DYNAMIC INTERACTIONS BETWEEN THE MARKETS OF CRUDE OIL AND FINE WINE IN LIGHT OF THE GLOBAL ECONOMIC GROWTH

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ABSTRACT

The purpose of this paper is to investigate the dynamic interactions of return and volatility transmission between crude oil and fine wine prices accounting for the global economic activity. Within a multivariate framework and using monthly data over the period 1988-2012, we addressed the co-movement between crude oil and fine wine markets by means of time-varying conditional variance and correlation. Empirical results indicate that the crude oil mean return dominates that of the wine market. The effects of negative shocks are asymmetric between the two markets. Besides high levels of volatility persistence, innovations in each market can help investors and risk managers in predicting the volatility in other markets. Finally, we found evidence that the linkages between the two markets are affected by the global industrial production levels.

Keywords
Conditional correlations, crude oil, fine wines, multivariate GARCH, global economic growth, volatility transmission

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1. INTRODUCTION

The sustained rise in energy and agriculture commodity prices of this century inevitably characterises the macroeconomic pictures and becomes an interesting field of research. Not just crude oil is an interesting asset in the commodity asset group, agriculture commodities also become an asset class for fund managers to consider (Robles et *al.*, 2009; Gilbert, 2010). According to Abbott et *al.* (2008) and (2009), three factors cause the boom in the agricultural commodity prices: USD depreciation, changes in supply and demand, and the energy/agriculture linkage. Focusing on the final factor has been a recent growing trend in the literature as the coming paragraph on literature review will illustrate.

Numerous researchers emphasize the close linkage between the oil and the agriculture market (Radetzki, 2006; Baffes, 2007; Baffes and Haniotis, 2010; Chang and Su, 2010; Gilbert, 2010; Nazlioglu and Soytas, 2010). Others highlight the importance of oil prices and bio-fuels demand in shaping the agriculture commodity prices (Headey and Fan, 2008; Mitchell, 2008; OECD, 2008; Rosegrant et al., 2008; Gilbert, 2010; Zhang et al., 2010).

On the other hand, Baffes (2007) suggests that an individual and separate investigation of oil and commodity prices linkages is needed. Accordingly, Yu et al. (2006) and Kaltalioglu and Soytas (2009) examined the impact of oil prices behaviours on several edible oil prices and found no statistically significant relationship. Chen et al. (2010) document no transmission of oil price to that of wheat, corn, and soybean. Zhang and Reed (2008) show no transmission of oil price to that of corn, soy meal, and pork in China. Oil and agricultural commodity prices display similar behaviour in Turkey (Nazlioglu and Soytas, 2011). Campiche et al. (2007) argue that no co-integration exists between oil and sugar, corn, sorghum, soybeans, soybean oil, and palm oil markets. However, Du et al. (2010) found evidence of volatility linkage among crude oil, wheat, and corn markets. Esmaeili and Shokoohi (2011) reveal a significant impact of oil price on that of agriculture food index. Zhang and Reed (2008) conclude that oil prices are not the major determinants of rising agriculture commodity prices. While, Mutuc et al. (2010) discovered a weak effect of oil prices on US cotton prices.

In parallel, the transparency and liquidity of the wine market resulting from its growing popularity and size have emerged fine wines from being pure consumer goods, made from different varieties of grapes, to become an alternative investment vehicle (Fogarty, 2010; Masset and Henderson, 2010). Burton and Jacobsen (2001) show evidence that fine wines generate positive investment returns throughout the analysed period and outperform the US equities in some years. In Australia, Fogarty (2006) found similar returns but a lower volatility of wines as compared to Australian equities. Fogarty (2007) and Sanning et al. (2008) conclude that fine wine excess return and low correlation with financial markets promote portfolio diversification possibilities. Fogarty (2010) and Masset and Henderson (2010) reveal similar results during the turmoil of 2001 and 2008. While oil is a crucial commodity closely linked to economic output, fine wine is also regarded as a superior good (Cevik and Sedik, 2011).

A main challenge in commodity markets is the volatility of prices, often because of events outside the control of decision makers. In particular, the persistence of price volatility and the degree of interdependence between the volatility of commodities are key variables to portfolios and risk managers. The question of whether the interdependence of fine wines and crude oil markets can help us to predict the volatility in a given market remains a key objective for academics and practitioners alike. When market disruptions adversely affect portfolios, often investors ask themselves whether anything could have been done in a different way. The analysis of the conditional variances and correlations in turmoil episodes can enable investors to adjust the allocations of oil and fine wines within their portfolios in order to reduce risk and optimize return. It can also assist policy-makers and regulators in properly monitoring commodities market in stress periods. To this end, we sought to analyse and understand fine wines and crude oil prices co-movements and their interaction with the global economic growth before and after the financial crisis of 2008. During this turmoil period, fine wines prices fell by only 20% from a high of 248.32 to 198.28. On the other hand, the average crude oil price (West Texas Intermediate and Brent crude oil) dropped by nearly 70% from a record high of $133.10 per barrel to $40.53 per barrel. Although the Liv-ex Fine Wine Investables Index hit another record high of 369.81 in May 2011, crude oil price remained below its previous peak of June 2008 (see figure 1).

We intended to contribute to economic commodity literature in fourfold. First, as the aforementioned empirical studies consider fine wines to be an asset class on its own, we sought to extend the wine existing literature beyond the simple framework of risk and return trade-off. Second, we aimed to close the research gap opened by Baffes (2007) who suggested that an individual and separate investigation of oil and commodity prices linkages is needed. Third, we built upon the work of Cevik and Sedik (2011) who analysed crude oil and fine wines prices to identify their common macroeconomic determinants. Their empirical results showed that the two commodities prices are sensitive to macroeconomic shocks and that aggregate demand growth in advanced and emerging markets is the key determinants of fine wine and crude oil prices. With new insights and taking into consideration the growth in the global industrial production, we aimed to shed the light on the return and volatility co-movements between fine wines and crude oil markets, an unexplored area of research. Finally, in terms of econometric model, we employed a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, in an extension of Engle and Kroner (1995) work, which can capture the asymmetric impact of information on returns volatility.

We found no empirical evidence supporting co-integration between fine wines and crude oil prices, or between any of the two variables and the global industrial production index. We showed that crude oil transmits its mean to the wine market. We also uncovered strong evidence on the persistence of price volatility. The volatilities of the two commodities are inter-connected, and the transmission of cross-innovations is somewhat bi-directional. The global industrial production seems to influence the dynamic volatility transmission between the oil and wine markets.

Following the introduction, Section two presents data and statistical properties of the time series. Econometric methodology to examine the transmission of mean and volatility is the focus of Section three. Section four reports our empirical results and analysis. Finally, Section five puts forward the conclusions.

2. THE DATA

The empirical investigation was carried out with monthly data on prices of the Liv-ex Fine Wine Investables Index as well as average prices of West Texas Intermediate (WTI) and Brent crude oil, over the period between January 1988 and December 2012. The Liv-ex Fine Wine Investables Index consists of Bordeaux red wines from 24 leading chateaux which are chosen on the basis of Robert Parker's rating, a leading critic. The wines are priced using the Liv-ex Mid Price, which are derived from live bids, offers and transactions on Liv-ex - the Fine Wine Exchange, the global trading platform for fine wine. The index dates back to January 1988 and is calculated monthly. To eliminate the currency effects, the sterling-denominated Liv-ex Fine Wine Investables Index is converted into US dollar based series. Particularly, the data coverage allowed us to deal with the financial crisis of 2007-2008. Using the database of Reuters DataStream, we selected a total of 300 common monthly observations between oil and fine wines prices. The choice of a Liv-ex index to proxy fine wine prices resides in the fact that there is no global wine price similar to that of crude oil. We also generated a proxy for monthly GDP as the available data are on a quarterly basis. Instead of simply using the monthly industrial production data series to generate such a proxy, we chose not to do so since it provides a limited measure of overall economic activity.

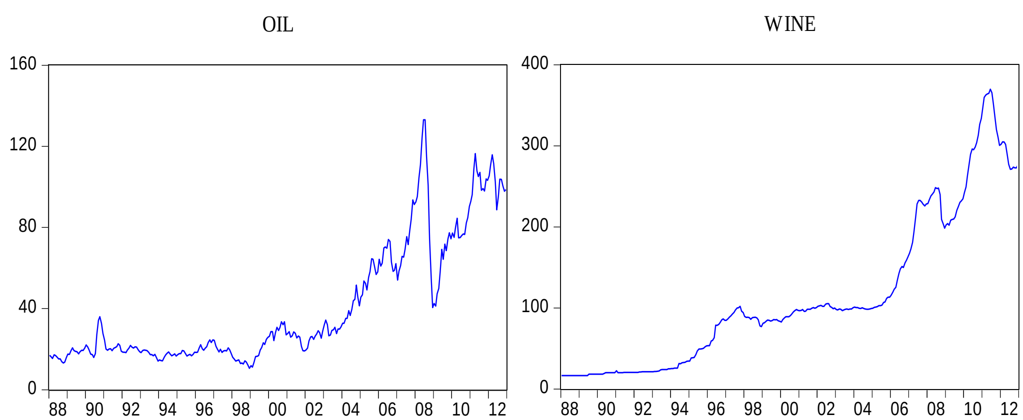

Figure 1: Monthly prices

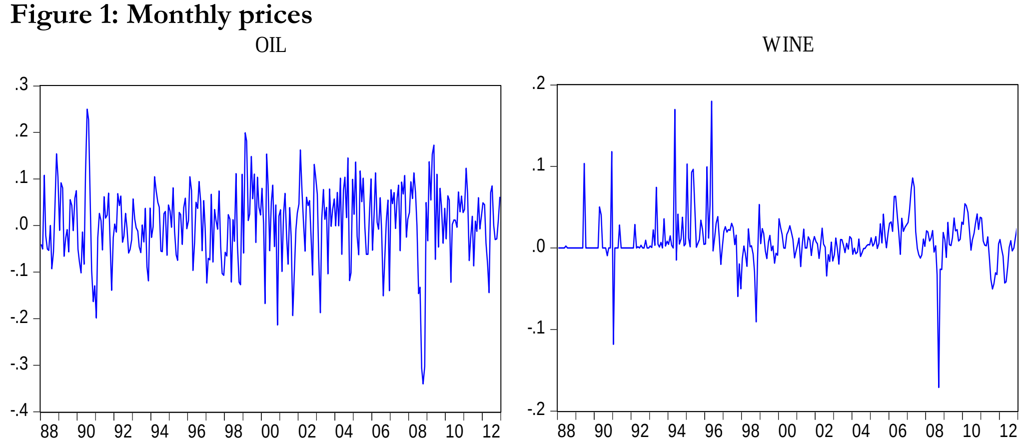

Figure 2: Monthly returns

To this end, we aggregated the industrial production series using GDP weights, and constructed industrial production series for 55 economies (20 advanced economies and 35 emerging economies) representing more than 90% of world GDP. For each series, we calculated monthly returns as the log differences of monthly closing prices.

Figure 1 and 2 represent respectively the level series and returns of oil and wine prices. In both series and similar to most of the financial series, the volatility clustering persists. Large changes tend to be followed by further large changes and a series of small changes tend to be followed by further small changes.

The first step involves the examination of the statistical properties of the data presented in Table 1. As shown in Panel A, the mean return in both series is positive. However, wine exhibits the highest mean return (0.946%) and the lowest standard deviation (3.100%). For both oil and wine series, the Jarque and Bera (1980) statistics conclusively rejected the null hypothesis of normality in the return distribution at 1% percent significance level. The JB test measures the departure from normality of a sample, based on skewness and kurtosis. The return distribution of wine was positively skewed and more peaked than a normal distribution. In fact, kurtosis and skewness measured 16.151 and 1.642, respectively. The latter value implies that large positive returns are more common than large negative returns in the wine market. Moreover, the return distribution of oil had higher peak, but it was negatively skewed. The results of the Ljung and Box (1979) Q-statistics convincingly indicated that, up to 10 lags, serial autocorrelation in the returns was significant.

The aforementioned characteristics of return distributions suggested that variances may be time-varying.

Table 1: Data statistics

Panel A: Descriptive statistics						
	Mean	**SD**	**Kurtosis**	**Skewness**	**JB**	**LBQ(10)**
WINE Prices	114.302	94.705	3.037	1.025	52.790[a]	2 410.800[a]
OIL Prices	40.739	30.465	3.132	1.179	69.320[a]	1 988.500[a]
WINE Returns	0.00946	0.031	16.151	1.642	2 295.789[a]	58.335[a]
OIL Returns	0.00608	0.085	5.608	-0.188	86.520[a]	51.620[a]

Pane B: Unconditional correlation coefficient (oil – wine)			
Periods	**1988-2012**	**1988-2007**	**2008-2012**
Correlation coefficient of prices	0.908	0.776	0.545
Correlation coefficient of returns	0.148	0.037	0.525

Notations: SD (Standard Deviation), LBQ (Ljung and Box Q-statistics). For JB (Jarque-Bera) and Ljung-Box tests, [a], [b], [c] indicate statistical significance at 1%, 5% and 10% levels, respectively.

Regarding the unconditional correlation coefficients, financial literature provides ample evidence that correlations tend to be quite unstable over time. As such, different financial assets can provide varying degrees of diversification. Panel B reports the contemporaneous and unconditional correlation as a simple measure of co-movements between the series. Fine wines and oil prices tend to move in tandem with positive mid to high correlations coefficients values ranging from 0.908 to 0.545. On the other hand, the correlation of returns piles on in the ex-post sub-sample and reaches 0.525. As such, risk reduction benefits diminish.

3. METHODOLOGY SPECIFICATION

This section provides a statistical methodology for employing a multivariate model in order to examine the dynamic of mean and volatilities of returns between oil and wine markets, taking into consideration the impact of specific macroeconomic variables that are susceptible to impact the dynamic, mainly the global industrial production growth. The rationale behind the selection of this economic variable is justified in the empirical work of Cevik and Sedik (2011) who imply that mainly the aggregate global demand influences the behavior of oil and wine prices.

We applied the Baba-Engle-Kraft-Kroner (BEKK) multivariate GARCH defined in Engle and Kroner (1995) to examine transmission effects into mean and volatility. Transmission effects in mean (or variance) occur when a change in returns (or volatility of returns) in one market has a lagged impact on returns (or volatility of returns) in one or several other markets. The effect of squared residuals in one market on the other is interpreted as volatility shock. The markets affect each other contemporaneously. As a result, there was no need to incorporate the squared residuals as lagged variables into the econometric model. This simultaneous methodology to model all the data series at once (Bala and Premaratne, 2004) allows the conditional variances and co-variances of series to influence each other and to produce conditional covariance matrices that are positive definite. We further seized the asymmetries of returns by adding an asymmetric term to the conditional variance equation. As such, we captured the so-called leverage effect mentioned by Black (1976) which corresponds to the typically negative correlation between an asset return and its changes of volatility i.e. bad news gives a greater impact on the volatility of returns than good news. The model is specified as follows:

$$R_t = \Omega + S\,R_{t-1} + \theta\,\Delta(GIP)_t + \varepsilon_t \qquad (1)$$

where $\varepsilon_t \sim GED(0, H_t)$

where R_t is a 2×1 vector of daily returns at time t for each index, Ω is a 2×1 vector that denotes the constants, S is a 2×2 matrix of parameters sij that measures the effects of own lagged and cross mean transmission from market i to market j between the two markets, θ is a 2×2 matrix of parameters θij that measures the impacts of global industrial production, ΔGIP is the change in the global industrial production index, and the error εt is a 2×1 vector of the innovation for each market at time t and has a 2×2 conditional variance-covariance matrix, Ht .

The conditional variance is specified as follows:

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon'_{t-1})A + G'H_{t-1}G + D'(\varepsilon_{t-1}\varepsilon'_{t-1}d_{t-1})D + P'P \qquad (2)$$

Ct is a matrix of constants with 2×2 symmetric elements cij, A is a matrix with 2×2 symmetric elements aij that measure the effects of lagged and cross innovations (squared residuals) from market i to market j, G is a matrix with 2×2 symmetric elements gij that measure the persistence of conditional volatility between market i and j, dt-1 is a dummy variable equal to 1 if εt-1 <0 and 0 otherwise, D is a matrix with 2×2 symmetric elements dij that measure lagged and cross asymmetric effects from market i to market j, and P is a matrix with 2×2 symmetric elements pij that measure the impacts of the growth in the global industrial production.

Given that the return distribution of the series departs from normality, we estimated the models assuming multivariate General Errors Distribution (GED) of the residuals term. To produce the maximum likelihood parameter estimates, we used the Berndt-Hall-Hall-Hausman (1974) algorithm. We also evaluated the robustness of the results using the LBQ tests.

The simple form of equation (2) can be written as:

$$h_{11,t} = c_{1,1}^2 + a_{1,1}^2 \varepsilon_{1,t-1}^2 + g_{1,1}^2 h_{1,1,t-1} + d_{1,1}^2 \varepsilon_{i,t-1}^2 d_{1,t-1} + p_{1,1}^2 \tag{3}$$

To examine the time-varying correlations between conditional variances and past innovations we specified the following conditional correlation formula:

$$\rho_{12,t} = \frac{h_{12,t}}{(\sqrt{h_{11,t}}\sqrt{h_{22,t}})} \tag{4}$$

4. Empirical analysis

Preceding the estimation of the multivariate GARCH model (equations 1 and 2), the output of a rigorous analysis of the characteristics of data series, including Granger causality, stationarity, and co-integration analysis are presented along these lines.

4.1. Granger causality

We first employed the Granger (1969) causality test on all the series. It tests the null hypothesis that a series Xt does not Granger-cause another series Yt. We picked arbitrarily a 2 lag length following the work of McMillin and Fackler (1984). Table 2 reports the results of Granger-causality between oil and wine, global industrial production and oil, as well as between global industrial production and wine.

There is evidence of bi-directional causality between oil price and wine price at the 10% significance level in the pre-crisis period. Moreover, the global industrial production index granger causes oil and wine prices, whereas oil price also granger causes the production index in the full sample. In term of the cross-mean returns, the results indicate independency between the two commodities. On the other hand, there is a bi-directional causality between the growth in the global industrial production and oil return as well as with wine return at the 10% significance level. These weak results of returns independencies will be re-examined by the application of the multivariate GARCH model.

Table 2: Granger causality (lag = 2)

	1988-2012 *F*-Statistic	Probability	1988-2007 *F*-Statistic	Probability	2008-2012 *F*-Statistic	Probability
WINE price does not Granger Cause OIL price	11.275[a]	0.000	2.395	0.108	1.359	0.261
OIL price does not Granger Cause WINE price	1.329	0.268	3.241[b]	0.040	2.150	0.122
GIP does not Granger Cause OIL price	4.725[a]	0.001	1.395	0.248	8.567	0.000
OIL price does not Granger cause GIP	5.344[a]	0.005	1.461	0.230	4.201	0.025
GIP does not Granger Cause WINE price	7.588[a]	0.000	3.225[b]	0.040	8.447[a]	0.000
WINE price does not Granger cause GIP	1.659	0.193	0.194	0.828	4.375[b]	0.017
WINE return does not Granger Cause OIL return	2.143	0.119	0.833	0.439	2.025	0.142
OIL return does not Granger Cause WINE return	0.653	0.529	0.129	0.882	0.180	0.831
GIP growth does not Granger Cause OIL return	3.350[b]	0.035	2.163	0.117	0.479	0.621
OIL return does not Granger Cause GIP growth	1.567	0.210	0.925	0.392	2.867[c]	0.065
GIP growth does not Granger Cause WINE return	2.912[c]	0.055	0.284	0.750	3.508[b]	0.039
WINE return does not Granger cause GIP growth	2.118	0.121	0.377	0.693	2.431[c]	0.097

Notations: GIP (global industrial production). The F-statistic is the Wald statistic for the joint hypothesis: $B_1 = B_2 = \ldots = B_t = 0$. [a], [b], [c] indicate statistical significance at 1%, 5% and 10% levels respectively.

4.2. Stationarity of time series

It is essential to examine the order of integration of the time series properties of the data so that we prevent spurious conclusions. A time series is defined as stationary if the mean and auto-covariance of the data series do not depend on time. If a non-stationary series Yt, must be differenced d times before it becomes stationary, then it is said to be integrated of order d; we write Yt ~ I(d). We adopted the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and Phillips-Peron (PP) unit root tests (Philips and Perron, 1988), and tested the null hypothesis (H0) that a time series Yt ~ I(1) i.e. has a unit root against the alternative hypothesis (H1) that the time series Yt ~ I(0) i.e. time series is stationary. Table 3 reports the result of both unit root tests. The optimal lag length is chosen on the basis of the Akaike Information Criterion (AIC) for the ADF test and the Newey-West Bandwith using Barlett Kernel for the PP test, respectively.

Table 3: Unit roots tests

	Wine		Oil		GIP	
	Level	1st difference	Level	1st difference	Level	1st difference
ADF	0.522	-12.859[a]	0.175	-13.905[a]	-0.198	-0.165[a]
PP	-0.129	-12.314[a]	-0.925	-14.522[a]	-0.147	-0.459[a]

Notations: GIP (global industrial production), ADF (Augmented Dickey-Fuller), PP (Philips and Perron). Both ADF and PP statistics are computed with a constant term on the full sample. [a], [b], [c] indicate statistical significance at 1%, 5% and 10% levels respectively.

For the full sample, the ADF and PP t-statistics for the first-differences were statistically significant at the 1% significance level. We rejected the null hypothesis that the return has a unit root and thus all series were integrated of order one. This indicates a possible long-run relationship between the series. As a result, we ran co-integration tests.

4.3. Co-integration test

In order to examine the possibility of a long-run relation between two variables, we applied the Johansen's (1995) maximum likelihood test statistics that are based respectively on trace and maximum Eigen-values. We thus tested the null hypothesis of no co-integration between the series. The co-integration results reported in Table 4 fail to quantify the dynamic of cross means between all the series. The results of the Johansen test indicated that all price series were not co-integrated in the three samples. The trace statistics and the maximum Eigen-values implied that there was no empirical evidence supporting long-run equilibrium relationships across all the series.

To sum, the causality test cannot capture the sign and the magnitude of cross mean transmission, but only displays its source. Add to that, the departure from normality, the volatility clustering, as well as the positive correlations in the series returns lead us to choose the aforementioned multivariate GARCH framework which was specified in order to model the transmission of means and conditional variances between oil and wine prices, and to derive the conditional correlation between the series returns. Particularly, the modeling will take into consideration the impact of the global industrial production on the estimates.

Table 4: Johansen co-integration test

Number of co-integrating vectors	t-statistic Trace	t-statistic Max-Eigen	Critical values of 5% Trace	Critical values of 5% Max-Eigen	Critical values of 1% Trace	Critical values of 1% Max-Eigen
Panel A: Oil and wine						
Full sample (1988-2012)						
No relation	13.390	13.384	15.522	14.265	19.937	18.520
At most 1 relation	0.005	0.005	3.841	3.841	6.634	6.634
Sub-sample (1988-2007)						
No relation	14.372	12.180	15.522	14.265	19.937	18.520
At most 1 relation	3.188	3.188	3.841	3.841	6.634	16.554
Sub-sample (2008-2012)						
No relation	15.210	14.081	15.522	14.265	19.937	18.520
At most 1 relation	3.162	3.162	3.841	3.841	6.634	6.634
Panel B: Oil and GIP						
Full sample (1988-2012)						
No relation	7.322	4.588	15.522	14.265	19.937	18.520
At most 1 relation	2.730	2.739	3.841	3.841	6.634	6.634
Panel C: Wine and GIP						
Full sample (1988-2012)						
No relation	2.950	2.799	15.522	14.265	19.937	18.520
At most 1 relation	0.142	0.142	3.841	3.841	6.634	6.634

Notations: GIP (global industrial production index). [a], [b], [c] indicate rejection of the null hypothesis at 1%, 5% and 10% significance levels respectively. The optimal lag length is chosen on the basis of the AIC and SC. We did not report the results of co-integration between oil and GIP as well as between wine and GIP in the sub-samples; however, the results fail to provide evidence of any equilibrium relationship.

4.4. Mean and volatility estimates

In this paragraph, we report and analyze the empirical results of mean and volatility dynamics between the oil and wine markets, taking into account the growth in the global industrial production index which may has impact on conditional variances and correlations.

After a rigorous analysis of the variables order of integration, we found that most of the series can be characterized as unit root (I(1)) processes. We also checked the series that exhibit I(1) characteristics for the possibility of a long-run relationship, but we failed to establish a co-integration relationship between the different pairs involved, including the economic factor. With this evidence, we only used the first differences of the series in the multivariate GARCH system. Table 5 displays the estimated parameters for the conditional mean return in equation (1), whereas Table 6 presents the estimated coefficients for MTGARCH conditional variance covariance in equation (2). However, for simplicity, the constant parameters of matrix Ω and C are not reported in the two tables.

Most of the coefficients of own mean transmission effects of matrix S were positive and statistically significant, suggesting that the returns rely on their first own lags with positive drift patterns. In computing the coefficients of cross mean transmission effects, represented by the off-diagonal parameters of matrix S, oil is the only mean transmitter. The influence of the economic variable in the mean equation estimates turned out to be insignificant for the wine mean return. On the other hand, the same variable was significant for the oil mean return in the full sample and the sub-sample (2008-2012) at the 10% and 5% significance levels, respectively.

Table 5: Estimates of the multivariate mean equation

	Full sample (1988-2012)		Sub-sample (1988-2007)		Sub-sample (2008-2012)	
	WINE (i = 1)	OIL (i = 2)	WINE (i = 1)	OIL (i = 2)	WINE (i = 1)	OIL (i = 2)
s_{i1}	0.018[a]	0.007	0.014[a]	0.055	0.039[b]	-0.039
	0.023	**0.012**	**0.010**	**0.054**	**0.025**	**0.061**
s_{i2}	0.021[a]	0.059[a]	0.025[a]	0.052[a]	0.020[b]	0.061[a]
	0.017	**0.025**	**0.014**	**0.014**	**0.010**	**0.030**
θ_{i2}	0.072	0.090[c]	0.059	0.084	0.063	0.099[b]
	0.065	**0.109**	**0.105**	**0.093**	**0.115**	**0.086**

Notations: [a], [b], [c] indicate statistical significance at 1%, 5% and 10% levels respectively. Standard errors are reported in bold.

Table 6: Estimates of the multivariate variance covariance equation

	Full sample (1988-2012)		Sub-sample (1988-2007)		Sub-sample (2008-2012)	
Country	WINE (i = 1)	OIL (i = 2)	WINE (i = 1)	OIL (i = 2)	WINE (i = 1)	OIL (i = 2)
a_{i1}	-0.003[a]	0.007[a]	0.001[a]	-0.025[a]	0.002[c]	0.005[a]
	0.002	**0.005**	**0.005**	**0.021**	**0.030**	**0.012**
a_{i2}	0.007[a]	0.009[a]	-0.025[a]	-0.014[c]	0.005[a]	0.009[b]
	0.005	**0.007**	**0.021**	**0.035**	**0.012**	**0.014**
g_{i1}	0.981[a]	0.950[a]	0.957[a]	0.883[a]	0.909[a]	0.914[a]
	0.008	**0.012**	**0.009**	**0.017**	**0.012**	**0.018**
g_{i2}	0.950[a]	0.923[a]	0.883[a]	0.801[a]	0.914[a]	0.954[a]
	0.012	**0.014**	**0.017**	**0.059**	**0.018**	**0.017**
d_{i1}	0.020[b]	0.034[c]	-0.005	0.023[b]	0.012[b]	0.021[a]
	0.007	**0.032**	**0.009**	**0.025**	**0.008**	**0.014**
d_{i2}	0.034[c]	0.052[a]	0.023[b]	0.115[a]	0.021[c]	0.050[a]
	0.032	**0.018**	**0.025**	**0.031**	**0.014**	**0.014**
p_{i1}	0.050	0.081[a]	0.059	0.031[c]	0.030	0.039[a]
	0.032	**0.035**	**0.032**	**0.025**	**0.017**	**0.014**
p_{i2}	0.081[a]	0.075[a]	0.031[c]	0.035[b]	0.039[a]	0.034[a]
	0.035	**0.021**	**0.025**	**0.023**	**0.014**	**0.021**
Half Life	39.804	18.702	189.297	5.025	22.972	19.021
MLB-Q^2 (10)	35.812		32.212		39.981	

Notations: M LB-Q^2 (Multivariate Ljung and Box Q-statistics on the squared residuals). [a], [b], [c] indicate statistical significance at 1%, 5% and 10% levels respectively. Standard errors are reported in bold.

Most of the parameters of matrix A, which measure the volatility transmissions from market i to market j, were positive and statistically significant in both markets. The parameters of innovations between the two markets were also significant. These results imply that if innovations in the two markets have the same sign, the covariance will be influenced in a positive manner suggesting a possible volatility transmission between the two markets.

The parameters of matrix G measure the volatility persistence. The latter is considered to be high if its value is close to one. The results revealed high own and cross volatility persistence in the two markets, implying that both markets sustain volatility for some time into the future. In order to measure the period of time it takes a shock to diminish to one half, we computed the persistence of information shocks in days as follows:

$$Half\ life = ln(0.5)/\ln(\delta) \quad (5)$$

where ln designates the natural logarithm, and δ denotes the sum of estimated ARCH and GARCH coefficients for each market.

Compared to the wine market, the crude oil market is more efficient. It exhibits the lowest durations of shock impact i.e. in the oil market, the effects of the shocks take a shorter time to decay.

The parameters in matrix D measure the leverage effect from market i to market j. The coefficients of the asymmetric response to bad news were statistically significant, suggesting that the effects of negative shocks are asymmetric between the two markets. The impact of the global industrial production index was particularly significant for the oil market at the 1% significance level in the full sample and the sub-sample of 2008-2012. On the other hand, the same economic variable was significant for the wine market at the 10% level for the sub-sample of 1988-2007. This implies that the global economic output plays a role in the conditional volatility of the two commodities with different magnitude levels.

The robustness of the estimated model is confirmed by the LBQ statistics which indicated that the multivariate squared residuals exhibit a random behaviour.

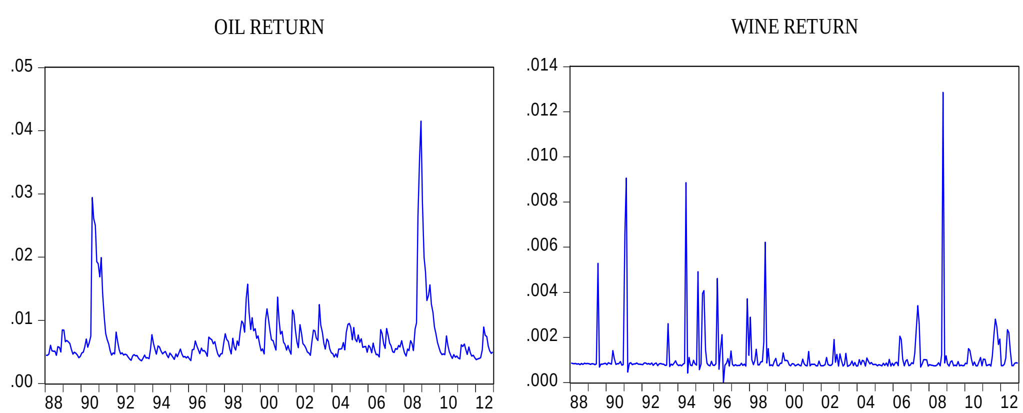

Figure 3: Conditional variances

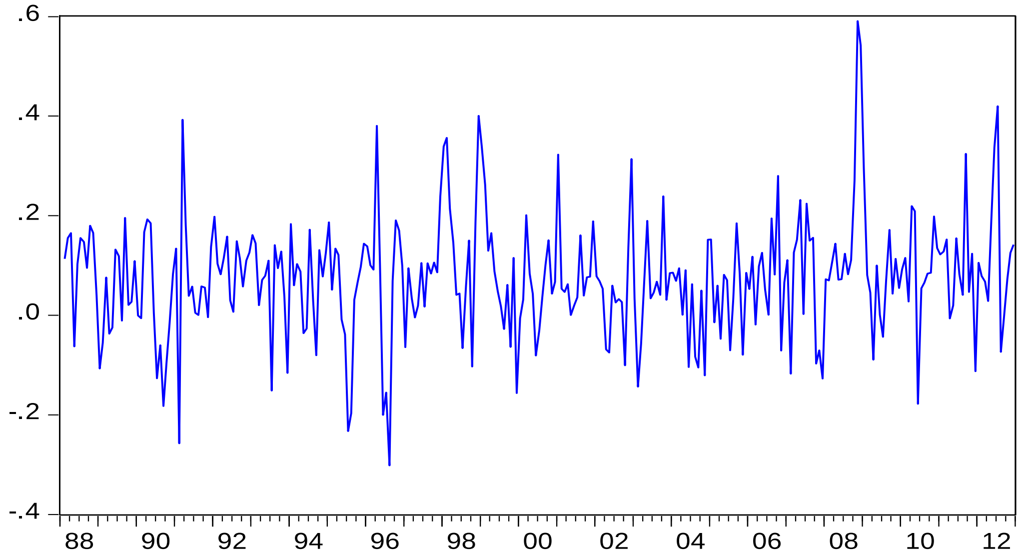

Figure 4: Conditional correlation (wine – oil)

It is interesting to see what the conditional variances and correlations of returns are and how they fluctuate over time. Figure 3 plots fine wines and crude oil conditional variances, while figure 4 plots conditional correlations. Obviously, the plots show that conditional variances and correlations are not constant over time. The variances of oil and wines prices do not follow a trend; especially oil variances tended to cluster during the second half of 2008. However, the conditional correlation is very variable, changing from negative to positive sign quite frequently. This suggests a weak relationship between shocks in the wine and oil markets, reducing diversification benefits. The conditional correlation increased during the fourth quarter of 2008, indicating a possible volatility transmission between the two commodities. The conditional variances of oil and wine prices attain its highest value in the same period. Since that time, they have been quite low and stable, despite the correction in wine prices that began in the summer of 2011.

5. Conclusion

Recent behaviours of commodity prices and volatilities provided exceptional ground for our research to examine the magnitude of mean and volatility transmissions between fine wines and crude oil markets, over the period 1988-2012. Remarkably, the Granger causality runs from wine prices to oil prices. We performed co-integration tests to examine long-run equilibrium relationship between all data series, but found no empirical evidence supporting co-integration. Yet, the descriptive statistics of our data indicated that the series returns are non-normally distributed and serially correlated, suggesting that shocks generate volatility clustering and that the variance may be time-dependent. To benefit from this excess of information in the residuals of the data, we employed a multivariate GARCH framework, based on the work of Baba-Engle-Kraft-Kroner (BEKK) defined in

Engle and Kroner (1995) model, that can seize the time-varying conditional variances and correlations of returns.

We summarize our findings as follows. First, we recorded mean transmission from the oil to the wine market. This outcome was not a surprise giving that oil is the world's most traded commodity. This form of efficiency regarding information transmission from the oil market makes the inclusion of fine wines and crude oil in an investment portfolio that does not allow portfolio risk to be reduced significantly. This finding corroborates Cevik and Sedik (2011) conclusions, but contradicts other studies (Sanning et al., 2008; Fogarty, 2010; Masset and Henderson, 2010). Second, own lagged innovations were statistically significant in the two markets. Third, we demonstrated that oil and wine return data sets have high volatility persistence. As such, the volatility in every market will be more influenced by its own past conditional variance than by the effect of cross shocks transmission from other market. Fourth, the responses to information between the two markets were asymmetric. Fifth, an interesting feature of this study helps uncover empirically the obscure linkages between fine wines and crude oil markets amid the variability in the global industrial production levels. The latter seems to play an important role in the relationship between the two markets.

Policy makers, investors, hedgers, and arbitrageurs can benefit from our results to understand the dynamic linkages between fine wine and crude oil markets, accounting for the role of the global economic output, and capture volatility shocks across the two commodity markets. As such, they can more precisely forecast the next period changes in conditional variances.

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