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Do Fine Wines Blend with Crude Oil? Seizing the Transmission of Mean and Volatility Between Two Commodity Prices*

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Abstract

This study applies a multivariate model to examine the dynamics of mean and volatility transmission between fine wine and crude oil prices using daily observations from January 2004 to December 2011. The results suggest that the crude oil mean determines the wine market. In each series, volatility persistence is high and significant; innovations in each market seem to include figures that are valuable to risk managers seeking to predict volatility in other markets. During the financial crisis of 2008, wine and oil conditional volatilities climbed but then returned to their overall pre-crisis levels. (JEL Classifications: G11, G15, Q14, Q40)

Keywords: Conditional correlation, conditional volatility, crude oil, fine wines.

I. Introduction

The main challenge in commodity markets has been the volatility of prices, often caused by events outside the control of market participants. Since the volatility of commodity prices can reveal information different from that derived from average price levels, understanding volatility is crucial for hedgers and arbitrageurs in making financial decisions and quantifying potential risk. As crises can modify the relationship across commodities markets, market participants should take into account the volatility dynamics and the conditional correlations between the commodities in their portfolio allocations to reduce risk and maximize returns.

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In addition to crude oil, agriculture commodities have become a popular asset class that many fund managers keep as part of their portfolios (Gilbert, 2010; Robles et al. 2009). According to Abbott et al. (2008, 2009), three factors triggered the boom in agricultural commodity prices: depreciation of the U.S. dollar, fluctuations in supply and demand, and the energy/agriculture linkage.

Many researchers have examined the relationship between the oil market and various agriculture markets (e.g., Baffes, 2007; Baffes and Haniotis, 2010; Chang and Su, 2010; Gilbert, 2010; Hanson et al. 1993; Nazlioglu and Soytas, 2011; Radetzki, 2006). More recently, a growing body of literature has explored the impact of oil prices and demand for biofuel on agricultural commodity prices (e.g., Gilbert, 2010; Headey and Fan, 2008; Mitchell, 2008; Rosegrant et al. 2008; Zhang et al., 2010). While some analyses find strong evidence of a price level and volatility linkage between crude oil, wheat, and corn prices (Du et al., 2010; Esmaeili and Shokoohi, 2011; Nazlioglu and Soytas, 2011), others find only weak effects (e.g., Chen et al. 2010; Yu et al., 2006; Zhang and Reed, 2008).

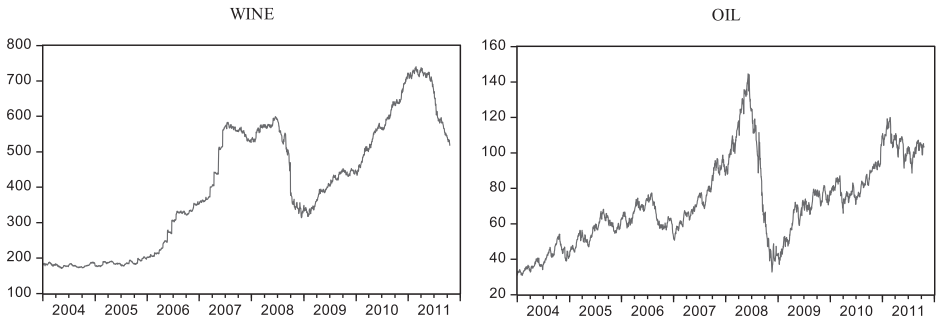
At the same time, there has been growing interest in wine as an investment asset (Fogarty, 2010; Masset and Henderson, 2010; Storchmann, 2012).

The question of whether a relationship exists between fine wines and crude oil markets can help us predict the volatility of a given market remains a stimulating topic for academics and practitioners. The latter can also profit from the analysis of the conditional correlation in turmoil episodes to adjust their oil and fine wine allocation in their portfolios. Furthermore, uncovering mean and volatility transmitters is important for regulators and policy makers seeking to stabilize the highly vibrant commodity markets through timely responses to shocks. We analyze and explain fine wine and crude oil prices' co-movements before and after the financial crisis of 2008, since this helps us further understand these fluctuations. During this turbulent period, fine wine prices (measured by the London International Vintners Exchange [Liv-ex] Claret Chip Index) dropped more than 40%, from 599.20 to 316.15, whereas West Texas Intermediate (WTI) crude oil price plunged more than 75% from a record high of $145.31 to $30.28 per barrel. However, the Liv-ex Claret Chip Index hit another high record of 740.29 in May 2011, whereas the WTI crude oil price remained below its previous peak of June 2008 (see Figure 1).

We aim to contribute to the literature of economic commodities in several ways. First, we want to enrich the existing literature on wine as an asset class beyond the framework of risk and return trade-off. Second, we build upon the work of Cevik and Sedik (2011), who analyze crude oil and fine wine prices to identify their common macroeconomic determinants. This paper examines the volatility and co-movements in the wine and oil markets. To capture captures the asymmetric impact of information on return volatility, we employ a multivariate threshold generalized autoregressive conditional heteroskedasticity (MTGARCH) model, based on the work of Engle and Kroner (1995).

Figure 1

Charts of Oil and Wine Prices for the Full Sample



Using a co-integration test, our results suggest the absence of a long-run equilibrium relationship between fine wine and crude oil prices. The two commodities are connected by their volatility, but crude oil is transmitting its mean to the wine market. Furthermore, we reveal strong empirical evidence on the persistence of price volatility. Despite the large size of the oil market, the transmission of cross-innovations between the two commodities markets is bidirectional. However, the asymmetric responses to bad news in the two markets are statistically significant.

Four sections follow this introduction. Section II. presents the data and statistical properties of the time series. The econometric methodology employed to examine the transmission of mean and volatility is the focus of Section III. Section IV reports our empirical results. Finally, the conclusions of this study are the subject of Section V.

II. Examination of Variables

A. Selection of a Wine Price Index

To construct and study wine price indices, researchers have employed the hedonic regression or the repeat sales regression (RSR). Both of these options necessitate onerous data requirements and are far from flawless.

The hedonic approach to compute indices of wine prices adds to the quantitative measurement of price appreciation/depreciation a qualitative attribute such as quality and rarity. Such hedonic regression accounting explicitly for the heterogeneity among the different wines often leads to multicollinearity problems and delivers inaccurate and unreliable index coefficients (Masset and Henderson, 2010).

A second approach to estimate wine price indices is the RSR method initially introduced by Bailey et al. (1963) for estimating house price indices, later adopted by

Goetzmann (1992) for computing art price indices. The RSR method, studied by Burton and Jacobsen (2001) for estimating wine price indices, considers only similar wines that have been traded more than once during the period under examination. The computed returns between those two or more transaction prices in that period are then averaged, and a growth rate (return) is calculated. Compared to the hedonic method, the RSR has the advantage of comparing the price evolution of similar goods and of depending only on accurate price data and transaction dates (Masset and Henderson, 2010). However, it may suffer from biased results as the sample used to calculate a price index is often reduced (Masset and Weisskopf, 2010). Since the RSR approach only uses a portion of the transaction dataset (the matched pairs of transaction prices) and ignores the explanatory and informative power of the remaining portion of data (the unmatched pairs of transaction prices), it may lack information efficiency. Furthermore, a weak assumption in the RSR model estimated by Burton and Jacobsen (2001) is that the error terms of the regressions have zero means, constant variances, and are uncorrelated. In particular, the assumption of constant variances is often found to be violated in ordinary least squares (OLS) estimations (Case and Shiller, 1987), potentially resulting in a biased wine price index.

An alternative to the hedonic and the RSR methods consists of employing indices from a foremost fine wine exchange such as the Liv-ex. This is the world's leading on-line marketplace for fine wine with members (wine merchants and professional wine traders) in 29 countries spread across five continents. The Liv-ex exchange provides transparent and standardized fine wine prices collected from a wide range of sources including trade-to-trade transactions, merchant list prices, and auction hammer prices. Liv-ex indices, widely recognized as the fine wine industry's pricing benchmarks for wine investors, are computed as weighted averages of the indices components wines prices. In contrast to the RSP method, the computation of the Liv-ex indices considers quantities sold, and the computation is based on mid prices rather than on transaction prices. A valuation committee to ensure the robustness of each number then verifies each price.

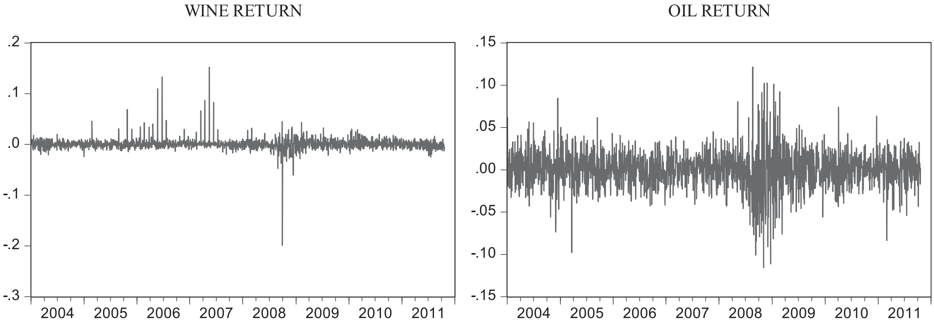
Based on the above arguments and following Masset and Henderson (2010), we favor a Liv-ex index.

B. Data

Our datasets consist of the daily closing prices of the Liv-ex Claret Chip Index and the daily average closing prices of West Texas Intermediate (WTI) and Brent crude oil. The Liv-ex Claret Chip Index is constructed of the five Bordeaux First Growths: Haut Brion, Lafite, Latour, Margaux and Mouton Rothschild, with an Robert Parker score of 95 points or above. This index is calculated at 5 p.m. (UK time) each working day using Liv-ex mid prices for each component wine. We converted the sterling denominated Liv-ex Claret Chip Index from pound sterling to U.S. dollars. The data only covers the period from December 31,

Figure 2

Charts of Oil and Wine Returns for the Full Sample



2003, to December 30, 2011, as the Liv-ex Claret Chip Index is not available before this date.

Monthly data of other Liv-ex indices are available for 1988. Yet the daily dynamics of co-movements between the examined variables will be disregarded if monthly observations are used instead. Nevertheless, our data coverage allows us to cover the economic boom of 2003–2007 as well as the financial crisis of 2007–2008. Using the Reuters DataStream database, we smooth our data to adjust for holidays and nontrading days and select a total of 2,036 common daily observations. We calculate the continuously compounded return of the time series as the natural logarithm of daily closing prices. Figure 1 shows daily closing prices for both wine and oil. On the other hand, Figure 2 shows daily returns for both wine price and oil price. For each time series, large changes tend to be followed by further large changes, and small changes tend to be followed by further small changes. This phenomenon, known as volatility clustering, is commonly associated with financial time series.

C. Descriptive Statistics of the Data

Table 1 summarizes the statistical characteristics of our data. For the two series, the mean returns are positive and oscillate around zero. Oil exhibits the highest volatility (2.1%), measured by the unconditional standard deviation, and has the highest mean return (0.059%).

We tested the normality distribution of daily returns by using the Jarque-Bera (1980) statistics. For the two series, the Jarque-Bera statistic rejects the null hypothesis of normality of returns at the 1% percent level. The skewness for the wine return series is positive, suggesting that large positive returns are more common than large negative returns. Compared to oil, fine wines are attractive to investors concerned about the skewness of their portfolios. Nevertheless, the inclusion of kurtosis into the analysis of returns alters the previous outcome. In both series, the

Table 1
Descriptive Statistics of the Data

	Wine Prices	*Oil Prices*	*Wine Returns*	*Oil Returns*
Mean (%)	398.527	71.804	0.052	0.059
Maximum	740.291	144.635	0.152	0.121
Minimum	171.027	30.871	−0.199	−0.115
Standard Dev.	176.723	22.395	0.011	0.021
Skewness	0.127	0.512	0.436	−0.124
Kurtosis	1.737	2.744	93.398	6.634
Jarque-Bera	140.881*	94.592*	692,967.700*	1,125.430*
LB-Q (5)	9,997.300*	10,153.000*	15.863**	17.977*
Observations	2,036	2,036	2,035	2,035

LB Q (Ljung and Box *Q*-statistics). For Jarque-Bera and Ljung-Box, *,** statistical significance at 1% and 5% levels, respectively.

Table 2
Unconditional Correlation Coefficients Between Oil and Wine Markets

Periods	*2004–2011*	*2004–2007*	*2008–2011*
Correlation coefficient of prices	0.835	0.761	0.783
Correlation coefficient of returns	0.177	0.055	0.267

return is nonnormally distributed, as implied by the large value of kurtosis and skewness relative to normal. A normal distribution has zero skewness and a kurtosis of 3. Both wine and oil series have skewness of 0.436 and –0.124, respectively. The kurtosis value of every market return by far exceeds 3. It attains 93.398 in wine and 6.634 in oil.

The Ljung and Box (1979) *Q*-statistics (LB-Q), which measure autocorrelation, provides strong evidence of auto correlated returns with up to 5 lags. This suggests that the variance may be time dependent and that exogenous shocks may generate volatility clustering.

D. Unconditional Correlation Between the Series

The contemporaneous and unconditional correlation between oil and wine prices is a simple approach to measure the respective linkages. Table 2 displays the correlation coefficients separately for the full and subsamples.

For all samples, fine wine and oil prices tend to move into the same direction. The two commodities exhibit high and positive correlation coefficients ranging from 0.761 to 0.835. Conversely, the relatively low correlation of returns trend upward from 0.055 prior to the crisis and reach 0.267 in the subsample of 2008–2011. This positive slope in the correlation of returns indicates that the possibility of risk reduction in a portfolio that includes crude oil and fine wines is diminishing. However, correlations do not imply causation.

III. Econometric Methodology

A. Granger Causality

The first step in our analysis is the Granger (1969) approach to test whether oil prices affect wine, or vice versa, or whether it is a two-way causation. Suppose the two time series Y_t and $X_{t,}$ in the bivariate Granger-causality regressions have the following form:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \ldots + \alpha_l Y_{t-2} + \beta_1 X_{t-1} + \ldots + \beta_l X_{-1} + u_t \tag{1}$$

$$X_t = \alpha_0 + \alpha_1 X_{t-1} + \ldots + \alpha_l X_{t-1} + \beta_1 Y_{t-1} + \ldots + \beta_l Y_{-l} + v_t \tag{2}$$

where u_t and v_t are assumed to be uncorrelated disturbances terms.

The reported *F*-statistics are the Wald statistics for the joint hypothesis: $\beta_1 = \beta_2 = \ldots = 0$. *Y* is said to be Granger caused by *X* if the coefficients on the lagged *X*s are statistically significant. We test the null hypothesis that *X* does not Granger cause *Y* in the first regression and that *Y* does not Granger cause *X* in the second regression.

B. Stationarity Tests

Before the analysis of the temporal relations across return variables, testing the stationarity of prices and returns is quite relevant. A time series is said to be stationary if it has no drift and no seasonality, that is, the time-series moments do not change over time. As a result, time series whose mean, variance, or covariance is time dependent are nonstationary. If a nonstationary series Y_t must be differenced *d* times before it becomes stationary, then it is said to be integrated of order *d*; we write $Y_t \sim I\ (d)$. By performing augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) unit-root tests (Phillips and Perron, 1988), we test the null hypothesis (H_0) that a time series $Y_t \sim I\ (1)$, that is, has a unit root, against the alternative hypothesis (H_1) that the time series $Y_t \sim I\,(0)$, that is, the time series is stationary.

C. Co-Integration Test

To test the null hypothesis that there are at most *r* co-integrating vectors, we propose Johansen's (1995) maximum likelihood test statistics that are based on trace and maximum eigenvalues, respectively. The trace statistic for the null hypothesis of *r* co-integrating relations is computed as follows:

$$LR_{tr}(r/k) = -T \sum_{i=r+1}^{k} \log(1 - \lambda_i) \tag{3}$$

where LR is the log likelihood ratio, and λ_i is the *i*-th largest eigenvalue.

However, the maximum eigenvalue statistic tests the null hypothesis of *r,* co-integrating relations against the alternative of *r +1* co-integrating relations. This test statistic is computed as follows:

$$\begin{aligned} LR_{\max}(r/r+1) &= -T\log(1-\lambda_{r+1}) \\ &= LR_{tr}(r/k) - LR_{tr}(r+1/k) \quad \text{for } r = 0, 1, \ldots, k-1. \end{aligned} \tag{4}$$

D. Mean and Volatility Transmissions

This section presents the structure of the multivariate model to be employed in order to capture the dynamic of means and volatilities of returns between oil and wine markets. 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. If markets affect one another contemporaneously, there is no need to incorporate squared residuals as lagged variables into the econometric model.

Volatility co-movements across a set of markets are best modeled simultaneously (Bala and Premaratne, 2004). This methodology has several advantages over the vector auto regressive (VAR), the causality, and the univariate GARCH approaches. The VAR method disregards nonlinearity and conditional heteroskedasticity (Stock and Watson, 2001); the causality tests do not capture the sign and the magnitude of cross-mean and volatility-transmission effects, but only displays their sources, while the univariate GARCH type method manifests deficiency in seizing at once the co-movements of variances among two or more time series. Therefore, we apply the multivariate GARCH (MGARCH) defined in Engle and Kroner (1995) to examine transmission effects into mean and volatility. The advantage of using this specific MGARCH model is that its conditional covariance matrices are positive definite by construction. This model also allows the conditional variances and co-variances of markets to influence one another. However, the symmetric characteristic of the MGARCH model cannot seize the asymmetries of returns; instead, it treats bad news, expressed by negative signs, with the same influence on the volatility as good news, expressed with positive signs. In fact, bad news has a greater impact on the volatility of returns than does good news. This negative correlation between asset returns and volatility, also called the leverage effect, was first mentioned in Black (1976). In order to catch the asymmetric effects of information, we will add an asymmetric term to the conditional variance equation. The new model becomes an MTGARCH and has the following form:

$$\begin{aligned} R_t &= \varphi + MR_{t-1} + \varepsilon_t \\ \varepsilon_t &\sim \mathrm{GED}(0, H_t) \end{aligned} \tag{5}$$

where R_t is a 2×1 vector of daily returns at time t for each index, φ is a 2×1 vector that denotes the constants, M is a 2×2 matrix of parameters m_{ij} that measures the effects of own lagged and cross-mean transmissions from market i to market j, and the error ε_t is a 2×1 vector of the innovation for each market at time t and has a 2×2 conditional variance-covariance matrix, H_t.

The variance can be specified as:

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon'_{t-1})A + G'H_{t-1}G + D'(\varepsilon_{t-1}d_{t-1})D \tag{6}$$

C_t is a matrix of constants with 2×2 symmetric elements c_{ij}, A is a matrix with 2×2 symmetric elements a_{ij} that measure the effects of lagged and cross innovation (squared residuals) from market i to market j, G is a matrix with 2×2 symmetric elements g_{ij} that measure the persistence of conditional volatility between market i and j , d_{t-1} is a dummy variable equal to 1 if $\varepsilon_{t-1}<0$ and 0 otherwise, and D is a matrix with 2×2 symmetric elements d_{ij} that measure lagged and cross asymmetric effects from market i to market j.

The simple form of Equation (6) can be written as:

$$h_{11,t} = c^2_{1,1} + \alpha^2_{1,1}\varepsilon^2_{1,t-1} + g^2_{1,1}h_{1,1,t-1} + d^2_{1,1}\varepsilon_{1,t-1}d_{1,t-1} \tag{7}$$

Moreover, the above model allows temporal interactions between innovations in the two markets by estimating the conditional covariance. This allows the assessment of time-varying correlations between conditional variances and past innovations. The conditional correlation can be calculated as follows:

$$\rho_{12,t} = \frac{h_{12.t}}{\left(\sqrt{h_{11,t}}\sqrt{h_{22,t}}\right)} \tag{8}$$

As R_t can follow different density distributions, the estimation of the model requires an assumption about the conditional distribution of the residuals term ε_t. Nevertheless, to catch the characteristics that are associated with oil and wine series, we suggest the estimation of our models assuming multivariate general errors distribution (GED) of the residuals term. To produce the maximum likelihood parameter estimates and increase the chance of the accuracy of the data, we use the Berndt-Hall-Hall-Hausman (1974) algorithm. We assess the robustness of our results using the LB-Q tests.

IV. Empirical Results and Analysis

A. Granger Causalities

Following the work of McMillin and Fackler (1984) we pick a 2-lag length. Table 3 reports the results of Granger-causality between oil and wine.

Table 3
Granger Causality (lag: 2)

	2004–2011		*2004–2007*		*2008–2011*	
	F-Stat.	*Prob.*	*F-Stat.*	*Prob.*	*F-Stat.*	*Prob.*
Wine price does not Granger cause oil price	2.472***	0.084	2.432***	0.088	1.283	0.277
Oil price does not Granger cause wine price	3.552**	0.029	0.768	0.465	2.542***	0.079
Wine return does not Granger cause oil return	0.664	0.514	0.864	0.421	0.691	0.502
Oil return does not Granger cause wine return	3.843**	0.021	1.532	0.216	1.887	0.151

Notes: The *F*-statistic is the Wald statistic for the joint hypothesis: $B_1 = B_2 = \ldots = B_t = 0$; **, *** statistical significance at 5% and 10% levels respectively.

Table 4
Unit-Root Tests

	Wine		*Oil*	
	Level	*First Difference*	*Level*	*First Difference*
Full sample (2004–2011)				
ADF	–1.095	–5.685*	–1.882	–12.972*
PP	–1.134	–43.389*	–1.925	–45.432*
Sub-sample (2004–2007)				
ADF	–0.439	–5.257*	–0.337	–34.392*
PP	–0.291	–31.819*	–0.291	–34.351*
Sub-sample (2008–2011)				
ADF	–1.395	–4.430*	–1.583	–11.863*
PP	–1.132	–29. 800*	–1.571	–30.732*

ADF = Augmented Dickey-Fuller; PP = Phillips and Perron. Both ADF and PP statistics are computed with a constant term. * statistical significance at 1%.

Regarding the Granger causality of returns, we only find an unidirectional causality from oil to fine wines at the 5% significance level. This weak independency of cross-mean returns will be re-examined by employing a MTGARCH model.

B. Sationarity Tests

The optimal lag length is chosen on the basis of the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) for the ADF test and the Newey-West bandwidth using Barlett Kernel for the PP test, respectively. Table 4 reports the results of both unit-root tests.

For the full sample and subsamples, the ADF and PP *t*-statistics for the first differences are statistically significant at the 1% level. We reject the null hypothesis

Table 5
Johansen Co-Integration Test

Number of co-integrating vectors	t-*statistic*		*Critical Values of 5%*		*Critical Values of 1%*	
	Trace	*Max-eigen*	*Trace*	*Max-eigen*	*Trace*	*Max-eigen*
Full sample (2004–2011)						
None ($r=0$)	8.223	7.034	25.872	19.387	31.153	23.975
At most 1 ($r=1$)	1.184	1.184	12.517	12.517	16.554	16.554
Subsample (2004–2007)						
None ($r=0$)	12.052	8.238	25.872	19.387	31.153	23.975
At most 1 ($r=1$)	3.816	4.161	12.517	12.517	16.554	16.554
Subsample (2008–2011)						
None ($r=0$)	4.557	3.953	25.872	19.387	31.153	23.975
At most 1 ($r=1$)	0.603	0.603	12.517	12.517	16.554	16.554

Note: The optimal lag length is chosen on the basis of the AIC and SC.

that the return has a unit root. As a result, the two series are integrated of order one, that is, they follow a covariance-stationary process. The outputs of stationarity tests indicate a possible long-run relationship between oil and fine wine prices. Therefore, we proceed with the co-integration test.

C. Co-Integration Test

If the results of the co-integration test are statistically significant, we can model the price transmission within the error correction model (ECM) framework. Table 5 shows the results of the Johansen test. The values in Table 5 indicate that the two price series are not co-integrated in any of the three samples. The trace statistics and the max-eigenvalues imply that the null hypothesis ($r=0$) cannot be rejected. This result indicates that even following the 2008 financial crisis, a long-run equilibrium relationship between oil and wine prices cannot be established. As a result, the co-integration results fail to quantify the dynamic of cross means between the two series.

The Granger causality test cannot capture the sign and the magnitude of cross mean and volatility transmission but only displays their sources. In addition, the nonnormality, the volatility clustering, and the positive correlations among the series returns lead us to select the MTGARCH model. The latter can model the transmission of means and conditional variances between oil and wine prices and can reveal the conditional correlation between the series returns.

D. Analysis of Mean and Volatility Transmissions

In this section, we report and analyze the empirical results of mean and volatility dynamics between the two markets. For the sake of brevity, we do not report the constant parameters of matrix φ and C in the tables. Table 6 displays the estimated

Table 6
Estimations Outputs of MTGARCH Conditional Mean Equations

	Full Sample (2004–2011)		*Subsample (2004–2007)*		*Subsample (2008–2011)*	
	Wine (i=*1*)	*Oil* (i=*2*)	*Wine* (i=*1*)	*Oil* (i=*2*)	*Wine* (i=*1*)	*Oil* (i=*2*)
m_{i1}	0.037*	0.010	0.012	0.067	0.059**	−0.053
	[0.023]	[0.043]	[0.031]	[0.059]	[0.032]	[0.072]
m_{i2}	0.031*	0.068*	0.031*	0.059*	0.028*	0.079*
	[0.011]	[0.022]	[0.018]	[0.034]	[0.014]	[0.032]

Note: *, ** statistical significance at 1%, and 5% levels, respectively. Standard errors are reported in brackets.

Table 7
Estimations Outputs of MTGARCH Model

	Full Sample (2004–2011)		*Subsample (2004–2007)*		*Subsample (2008–2011)*	
	Wine (i=*1*)	*Oil* (i=*2*)	*Wine* (i=*1*)	*Oil* (i=*2*)	*Wine* (i=*1*)	*Oil* (i=*2*)
a_{i1}	−0.001*	0.003*	0.000*	−0.037*	0.002**	−0.004*
	[0.000]	[0.007]	[0.009]	[0.009]	[0.007]	[0.009]
a_{i2}	0.003*	0.012*	−0.037*	−0.022**	−0.004*	0.013**
	[0.007]	[0.001]	[0.009]	[0.031]	[0.009]	[0.012]
g_{i1}	0.971*	0.966*	0.997*	0.965*	0.966*	0.981*
	[0.005]	[0.009]	[0.005]	[0.014]	[0.008]	[0.008]
g_{i2}	0.966*	0.949*	0.965*	0.844*	0.981*	0.948*
	[0.009]	[0.011]	[0.014]	[0.065]	[0.008]	[0.013]
d_{i1}	0.022*	0.031**	−0.002	0.027**	0.018**	0.024**
	[0.005]	[0.014]	[0.006]	[0.013]	[0.007]	[0.011]
d_{i2}	0.031**	0.058*	0.027**	0.143*	0.024**	0.054**
	[0.014]	[0.019]	[0.013]	[0.055]	[0.011]	[0.022]
Half-Life	22.759	17.421	230.702	3.537	21.312	17.432
MLB-Q^2 (5)	29.304		23.711		34.075	

Notes: *,** indicate statistical significance at 1% and 5% levels respectively. Standard errors are reported in brackets. M LB-Q^2 (Multivariate Ljung and Box *Q*-statistics on the squared residuals).

parameters for the conditional mean return in Equation (5), whereas Table 7 presents the estimated coefficients for MTGARCH conditional variance covariance equations.

The coefficients of own-mean transmission effects of matrix M (except for wine in the pre-crisis period) are positive and statistically significant. This outcome indicates that the returns depend on their first own lags with positive drift patterns. In measuring the coefficients of cross-mean transmission effects, represented by the off-diagonal parameters of matrix M, oil is the only mean transmitter in the two markets. These findings contradict the above-mentioned Granger causality and imply that crude oil has a dominant mean effect on fine wines market.

The parameters of matrix A (in Table 7) measure the volatility transmissions from market i to market j. Most of the own lagged ARCH parameters are positive and statistically significant in oil and wine markets. Also, the parameters of innovations between the two markets are significant. These results suggest that if innovations in the two markets have the same sign, the covariance will be influenced in a positive manner, which implies a possible volatility transmission between the two markets.

The parameters of matrix G (in Table 7) measure the volatility persistence, which is considered high if its value is close to one. In measuring volatility persistence in terms of conditional variance, the results reveal a high own- and cross-volatility persistence in both markets and across all samples. Nevertheless, the lowest own-lagged persistence is for oil (0.844) during the pre-crisis period. The evidence of large and significant own-volatility persistence indicates that fine wines and crude oil markets remain volatile for some time into the future. To compute the persistence of information shocks in days, we use the following formula that measures the half-time of a shock's effect:

$$Half - life = ln(0.5)/ln(\Omega) \tag{9}$$

where ln symbolizes the natural logarithm, and Ω denotes the sum of the estimated ARCH and GARCH coefficients for each series.

We find the lowest durations of shock impacts for the crude oil market, which may suggest a higher efficiency of the oil market compared to the wine market.

The parameters in matrix D (in Table 7) measure the leverage effect from market i to market j. The coefficients of the asymmetric response to bad news are statistically significant, suggesting that the effects of negative shocks are asymmetric between the two markets.

Regarding the robustness of our model, the Ljung-Box statistics point to random behavior of the multivariate squared residuals.

We further examine the correlations between the commodity returns and their fluctuation over time. Figure 3 plots fine wines and crude oil conditional variances, while Figure 4 plots the conditional correlation. The plots show that the conditional variances and correlation are not constant over time.

The variances of oil and wines prices do not follow a certain trend and, instead, tend to cluster. Particularly, they increase and reached their highest level after Lehmann Brothers' collapse in September 2008.

Oil conditional variance series displays clear outliers (observations that are unlikely to follow the imposed model) during the second half of 2008. During that period, the credit crunch slipped the world economy into the deepest recession since

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Figure 3

Full Sample Wine and Oil Conditional Variance

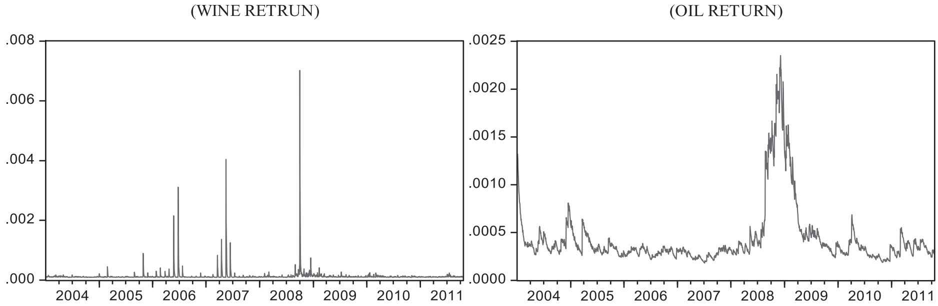
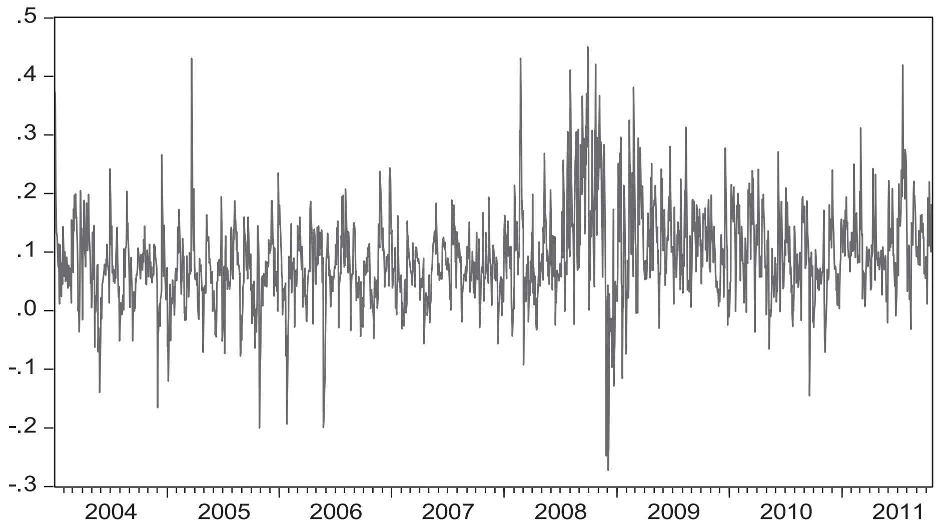


Figure 4

Full Sample Conditional Correlation Between Wine and Oil Prices



the Great Depression, provoking a collapse in global economic activity. As a result, global demand for energy suddenly fell and crude oil prices plunged more than 75% from its peak level.

The conditional variance series for fine wines includes three major sets of outliers (in 2006, 2007, and 2008), indicating a high degree of volatility. In the second half of 2008, a negative shock in the wine market produced the uppermost outlier in the conditional variance. Negative economic and financial effects resulting from the 2008 financial crisis gathered pace, prompting a 47% drop in the price of fine wines.

Furthermore, the conditional correlations shown in Figure 4 switch from negative to positive signs quite frequently. This suggests a weak relationship between shocks

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Table 8
Estimations Outputs of MTGARCH Model with Crisis Dummy

	Full Sample (2004–2011)		*Subsample (2008–2011)*	
	wine (i=*1*)	*oil* (i=*2*)	*wine* (i=*1*)	*Oil* (i=*2*)
s_{i1}	0.021	0.032	0.030	0.052*
	[0.016]	[0.025]	[0.021]	[0.031]
s_{i2}	0.025	0.036	0.023	0.063*
	[0.016]	[0.021]	[0.014]	[0.035]

Note: Only the coefficients s_{ij} of the dummies matrix S_t are reported; However, all variables of the MTGARCH conditional variance in Equation (10) are included in the estimations; * statistical significance at 1%; standard errors are reported in brackets.

in the wine and oil markets, increasing the possibility of portfolio diversification. Nevertheless, this correlation increased during the financial crisis of 2008, indicating a possible transmission of volatility between the two commodities and limiting the crucial benefits of portfolio diversification during periods of high volatility.

E. Sensitivity Analysis

The conditional variance series for both oil and wine display at least one common set of outliers from July 2008 to February 2009, which is associated with the financial crisis. This set of outliers is clearly visible in the conditional variance series and the original price and return series (see Figures 1 and 2). When the data is outlier contaminated, a few anomalous observations could affect the estimation and may produce upward-biased measurements of dependence between markets (Forbes and Rigobon, 2002). Thus, some sensitivity analysis in this regard is needed.

Initially, to measure the impact of the financial crisis on our results, we incorporate a crisis dummy into the original MTGARCH conditional variance equation (6), and we rerun the following model:

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon'_{t-1})A + G'H_{t-1}G + D'(\varepsilon_{t-1}d_{t-1})D + S\ crisis\ dummy \qquad (10)$$

where S is a matrix with 2×2 dummy elements $s_{ij.}$

The crisis dummy is a dichotomous variable that equals 1 for the period from July 2008 to February 2009 and 0 otherwise. Table 8 reports the estimated coefficients of the financial crisis dummy interactions with the conditional variances of wine and oil prices. For the full sample, the insignificant coefficients s_{ij} confirm that, on both markets, our main results from Table 7 are insensitive to the financial crisis. In contrast, in the subsamples, the financial crisis has a limited impact on the conditional variance estimates.

Second, we examine the impact of period definition modifications on our results. Following the method of Tai (2007), we regress both conditional variances and

Table 9
Impact of Outliers on Conditional Variances and Correlations

Panel A: Conditional Variance

	f_0	f_1	f_2
Wine	0.000*	0.000*	−0.000
	(16.516)	(50.930)	(–1.318)
Oil	0.000*	0.001*	−0.000
	(56.930)	(75.125)	(–0.052)

Panel B: Conditional Correlation

	f_0	f_1	f_2
Wine oil	0.009*	0.008*	0.000
	(14.502)	(7.021)	(1.083)

Notes: * statistical significance at 1% level; robust *T*-statistics are reported in parentheses.

correlation on crisis and post-crisis dummies. Thus, we run the following two regressions for wine and oil markets:

$$Conditional\ Variance_{j,t} = f_0 + f_1\ crisis\ dummy_t + f_2\ post\ crisis\ dummy_t + u_{j,t} \quad (11)$$

$$Conditional\ Correlation_t = f_0 + f_1\ crisis\ dummy_t + f_2\ post\ crisis\ dummy_t + v_t \quad (12)$$

where the crisis dummy is a dichotomous variable that equals 1 from July 2008 to February 2009 and 0 otherwise; the post-crisis is a dichotomous variable that equals 1 after February 2009 and 0 otherwise; u_t and v_t are assumed to be uncorrelated disturbances series.

In both regressions of the conditional variances reported in Panel A of Table 9, the estimated crisis dummy parameters (f_1) are statistically significant, suggesting a positive impact of the financial crisis on the conditional variance of wine and oil markets. Conversely, the slope coefficient for the post-crisis dummy variable (f_2) is negative but insignificant. Thus, conditional variance for both wine and oil did not increase after the crisis, compared to their pre-crisis level.

On the other hand, there is evidence of a positive financial crisis impact on the conditional correlation between the two markets. As shown in Panel B, the estimated crisis dummy parameter (f_1) is positive and statistically significant. However, this positive change in conditional correlation during the crisis did not extend into the post-crisis period as indicated by the insignificance of the dummy parameter (f_2).

Overall, the results of the sensitivity analyses reported in Tables 8 and 9 imply that higher conditional variance and correlation during the financial crisis of 2008 did not generally lead to higher interlinkage between wine and oil markets in the post-crisis period. Thus, the main results of this study are not entirely driven by the outliers caused by the crisis period.

V. Summary and Conclusions

This paper examines the source and magnitude of mean and volatility transmissions between fine wines and crude oil markets from the beginning of January 2004 to December.

With the two series being nonstationary processes that are integrated of order one, we apply the co-integration test to examine the long-run equilibrium relationship between oil and fine wines prices. However, co-integration is found to be insignificant. The univariate statistics of our data also imply that the series returns are nonnormally distributed, leptokurtic, and serially correlated. This result indicates that shocks generate volatility clustering and that the variance may be time dependent. In order to exploit the information provided by the residuals, we employ a MTGARCH model that captures the time-varying variances and correlations of returns.

First, using both the Granger causality and MTGARCH methods, we find a mean transmission from the oil to the wine market. This outcome is not a surprise given that oil is the world's most traded commodity. However, the information transmission from the oil market reduces the diversification benefits when both fine wines and crude oil are included in a portfolio. This finding is consistent with the conclusions in Cevik and Sedik (2011).

Second, own-lagged innovations are statistically significant in the two markets. We find ARCH effects across all samples.

Third, volatility persistence is high and affects the conditional variance in each series. However, own-volatility persistence is higher than cross-volatility persistence; this outcome indicates that volatility in every market will be more influenced by its own past conditional variance than by the effect of cross-shocks transmission from the other market.

Fourth, statistical evidence suggests that both markets display positive asymmetric information patterns that imply a stronger response to bad news.

Finally, during the financial crisis, wine and oil conditional volatilities rose, but then returned to their overall pre-crisis level. To some extent, conditional correlation demonstrates comparable movement.

Without addressing the causes of volatility, the findings of this study improve our understanding of the dynamic linkage between fine wine and crude oil markets. In forecasting the next period change in conditional variances, the inclusion of significant parameters of cross innovations will improve the accuracy of the forecast.

Such findings should be valuable to regulators, hedgers, and arbitrageurs in seeking to capture the transmission of volatility shocks across the two markets.

Further investigation into the analysis of third and fourth moments of return distribution is recommended.

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