called Covariate Augmented Dickey Fuller, CADF, test) and it exploits the information in related time series to improve power of stationarity tests and dominate their univariate counterpart whenever the correlation between the covariates and the dependent variable is non zero. When the zero frequency correlation is zero, these tests coincide with the univariate tests. As additional variable I select the labour input, a natural choice given the supply-side approach followed by ISTAT to estimate the shadow economy. Specifically, I regress the growth rate of GDP on a constant, time, the lag log-level of GDP, one lag of the growth rate of GDP, and one lag of the log-level of total employment[4] in full time equivalent units. I then perform an F test for the null hypothesis that the coefficient on the lag level of log GDP and the coefficient on time are jointly zero. This amounts to a test of the null hypothesis that the GDP is difference stationary, against the alternative that it is stationary about a linear trend.

Results reported in Appendix 2 (table 3) show univocal evidence that the level of Italian real GDP follows an I(1) process around a deterministic trend. NP and CADF tests fail to reject the null of unit root, KPSS rejects the null of stationarity. It holds when the tests are applied both to the logarithmic and to the natural level of the GDP. According to the above reported algebra, one can expect that the regular (Yr) and the irregular (Yi) part of the real GDP are DS or TS, but they should not be cointegrated because otherwise the GDP would be a stationary process. Actually, a unit root in GDP could be validly consistent with the cointegrated and I(2) nature of both Yr and Yi. I rule out this event because it would imply an accelerating equilibrium rate of growth for both the GDP components. In fact, there are rare applications of cointegrated VAR model for I(2) real data, and usually this choice is based on economic arguments (Juselius, 2004). Furthermore, the VARs estimated in the next sections would be unstable. Finally,

[4] KPSS and NP tests show that this variable is clearly TS. I do not report these tests, but they are available on request.

tentative applications of the NP and KPSS tests directly to Yr and to Yi show[5] that they could be DS or TS, but should not have a double root. Again, in the case of poor power tests it is always true that failure to reject a null hypothesis does not mean we can reject the alternative, so comparing NP and KPSS results is particularly relevant in the present context. To the extent Yr and Yi are not cointegrated, they do not share a common stochastic trend either, as shown by Stock and Watson (1988).

3. Vector Autoregression Analysis

The previous section concluded that the level of Italian real GDP is a DS process, and that we remain with only three possible outcomes for its components: i) both Yr and Yi are two (independent) DS processes, ii) and iii), alternatively, one is TS and the other is DS. They can not be cointegrated, neither both TS because these events contrast with the I(1) nature of the GDP. One way to carry on notwithstanding this "veil of ignorance" is to perform a battery of vector autoregression models according to the stochastic properties of the two components of the GDP. Through the analysis of the covariances, the VAR approach allows us to see if one market has a tendency to lead the other, if there are feedbacks between them, if there are contemporaneous movements, and how do impulses (shocks, innovations) transfer from one sector to another. The VAR approach (Sims, 1980) sidesteps the need for structural modelling by treating every endogenous variables in the system as a function of the lagged values of all the endogenous variables in the system. Consider the VAR(p) model

$$\Phi(L)\mathbf{y}_t = \varepsilon_t \qquad [9]$$

where $\Phi(L) = \mathbf{I} - \Phi_1 L - \Phi_2 L^2 - \ldots - \Phi_p L^p$.

[5] I do not report these tests, but they are available on request.

A basic assumption in the above model is that the residual vector follows a multivariate white noise. Also, in order that the VAR-model is stationary, it is required that roots of $| \boldsymbol{I} - \Phi_1 z - \Phi_2 z^2 - \ldots - \Phi_p z^p | = 0$ lie outside the unit circle. Provided that the stationary conditions hold we have the vector moving average representation of $\boldsymbol{y}_t$ as

$$\boldsymbol{y}_t = \Phi^{-1}(L)\varepsilon_t = \varepsilon_t + \sum_{i=1}^{\infty} \psi_i \, \varepsilon_{t-i} \qquad [10]$$

where ψ_i is an m×m coefficient matrix. The $\varepsilon_t's$ represent shocks in the system. Suppose we have a unit change in ε_t then its effect in $\boldsymbol{y}$ s periods ahead is $\frac{\delta y_{t+s}}{\delta \varepsilon_t} = \psi_s$. Accordingly the interpretation of the ψ matrices is that they represent marginal effects, or dynamic multipliers, or the model's response to a unit shock (or innovation) at time point t in each of the variables. The response of y_i to a unit shock in y_j is given by the sequence (known as the impulse multiplier function) $\psi_{ij,1}, \psi_{ij,2}, \psi_{ij,3}, \ldots,$ where $\psi_{ij,k}$ is the ijth element of the matrix ψ_k (i, j = 1,. . . . , m). Generally an impulse response function traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. Otherwise stated, the impulse response functions traces out how the variables will deviate from the path predicted by the model if there is a forecast error with respect to a specific equation at time t. Unforeseen movements in y_j are referred to as shocks and the state of the economy at the time t+m as responses. However, unless the error covariance matrix $E(\varepsilon_t \varepsilon_t')$ is a diagonal matrix, the shocks will not occur independent from each other. The conventional practice in the VAR literature is to single out the individual effects by first orthogonalize the error covariance matrix, *e.g.* by Cholesky decomposition, such that the new residuals become contemporaneously uncorrelated with unit variances. Unfortunately orthogonalization is not unique in the sense that changing the order of variables in $\boldsymbol{y}$ changes the results. The economic theory may be used to solve the ordering issue. The approach I follow here is agnostic and it is based on trying the two possible orderings (because of the bivariate VAR) to see whether the resulting interpretations are consistent. Since in a bivariate model the Granger-causality implies that one variable must react to a shock of the other, within this framework I can address the causality issues as well.

The uncorrelatedness of the new residuals allows the error variance of the s step-ahead forecast of y_{it} to be decomposed into components accounted for by these shocks. Because the innovations have unit variances, the components of this error variance accounted for by innovations to y_j is given by

$$\sum_{k=0}^{s} \psi^{*\,2}_{ij,k} \qquad [11]$$

where ψ^{*}_{i} is the orthogonalised version of ψ_i. Comparing this to the sum of innovation responses we get a relative measure how important variable y_j innovations are in the explaining the variation in variable i at different step-ahead forecasts, *i.e.*,

$$R^2_{ij,s} = 100 \frac{\sum_{k=0}^{s-1} \psi^{*\,2}_{ij,k}}{\sum_{h=1}^{m} \sum_{k=0}^{s-1} \psi^{*\,2}_{ih,k}} \qquad [12]$$

Thus, while impulse response functions traces the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Clearly, even the variance decomposition results depend on the ordering when there is contemporaneous correlation between the residuals. Again, for the robustness of the findings I replicate the two possible orderings of the bivariate VAR.

Another useful and workable set of experiments within the present statistical-atheoretical context is the analysis of the generalised impulse response functions. Pesaran and Shin (1998) have suggested a theoretically neutral way of deriving impulse responses that takes into account the information on the correlation of errors contained in the error covariance matrix. These authors construct an orthogonal set of innovations that does not depend on the VAR ordering.

The generalized impulse responses from an innovation to the j^{th} variable are derived by applying a variable specific Cholesky factor computed with the j^{th} variable at the top of the Cholesky ordering. It should be noted that the generalised response profiles derived in this way are not conveying information about economic causation among the variables. The exercise can be thought of as tracing out how the observation of a forecast error in one equation of the system would lead to revisions in the forecast path of all model variables.

Summing up, according to the hypothesised statistical properties of the time series and to the findings of the third section, I perform three VAR models[6]:

Model 1 Yr ~ DS; Yr ~ TS;

Model 2 Yr ~ TS; Yr ~ DS;

Model 3 Yr ~ DS; Yr ~ DS.

The analyses of VAR residuals reported in the appendix 1 (tables 2-4) suggest that the VARs seem to provide a fair description of the information in the data. Evidence satisfy both normality and the white noise assumption. The following figures (Appendix 2) plot the relative mean estimates of the (Cholesky and Generalised) impulse response functions and show the variance decomposition outcomes. The pure shape of impulse functions is not fully informative of whether a detected reaction path is also meaningful in a statistical sense. Thus I also display the upper and lower limits of a 95% Monte Carlo band. Clearly, if these bands contain the zero line one can conclude that there is evidence of no reaction. All these models have the same exogenous variables, namely a constant and a linear time counter, but (unreported) sensitivity analyses conduct adding a quadratic trend do not substantially change the stylised facts that emerge. They may be summarised in the following statements:

- the Italian real GDP seems to be composed by two orthogonal components, one regular, one irregular. In particular,

[6] Both the variables are logged because was not possible to obtain multivariate normal residuals using natural values.

- the non-observed economy shows neither Granger-causality, nor co-movements with regard to the regular activities;
- a less univocal evidence shows that the observed economy might react to shocks hitting the shadow economy.

Concluding Remarks

In this paper I presented a time series analysis of the Italian shadow economy throughout the period 1980-2001. Several univariate unit root tests suggest that the regular and the irregular parts of the real GDP should not be cointegrated. In turn, this implies that they do not share a common stochastic trend. Then, according to the DS and/or TS nature of the GDP components, a battery of unrestricted VARs is performed to see whether the two sides of the economy are linked someway. A visual inspection of the plots of impulse response functions and of the innovation accounting reveals that, no matter which model one prefers, the non-observed economy follows an univariate process. The results are not so univocal as regard to the regular GDP, which to some extent seems to be affected by shocks hitting the hidden sector. Sensitivity analyses based on different deterministic variables confirm the outcomes and, in the present context it is worth recalling that statistical experiments have stronger ability in negating than in supporting the occurrence of an event. Of course, I can not exclude that the outcomes are biased because of measurement errors that are unavoidable in empirical works dealing with the black economy.

In this paper my target is to establish stylised facts rather than to explain them. However, I am tempted to speculate in order to offer some tentative comment. For instance, if one thinks about the shadow employment as a buffer pool, the univariate nature of the underground activities may be explained by the presence of alternative “regular” tools for reacting to negative shocks, without increasing the number of hidden workers. As a matter of fact, in the decades under scrutiny early retirements (prepensionamenti), the special wage supplementation fund (Cassa

Integrazione Guadagni Straordinaria), the unduly increase of public sector employment, and the quasi-dependent (but formally self-employed) “collaborazione coordinata e continuativa” employment relationship might have been used for this purpose. The evidence that some percentage of the regular GDP variance might be due to shocks striking the shadow sector may find an explanation in the hiring subsidies and, especially, in the reiterate tax and foreign workers amnesties (“regularizations”), which impinge on the underground market before than, if any, on the regular one. Deeper and interesting analyses, *e.g.* to account for the potential informative content of variables such as the tax rate, are hampered by the scarcity of data and, at the moment, are relegated in the agenda.

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APPENDIX 1. Univariate and VAR Residual Analyses

Table 1. Unit root tests on Italian real GDP (annual data 1960-2003)

		MZa	MZt	MSB	MPT	KPSS*	CADF**
Test statistics	**GDP**	**-6.07492**	**-1.52662**	**0.25130**	**14.8071**	**0.211930**	**1.48**
	D(GDP)	**-21.2950**	**-3.23266**	**0.15180**	**4.46244**	**0.061826**	**----**
	Log(GDP)	**0.17475**	**0.10972**	**0.62787**	**87.9691**	**0.217302**	**2.66**
	Dlog(GDP)	**-79.1260**	**-6.28986**	**0.07949**	**1.15184**	**0.118034**	----
Critical Values	1%	-23.8000	-3.42000	0.14300	4.03000	0.216000	5.16
	5%	-17.3000	-2.91000	0.16800	5.48000	0.146000	3.22
	10%	-14.2000	-2.62000	0.18500	6.67000	0.119000	2.42

Lag length criterion: Modified AIC; MZa-MPT are the four tests suggested by Ng and Perron (2001). Constant and trend included. *H0: TS process; **F-test for H0: DS *vs* TS process.

Table 2. Tests on the VAR residuals. Model 1: Yr ~ DS; Yi ~ TS. Two lags. 1980-2001.

Single equation tests				
Portmanteau 3 lags Yi = 1.515 D(Yr) = 2.462	AR 1- 2F(2, 11) Yi = 0.277 [0.76] D(Yr) = 1.236 [0.33]	Normality χ^2 Yi = 2.7703 [0.25] D(Yr)=2.354 [0.31]	ARCH 1 F(1, 11) Yi=0.671 [0.43] D(Yr)=0.740 [0.41]	χ^2 F(8, 4) Yi = 0.30 [0.93] D(Yr) = 0.478 [0.83]
Recursive residuals (Cusum and Cusum square) show no signs of instability				
Multivariate tests				
Vector portmanteau 3 lags = 7.7407 [0.1016]	Vector AR 1-2 F(8, 16) = 0.9936 [0.4766]	Vector normality Chi^2 (4) = 6.9061 [0.1409]	Vector Chi^2 F(24, 6) = 0.23266 [0.9956]	

D(x)=first difference of variable x; endogenous variables in logs; constant and trend included; degrees of freedom of the tests in parentheses; p-values in squared brackets;

Table 3. Tests on the VAR residuals. Model 2: Yr ~ TS; Yi ~ DS. One lag. 1980-2001.

Single equation tests				
Portmanteau 3 lags D(Yi) = 2.326 Yr = 1.407	AR 1- 2F(2, 14) D(Yi) = 3.65 [0.053] Yr = 0.932 [0.42]	Normality χ^2 D(Yi) = 0.02 [0.99] Yr = 2.05 [0.36]	ARCH 1 F(1, 14) D(Yi) = 0.104 [0.75] Yr = 1.2219 [0.2876]	χ^2 F(4, 11) D(Yi) = 1.69 [0.22] Yr = 1.3788 [0.3035]
Recursive residuals (Cusum and Cusum square) show no signs of instability				
Multivariate tests				
Vect. Portm. 3 lags = 7.359 [0.49]	Vec. AR 1-2 F(8, 22) = 1.201 [0.3431]	Vect. Norm. χ^2 (4) = 1.966 [0.7420]	Vect. χ^2 F(12,24) = 1.4166 [0.2253]	Vec. Xi*Xj F(15, 22) = 1.0635 [0.4370]

See legend under table 2.

Table 4. Tests on the VAR residuals. Model 3: Yr ~ DS; Yi ~ DS. One lag. 1980-2001.

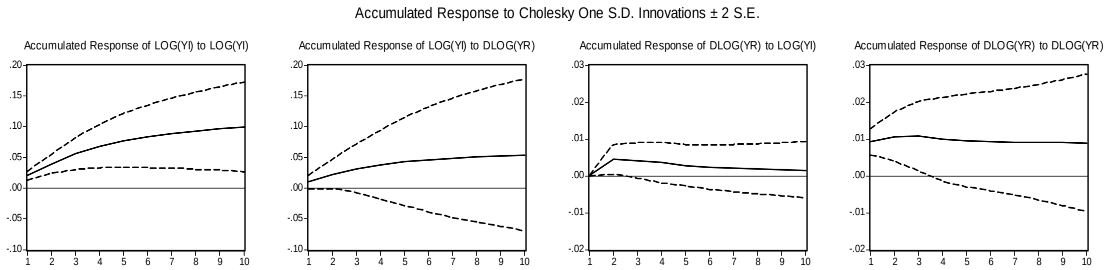
Single equation tests				
Portmanteau 3 lags D(Yi) = 0.76224 D(Yr) = 2.4355	AR 1- 2F(2, 14) D(Yi) = 0.392 [0.6830] D(Yr)= 1.217 [0.3257]	Normality Chi^2 D(Yi) = 0.37 [0.83] D(Yr) = 2.29 [0.32]	ARCH 1 F(1, 14) D(Yi)= 0.005 [0.94] D(Yr) = 0.50 [0.49]	Chi^2 F(4, 11) D(Yi) = 0.57 [0.68] D(Yr) = 1.68 [0.22]
Recursive residuals (Cusum and Cusum square) show no signs of instability				
Multivariate tests				
Vect. Portm. 3 lags = 6.0834 [0.64]	Vec. AR 1-2 F(8, 22) = 1.0879 [0.4074]	Vect. Norm. χ^2 (4) = 2.5622 [0.6335]	Vect. χ^2 F(12, 24) = 0.91443 [0.5475]	Vect. Xi*Xj F(15, 22) = 0.92194 [0.5552]

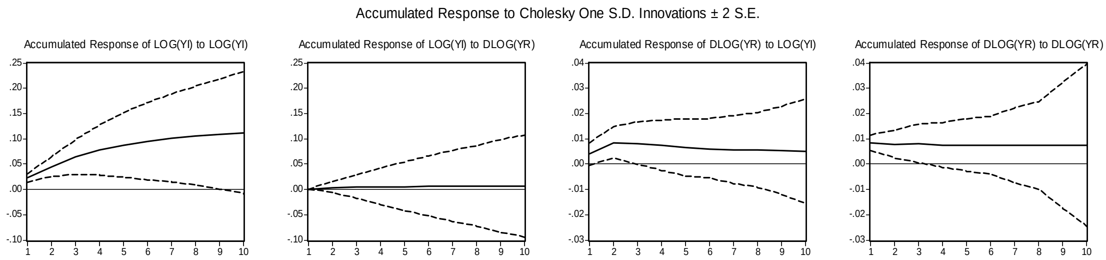
See legend under table 2.

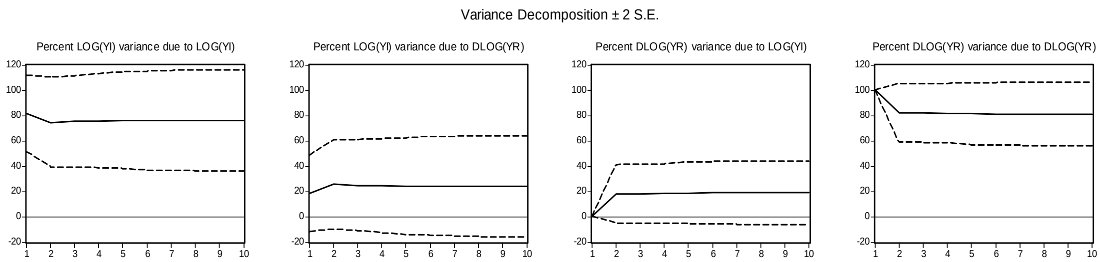
Appendix 2. Impulse Response and Innovation Accounting Analysis

In all the models i) there are a constant and a linear trend; ii) the ± 2 S.E bands are drawn from 1000 Monte Carlo replications; iii) the Cholesky ordering for the relative implulse functions and for the variance decomposition analysis is Yr-Yi => Yi-Yr.

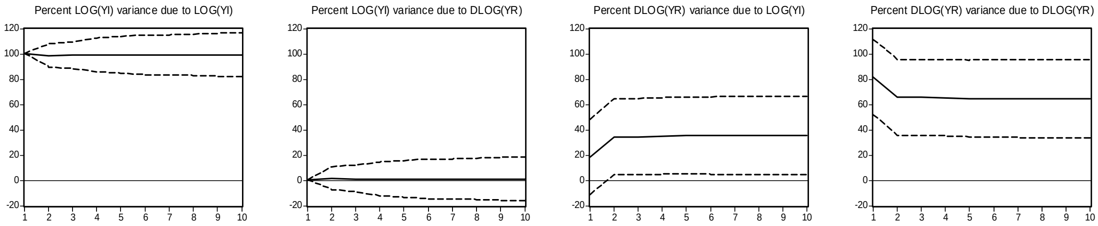
Model 1. <u>Yr ~ DS; Yi ~ TS.</u>

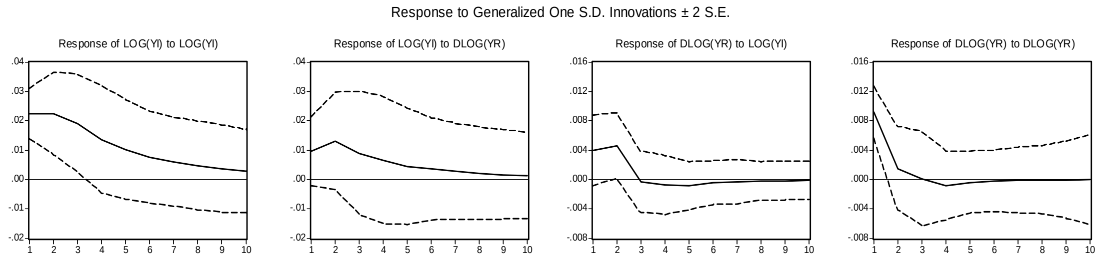




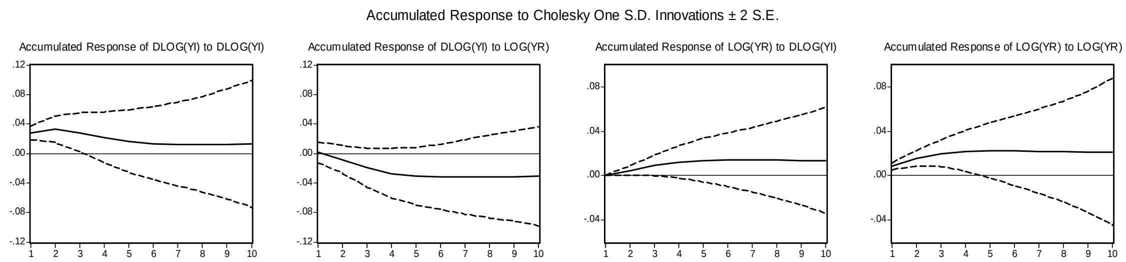


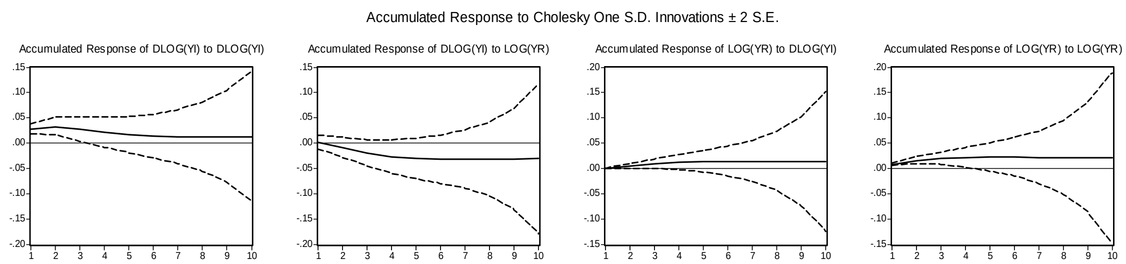
Variance Decomposition ± 2 S.E.

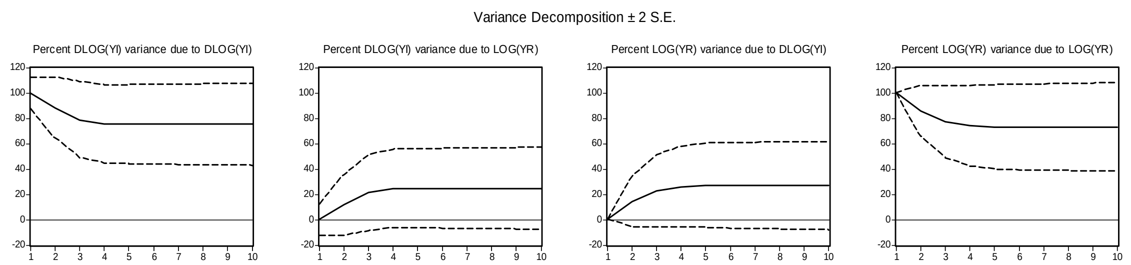




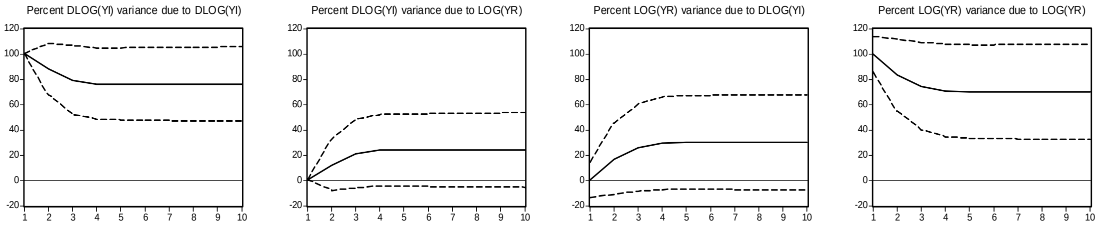
Model 2. <u>Yr ~ TS; Yi ~ DS.</u>



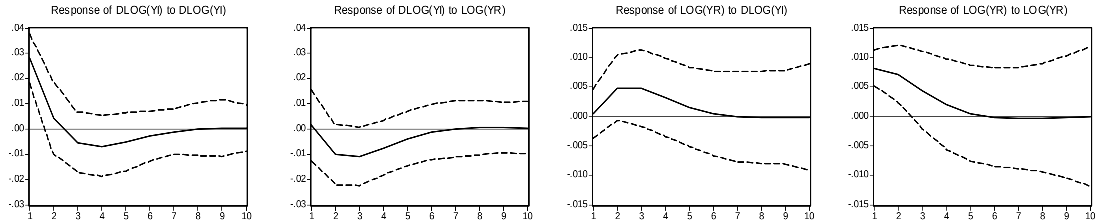




Variance Decomposition ± 2 S.E.

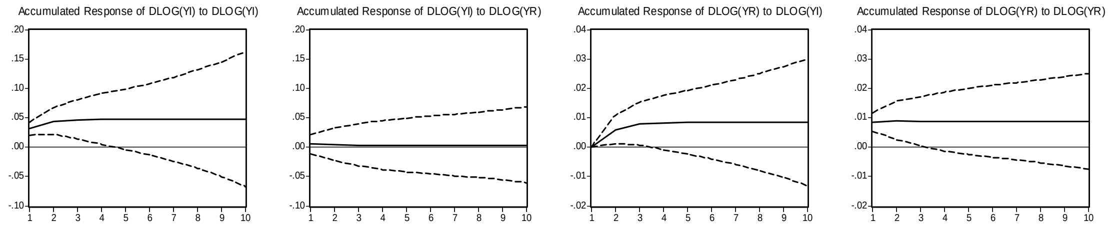


Response to Generalized One S.D. Innovations ± 2 S.E.

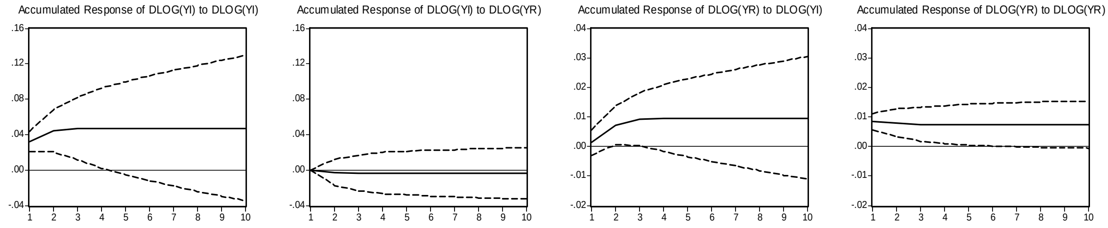


Model 3. <u>Yr ~ DS; Yi ~ DS</u>

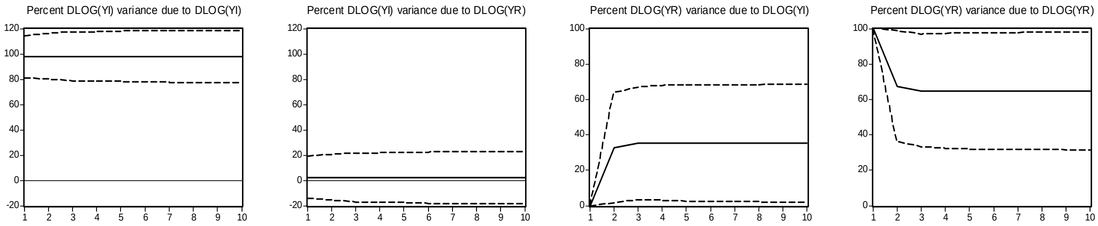
Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.



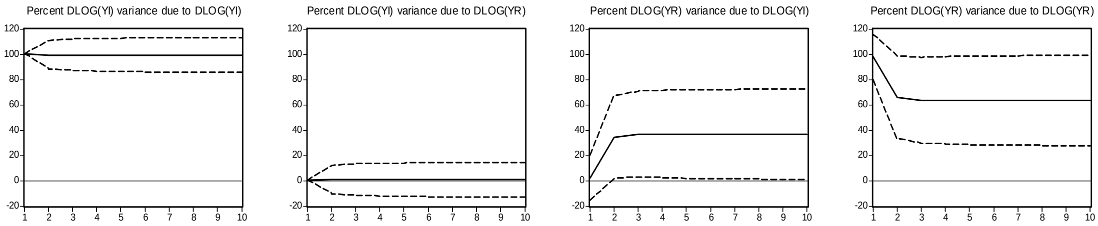
Accumulated Response to Cholesky One S.D. Innovations ± 2 S.E.



Variance Decomposition ± 2 S.E.



Variance Decomposition ± 2 S.E.



Accumulated Response to Generalized One S.D. Innovations ± 2 S.E.