THE FUTURE IMPACT OF OIL VOLATILITY ON COMMODITY PRICES

Juan Carlos Arreguin[a], Evelyne Kakooza[b], Zuzana Somogyiová[c]

[a] Nokia, Helsinki, Finland; [b] Wärtsilä, Helsinki, Finland; [c] The Technical University of Košice, Slovak republic

Abstract: *The aim of this research was to compare two methods used in terms of oil volatility and its effects on the development of different commodities. We tried to find out if there is any positive or negative relationship between price movements and if the volatility prices of oil affect the volatility prices of silver, copper and aluminium. For the purpose of this study we used GARCH and VAR models. When examining oil volatility by VAR model, we used the Granger-Causality test to find causality between commodities. And at the end of this research we examined by the impulse responses and the variance decompositions whether changes in the value of a given commodity have a positive or negative effect on other commodities in the system, or how long it would take for the effect of that commodity to work through the system.*

Keywords: *volatility, VAR, GARCH, commodity, oil*

1. Introduction

The economic importance of oil derives not only from the sheer size of the market, but also from the crucial role it plays in the economies of oil-exporting and oil-consuming countries. Oil prices drive revenues to oil-exporting countries in a large number of which, oil exports comprise over 20% of the GDP. On the other hand, costs of oil imports have a substantial impact on growth initiatives in developing countries. Energy price shocks have often been cited as causing adverse macroeconomic impacts on aggregate output and employment, in countries across the world.

In commodity markets, one can speculate on the rise but also fall in prices of these commodities. The investor tries to predict market trends to achieve the highest profit margin. The motivation to carry out this analysis is the detection of signals in the market that can help investors to invest their funds appropriately.

The accurate modelling and prediction of volatility is crucial for evaluating the effectiveness of trading and hedging strategies, and for asset and derivative pricing models.

Scientific research has been done from different perspectives to study the concept of volatility and their effects on different financial markets. The purpose of volatility is to help us predict future price movements; with increase in volatility increases also the chance that the option will do very well or very poorly. In other words, volatility refers to the amount of uncertainty or risk about the size of changes in an option value. That is why it is important to understand the volatility in the financial markets.

This research will try to explain the volatility or the level of risk of different commodities such as, oil, aluminium, silver and copper. Moreover, we will try to find whether there is any positive or negative relation between price movements of these commodities.

An investor who can forecast volatility better than the market should be able to use this advantage to make excess-returns. Thanks to the results of such research investors could be able to understand the options market's behaviour for decisions making regarding their future investments.

2. Methodology

Hypothesis

In this chapter the empirical tests of the study are presented. The hypotheses that will be tested in this study are:

1. H_0: Volatility shocks in oil prices have an impact on Copper (Cu)
2. H_0: Volatility shocks in oil prices have an impact on Silver (Ag)
3. H_0: Volatility shocks in oil prices have an impact on Aluminium(Al)

Data

This study utilizes the daily close prices (as seen in *Figure 1*) of Oil, Marathon Oil Corp. (MRO) at the NYSE against three strategic commodities metals; Silver, Ag (Pan American Silver Corp.) traded on the NASDAQ Exchange, Copper, Cu (Southern Copper Corp.) and Aluminium, Al (ACH) on the New York Stock Exchange and the sample covers daily period from February 2, 2002 to March 23, 2008. All the commodities are settled in a uniform currency, US dollars. The selected commodities fall into the most important commodities which are traded on commodity markets. In the time of doing this research, crude oil prices hit the highest level, not seen in the past 20-25 years, and because of this, oil prices have had major effects on almost all economies and this study assesses empirically the dynamic effects of oil price shocks on the output of the main strategic commodities.

Figure 2 shows daily log-return series for all the series over the years 2002 to 2007 for 1,546 observations, many financial return series data display volatility clustering.

Oil returns have many clusters over the estimation period implying high volatility followed by copper and silver, and aluminium.

To test the relationship between the commodities involved in our model GARCH (Generalized Autoregressive Conditional Heteroskedasticity model) and VAR (Vector Autoregressive model) models were chosen. The aim was to detect the existence of the dependance of price changes of oil in relation to other reference commodities (copper, silver and aluminum) and to determine whether it is possible to predict future trends within other commodities depending on the volatility in oil prices.

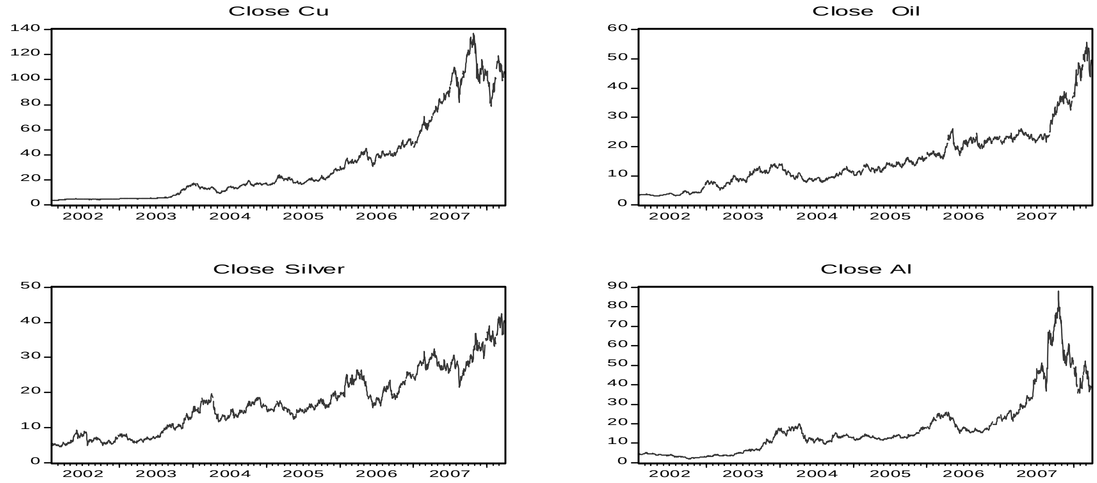


Figure 1: Close prices for all series

Source: Authors

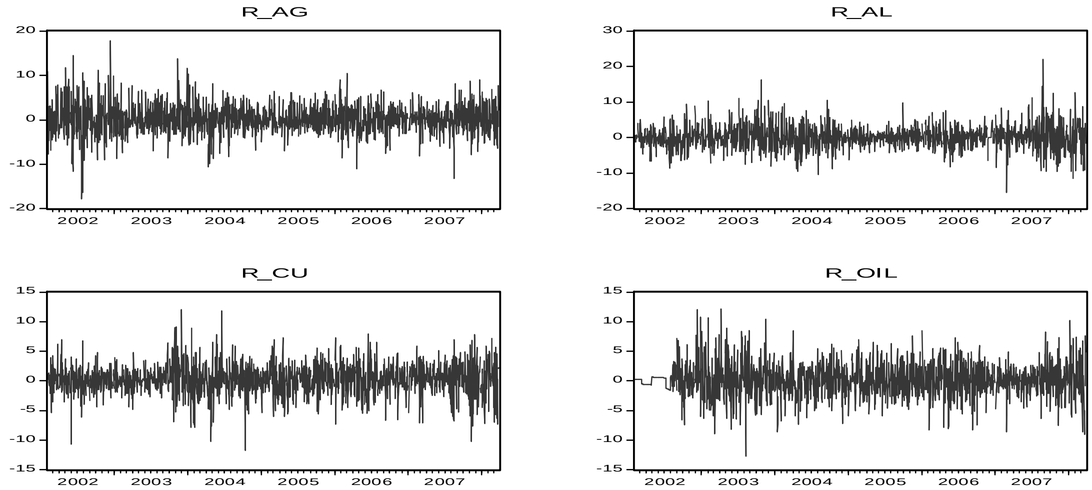


Figure 2: Return series

Source: Authors

GARCH model

Since the main objective of this study is to examine the volatility behaviour of strategic commodities in the presence of oil shocks, the basic GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model (Engle, 1982; Bollerslev, 1986), which describes conditional volatility in terms of the errors of potentially autoregressive (AR) conditional mean models and the conditional variance, is used in this study and is defined as follows:

$$r_t = a_0 + \sum_{i=1}^{m} a_i r_{t-i} + \sum_{i=1}^{n} b e_{t-i} + e_t,$$

$$e_t / y_{t-1} \sim N(0, s_t^2)$$

$$s_t^2 = w + \sum_{i=1}^{q} a_t e_{t-i}^2 + \sum_{i=1}^{p} b s_{t-1}^2,$$

Where e_t is serially uncorrelated with zero mean and constant variance.

The "(1, 1)" in GARCH(1, 1) indicates that s_n^2 is based on the most recent observation of u^2 and the most recent estimate of the variance rate. A gerenal formulation GARCH (p,q) model calculates s_n^2 from the most recent p observations on $u^2$and the most recent q estimates of the variance rate. GARCH(1, 1) is considered the most popular of the GRACH models.

In addition to the standard GARCH model we consider a new GARCH model variant, namely the Component-GARCH (CGARCH) model of Engle and Lee (1999). This model decomposes time-varying conditional volatility into a long-run component, and a short-run transitory component which reverts to trend following a shock.

In their development of the component model, Engle and Lee (1999) propose replacing the constant unconditional variance with a time-varying long-run volatility component, *qt*, yielding the joint process:

$$s_t^2 = q_t + a(e_{t-1}^2 - q_{t-1}) + b(s_{t-1}^2 - q_{t-1}) + h_{1i} oil_{t-1} + h_{2i} M_{t-1},$$

$$q_t = w + r q_{t-1} + f(e_{t-1}^2 - s_{t-1}^2)$$

Where the forecasting error, $e_t^2 - s_t^2$, serves as the driving force for the time-dependent movement of the long-run component, q_t and the difference between the conditional variance and long-run volatility, $s_{t-1}^2 - q_{t-1}$, defines the short-run, or transitory, component of the conditional variance, M_t represents shocks from the metals: silver, copper and aluminium.

The initial impact of a shock on the transitory component of the CGARCH model is quantified by a , whilst b indicates the degree of memory in the transitory component, the sum of these parameters provides a measure of transitory shock persistence. The initial effect of a shock to the long-run component is given by f, with persistence measured by the autoregressive root, r . More specifically, the transitory component converges to zero with powers of ($a + b$), whilst the long-run component converges to w with powers of r .

VAR model

VAR (Vector Autoregressive model) got into awareness thanks to Sims (1980). These models are used to capture the evolution and the interdependencies between multiple time series. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model.

The formulation of the VAR(p) system is written below :

$$s_t = a + \sum_{i=1}^{p} f_t s_{t-i} + e_t$$

where p denotes the lag order of the system, and $s_t = (s_{oil,t}, s_{sil,t}, s_{cu,t}, s_{al,t})$ is a covariance stationary 4x1 vector of volatility time series, a the 4x1 vector of intercepts, and e_t the 4x1 vector of white noise with zero mean and positive definite covariance matrix, and p denotes the lag order of the system.

Important decisions in the analysis of VAR models are to select sutaible variables and to determine an appropriate length of the delay p (lag). For the selection of a suitable length of lag the following information criteria are most commonly used- the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SC).

It is important to examine the stationarity of time series to detect the type of data used in calculations. Stationary time series in the long run converge to their constant mean value, and they also have a final variance, which is time-invariant and their correlogram is declining. For non-stationary time series in the long run there is no mean value they would converge to, the variance depends on the time and the final correlogram of time series decreases very slowly. If the original time series are stationary, they can be directly used to estimate unknown parameters of the model and to predict the future development of variables. But if the original time series are non-stationary (what is more common in practice), then by using a sutaible degree of difference we can make time series stationary. Then the only differentiated series can be used in the model. But this will cause that we can examine only the relationship between the growth of variables, or their growth rate, instead of long-term relationships between them.

Furthermore, it is necessary to determine the number of lags (delays). If the observations of time series are apart from each other by k (k = 0, 1, 2), then k is called lag or delay. The more of them, the better we can capture their impact on the explained variable. But on the other hand, there is a problem that more lags reduce the power of the test. We can use information criteria to estimate the number of lags in the model - for example the most common are the Akaike or the Schwarz information criteria (the minimum value of the criterion indicates the right number of lags).

The Granger-Causality tests is applied to interpret the estimated VAR(p) system and to detect if one variable affect another one. To explain whether changes in the value of a given variable have a positive or negative effect on other variables in the system, or how long it would take for the effect of that variable to work through the system, it is necessary to use also the VAR's impulse responses and variance decompositions.

3. Empirical Results

From the financial theory we know that return series (logs of the series) are stationary, therefore there was no need to carry out stationary tests and the descriptive statistics as seen in *Table 1*, which shows that copper has the highest annualized return followed by oil over the sample period. Silver has the lowest annualized return.

In terms of volatility silver with the lowest return has almost the highest volatility after aluminium and copper with the highest return is the least volatile. Oil remains at the average level of all the metals (see *Table 1*).

The distributions of these commodities are non-symmetric as manifested by the high kurtosis, which is an indication that the ARCH effect is possibly present.

Relatively strong correlations (*Table 2*) exist between oil and the commodities, with the highest between oil and silver, followed by copper then aluminium. Besides the relations to oil, we can also notice stronger correlation between copper and aluminium.

Table 1: Descriptive statistics and contemporaneus correlations

	Al	Ag	Cu	Oil
Mean	0,14067	0,137154	0,217173	0,17275
Median	0	0	0,204708	0,17746
Maximum	22,0603	17,80389	12,07677	12,1791
Minimum	-15,357	-17,85551	-11,72435	-12,7155
Std. Dev.	3,29695	3,284589	2,607967	2,84112
Skewness	0,36991	0,107484	-0,163538	0,14511
Kurtosis	5,80849	5,512239	4,673186	4,3852
Jarque-Bera	543,001	409,2678	187,1079	128,944
Probability	0	0	0	0
Annualized Return	36,575	35,66004	56,46498	44,914
Annualized volatility	52,3374	52,141234	41,400193	45,1013
Sum	217,341	211,9028	335,5327	266,892
Sum Sq. Dev.	16783	16657,48	10501,5	12463,1
Observations	1545	1545	1545	1545

Source: Authors

Table 2: Contemporaneus correlations

Panel B:				
	Al	Ag	Cu	Oil
Al	1			
Ag	0,21325	1		
Cu	0,4017	0,350332	1	
Oil	0,19194	0,538681	0,321188	1

Source: Authors

Table 3: **The joint AR(1)-CGARCH(1, 1) model estimates, standard errors and residual diagnostics investigating the impact of oil shocks on copper, silver and aluminium**

Dependent Variable: Ag					**Dependent Variable: Cu**					**Dependent Variable: Al**				
	Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.
C	-0.007182	0.054273	-0.132336	0.8947	C	0.126505	0.053003	2.386751	0.0170	C	0.000249	0.072987	0.003414	0.9973
Oil(-1)	-0.050485	0.022398	-2.254010	0.0242	Oil(-1)	0.037434	0.022359	1.674185	0.0941	Oil(-1)	-0.026720	0.027886	-0.958217	0.3380
Al(-1)	-0.006169	0.020492	-0.301066	0.7634	Al(-1)	-0.004848	0.017509	-0.276877	0.7819	Cu(-1)	0.071382	0.029458	2.423181	0.0154
Cu(-1)	0.022533	0.024492	0.920039	0.3576	Ag(-1)	0.026947	0.019255	1.399493	0.1617	Ag(-1)	-0.011273	0.025467	-0.442634	0.6580
AR(1)	-0.022888	0.029453	-0.777085	0.4371	AR(1)	-0.048121	0.029644	-1.623313	0.1045	AR(1)	0.036112	0.031290	1.154099	0.2485
	Variance Equation					**Variance Equation**					**Variance Equation**			
ω	-45.61656	205.4783	-0.222002	0.8243	ω	5.133599	0.307132	16.71462	0.0000	ω	12.71862	4.884035	2.604121	0.0092
α	1.000207	0.000906	1104.436	0.0000	α	0.973515	0.020777	46.85479	0.0000	α	0.996769	0.002072	480.9741	0.0000
ß	0.039018	0.006694	5.828895	0.0000	ß	0.014973	0.011085	1.350801	0.1768	ß	0.029949	0.006166	4.857289	0.0000
ρ	0.072529	0.026098	2.779144	0.0055	ρ	0.087847	0.026795	3.278467	0.0010	ρ	0.111705	0.027998	3.989752	0.0001
ϕ	0.218863	0.292158	0.749123	0.4538	ϕ	0.677867	0.114002	5.946075	0.0000	ϕ	0.341511	0.178728	1.910787	0.0560
R-squared	0.332887	Mean dependent var		0.135232	R-squared	0.253061	Mean dependent var		0.216587	R-squared	0.165903	Mean dependent var		0.141152
Adjusted R-squared	0.327655	S.D. dependent var		3.269223	Adjusted R-	0.247203	S.D. dependent var		2.609566	Adjusted R-squar	0.159361	S.D. dependent var		3.298890
S.E. of regression	2.680653	Akaike info criterion		4.558282	S.E. of regr	2.264161	Akaike info criterion		4.442160	S.E. of regressior	3.024633	Akaike info criterion		4.933662
Sum squared resid	10994.43	Schwarz criterion		4.603284	Sum square	7843.433	Schwarz criterion		4.487163	Sum squared res	13997.06	Schwarz criterion		4.978664
Log likelihood	-3503.714	F-statistic		63.62211	Log likeliho	-3414.127	F-statistic		43.19664	Log likelihood	-3793.320	F-statistic		25.35992
Durbin-Watson stat	2.004306	Prob(F-statistic)		0.000000	Durbin-Wat	1.983933	Prob(F-statistic)		0.000000	Durbin-Watson st	2.005474	Prob(F-statistic)		0.000000

Source: Authors

The AR(1)-GARCH(1, 1) model is estimated for each return series since it gives better results than the GARCH(1, 1): copper, silver and aluminium, and ***Table 3*** reports the joint AR(1)-CGARCH(1, 1) model estimates, standard errors and residual diagnostics investigating the impact of oil shocks on copper, silver and aluminium and any other impacts the metals could have amongst each other as seen from the mean equation.

In this model the impacts of oil shocks on volatility behavior of copper and silver are significantly positive at the 5% (0.0242) and 10% (0.0941) significance levels, this means that past oil shocks can be used to predict future volatilities for the two metals copper and silver then for aluminium. The results also show that there is a strong positive relationship between copper shocks and aluminium at the 5% (0.0154) significance level implying that copper can be used to predict future prices for aluminium. The estimates also suggest that short run volatility is more persistent than the long run volatility, it is more persistent with copper, which is less than one; for silver and aluminium, which are a little out of the convergence range.

For the long run volatility to converge to equilibrium it should be between 0.99 and 1 but from the estimates the long-run estimated parameters b_i for all the metals are very low implying that shocks to the long-run component decay very fast, and a shock does not continue to condition volatility over the long horizon. In other words, conditional volatility exhibits short memory.

The Engel's (1982: 1002) ARCH–test for 5 lags was also conducted to returns data. The test results are reported in ***Table 4***. The test examines if there is an autocorrelation in the squared residuals. During the estimation periods of return data, the F-statistic and the LM–statistic suggest absence of the ARCH effect in the return series.

Table 4: Lag order selection for the VAR(p) model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-14932.62	NA*	3244.008*	19.43607*	19.44996*	19.44124*
1	-14920.74	23.68285	3261.446	19.44143	19.51089	19.46728
2	-14910.29	20.77511	3285.092	19.44866	19.57368	19.49517
3	-14904.31	11.87462	3328.174	19.46169	19.64227	19.52888
4	-14896.60	15.23888	3364.300	19.47248	19.70863	19.56035
5	-14892.26	8.572093	3415.721	19.48765	19.77935	19.59619
6	-14883.82	16.59432	3449.530	19.49749	19.84476	19.62670
7	-14871.86	23.46500	3467.743	19.50275	19.90559	19.65264
8	-14866.72	10.05800	3517.127	19.51688	19.97528	19.68744

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

Source: Authors

All the information criteria, as represented in ***Table 4,*** indicate the absence of lead lag relationships and that there are no auto correlations in the residuals implying white noise, which is a sign of efficient markets where prices of the series are independent of each other.

One of VAR´s advantages is to use these models for forecasting. The structure of the VAR model provides information about the ability of one or more groups of variables to predict the other variables. Based on the Granger causality test, we can say that one variable affects another in terms of Granger causality. Or more specifically, the current and historical values of one variable provide an explanation and prediction of another variable. If the variable Y1 is considered to be useful in predicting the variable Y2, we say that Y2 is dependent on Y1 in the sense of Granger causality. Null hypothesis is that Y1 affects Y2. If we cannot reject the null hypothesis at the significance level, then the variable Y1 and Y2 are independent of each other.

Table 5: Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Probability
Cu does not Granger Cause Al	1543	0.17977	0.83548
Al does not Granger Cause Cu		1.66198	0.19010
Oil does not Granger Cause Al	1543	1.73230	0.17722
Al does not Granger Cause Oil		1.28503	0.27694
Ag does not Granger Cause Al	1543	1.35960	0.25707
Al does not Granger Cause Ag		1.77310	0.17015
Oil does not Granger Cause Cu	1543	2.04537	0.12968
Cu does not Granger Cause Oil		0.49570	0.60924
Ag does not Granger Cause Cu	1543	1.60855	0.20051
Cu does not Granger Cause Ag		0.19466	0.82313
Ag does not Granger Cause Oil	1543	0.72483	0.48457
Oil does not Granger Cause Ag		0.96947	0.37952

Source: Authors

Table 5 gives results for the pairwise Granger-Causality tests and these results show that oil does not have any lead lag relationship with silver, copper or aluminium. This implies that volatility expectations of the commodities are not affected by oil innovations or volatilities and we also observe that all the commodities are independent of each other, which is a sign of efficient markets.

Till now we have tried to estimate which of the variables in the model have statistically significant impacts on the future values of each of the variables in the system. But if we want to explain whether changes in the value of a given variable have a positive or negative effect on other variables in the system, or how long it would take for the effect of that variable to work through the system, we can examine such information from the VAR's impulse responses and variance decompositions.

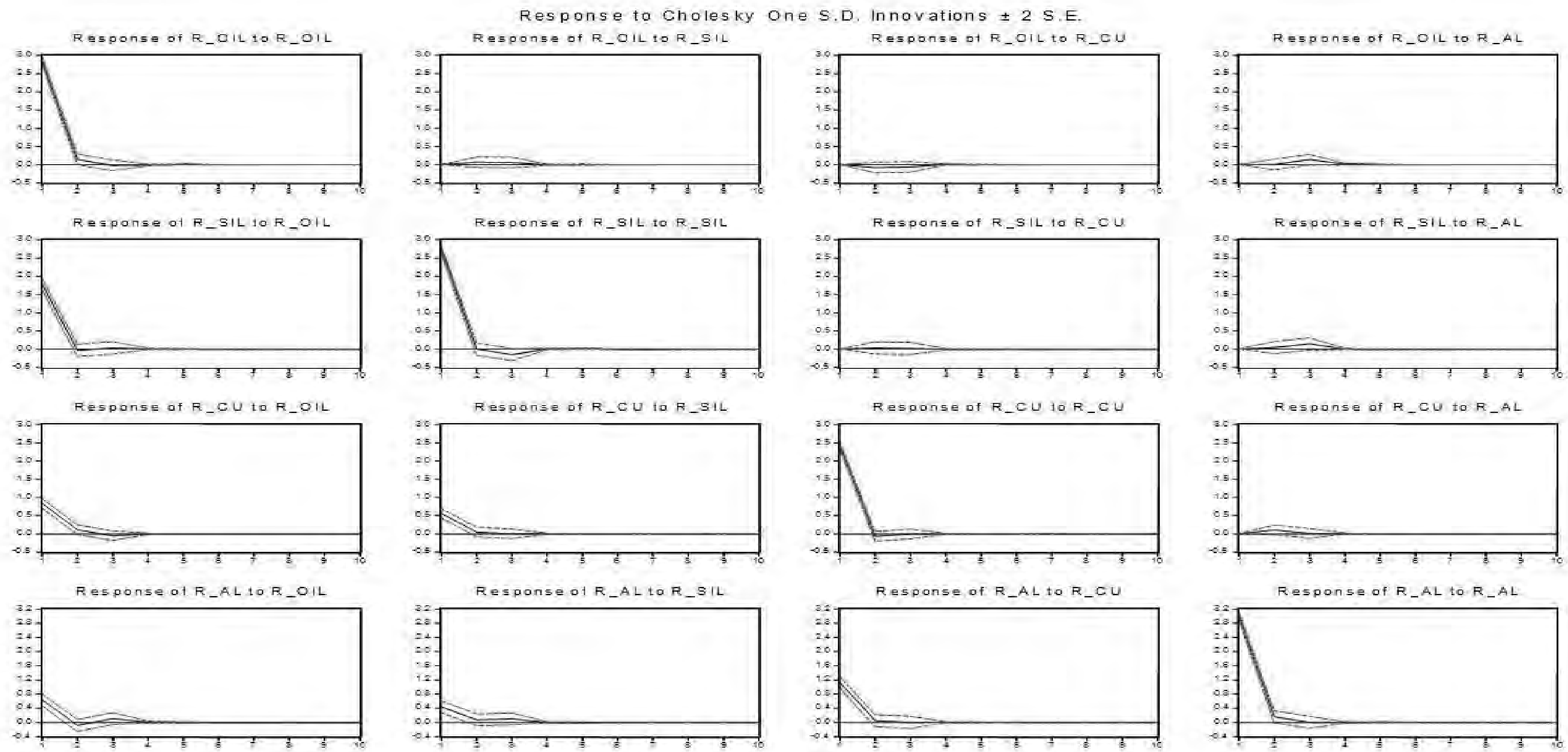


Figure 3: Impulse response functions

Source: Authors

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[1]. The graphs of the ***Figure 3*** present the impact of a generalised one-standard-deviation innovation in volatility of oil on itself and on other commodities, and the impact the commodities have amongst themselves.

The impulse response of copper, aluminium and silver to the shock in the volatility of oil indicates a positive impact after the contemporaneous day one effect which reduces and after day two there is no more impact due to the oil shocks. The impact of a shock in the volatility of oil seems to be incorporated into the expectations of copper, aluminium and silver returns during the first two days; however, this response is minimal. The impulse response from the oil shocks is the highest in silver, and this is also depicted from the strong correlation between the two series as seen in ***Table 1***.

If impulse response functions trace 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. The variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR.

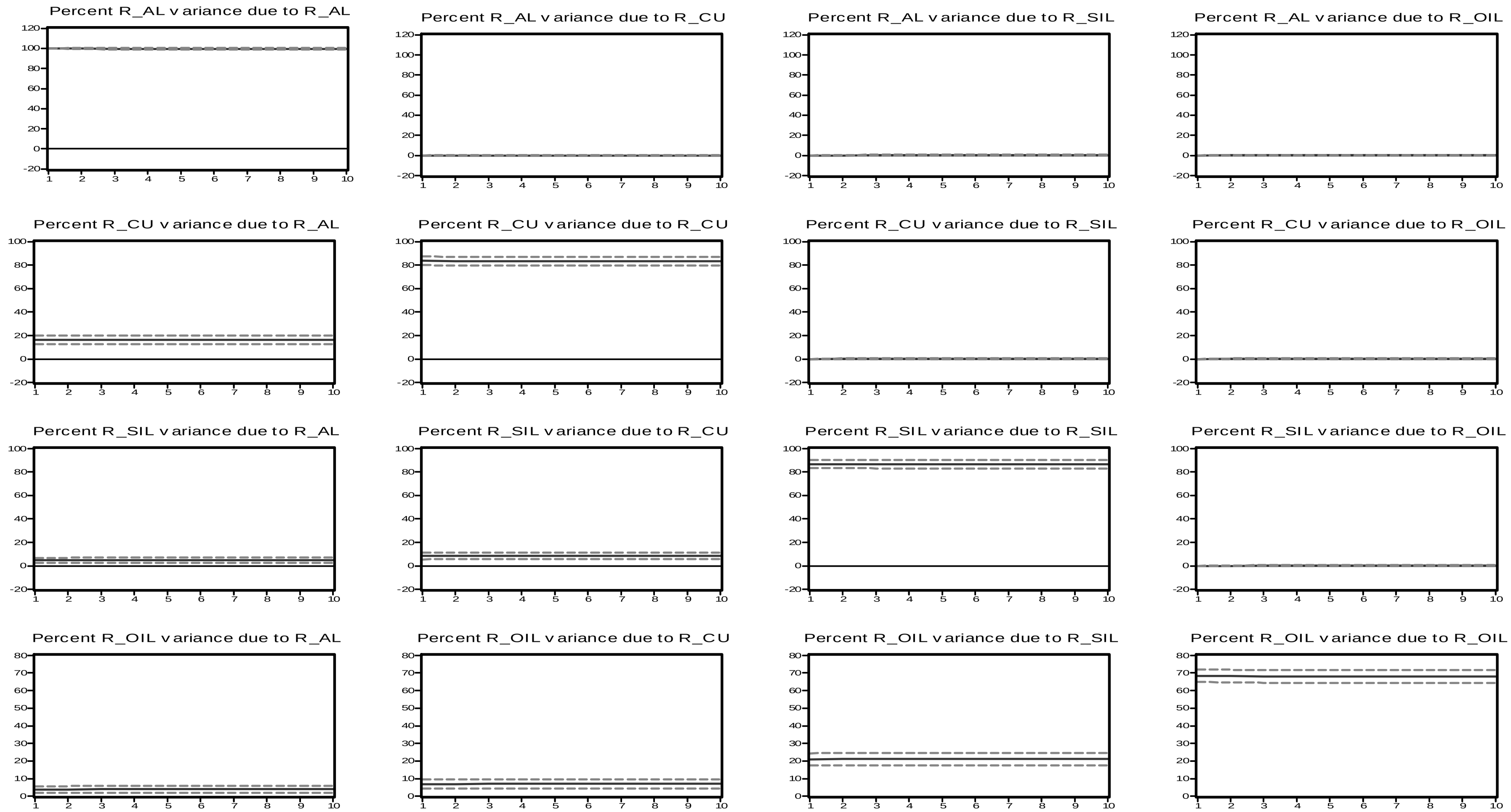
Finally, variance decomposition analysis is applied to separates the variation in the endogenous variables (copper, aluminium and silver) into the component shocks to the VAR system. Thus, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR system.

By analyzing graphs of the ***Figure 4,*** we can tell that volatility expectations of copper, silver and aluminium are not affected by oil. However, we see that that the 20% variation of copper is explained by aluminium and the 10% variation of oil is explained by copper and the 21% by silver. Therefore, the variance decompositions suggest that future volatilities of copper, silver and aluminium are not affected by expected volatility of oil.

---

[1] EViews 7 User's Guide II

Figure 5: Variance decompositions



Source: Author

4. Conclusion

Finally, this study explained that the volatilities of oil, aluminium, silver and copper prices are correlated somehow and investors need to take this kind of behavior into account when investing in options, futures or other derivatives. Volatility refers to the amount of uncertainty or risk about the size of changes in an option value. It is important to understand the volatility in the financial markets because when an investor can forecast volatility better than the market participants, it could lead to advantages in form of excess-returns. Thanks to the results of such research, investors could be able to understand the options market's behaviour for decision making on future investments.

From the AR-CGARCH(1,1) model we are able to accept the first two hypotheses and conclude that oil shocks do have an impact on copper and silver, but this impact is not significant enough to be explained by the VAR(p) system, as seen from the Granger-Causality tests. Following VAR(p) model and Granger-Causality tests, all the commodities are independent of each other, which is a sign of efficient markets. The used methods do not provide a clear conclusion. Therefore our future ambition is to continue this research and find a suitable and, if possible, the most reliable method of testing volatility for this purpose.

References:

[1] ANDERSEM, T., BOLLERSLEV, T., DIEBOLD, F. & LABYS, P. *The distribution of exchange rate volatility*. 2001. Journal of American Statistical Association 96. 42 – 55.

[2] GLOVA, J. *Oceňovanie investičných zámerov: študijný materiál pre externé vzdelávanie.* 1st Edition. (2009) Technical University of Košice/ Faculty of Economics ISBN 978-80-553-0273-7.

[3] HEIKKILÄ, J. *Test of symmetric and asymmetric GARCH–type model*. 2006. In: Forecasting crude oil market volatility, 53-74. Vaasa: University College of Vaasa.

[4] HULL, John C.: *Options, Futures and Other Derivatives*: Prentice Hall India Pvt. Ltd. 6th Edition (2005). ISBN 0131977059

[5] KRONER, K., KNEAFSEY, D., CLAESSENS, S. *Volatility Forecasting in Commodity Markets*. (1993). No 1226, Policy Research Working Paper Series from The World Bank, Online: http://www-wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/1993/11/01/000009265_3961005141748/Rendered/PDF/multi_page.pdf

[6] McMILLAN, David G., SPEIGHT, Alan E.H. *Non-ferrous metals price volatility: a component analysis*. 2001. Resources Policy 27, 199–207.

[7] NIKKINEN, J., SAHLSTRÖM, P., VÄHÄMÄ, S. *Implied volatility linkages among major European currencies.* 2005. Journal of International Financial Markets, Institutions and Money 16, 87-103.

[8] SABOL, T., FEGELI, J., MIHOKOVÁ, M., ŠOLTÉS, M. *Investovanie: študijný materiál pre dištančné vzdelávanie.* 1st Edition. (2002) Technical University of Košice/ Faculty of Economics ISBN 80-7099-888-1.

[9] WATKINS, C., McALEER, M. *Modelling time-varying volatility in Non-Ferrous metals markets.* 2002. Department of Economics, University of Western Australia

Contact Address:

Juan Carlos Arreguin
Nokia, Helsinki, Finland

Evelyne Namanda
Wärtsilä, Helsinki, Finland

Zuzana Somogyiová
Technical University of Košice
Slovak republic
Email: Zuzana.Somogyiova@tuke.sk