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Conditional Correlations and Volatility Links Among Gold, Oil and Istanbul Stock Exchange Sector Returns

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ABSTRACT: The aim of this research is to expand the literature of market return volatility for the Istanbul Stock Exchange (ISE) sector indices by analyzing the conjoint impact of oil and gold returns and their volatilities. We use both aggregated and disaggregated data in our study which differentiates it from the others in scope. The analysis is conducted by a multivariate CCC M-GARCH model in order to get some multidimensional interactions in the return and volatility processes of the selected variables. We consider 28 different portfolio investments consisting equal investments in oil, gold and each sector index by turn. We observe that oil GARCH effects are significant and close to unity in each model, positioning oil prices as a major source of portfolio volatility. Gold GARCH effects follow oil GARCH parameters in magnitude, implying that gold prices also have significant effects on portfolio volatility. We report negative correlation coefficients between gold and three sector indices, namely, holding, main metals and commercial sectors.

Keywords: Financial Modeling; Risk Analysis and Management; M-GARCH; Stock Markets; Sector Returns
JEL Classifications: C32; G11

1. Introduction

Worldwide economic crises diverted the stock markets to excessive volatility and to turmoil especially in the last two decades. The heightened volatility of the stock markets, impose significant risk on the investors, who cannot enjoy the benefits of international diversification due to the contagion effect of the global interaction. The stock market hazards adversely affect financial markets and depress the banking sector, which in the end give rise to distress in the real economy. Thus a growing literature highlights the need of other financial assets as a protection instrument from stock market volatility. In the recent years, demand of gold has expanded, carrying it to a status of a hedge instrument or a safe haven.

According to Ibrahim (2011), the emerging interest in gold in times of crises, stems from its historical use as a medium of exchange and standard of value, with a stable purchasing power over time; thus he asserts that gold can provide a safe haven to investors or at least can be used to diversify portfolio risk, following the researches of Capie et al. (2006), Hillier et al. (2006) and Baur and Lucey (2010). Hillier et al. (2006) evidence the hedging property of precious metals (gold, platinum, silver) at times of abnormal stock market volatility. Baur and Lucey (2010) arrive at the same conclusion about gold investments after examining the returns of US, UK and German stock markets and bond markets. Smith (2002) tests the short-run and long-run relationship of gold prices and stock exchange returns adducing a weak negative relation between stock indices and gold prices in the short-run and no relation in the long-run. Contrarily, Wang et al. (2011) assert that except US, long-term equilibrium relationships exist among gold prices, oil prices, exchange rates and stock prices after examining the short-term and long-term interactions between gold price, exchange rate, oil price and stock market indices in US, Germany, Japan, Taiwan and China.

On the other hand, oil prices have predictive power on stock values through different channels. Firstly, oil prices affect the inflation rates and interest rates in an economy which are directly reflected in the discount rates in the stock pricing equation. Secondly, oil prices determine the cashflows to businesses since oil is a key input for most of the industries and an output for some others. Previous studies document mixed results for the impact of oil price shocks on different stock markets or even different industries in the same stock market (Malik and Ewing, 2009; Sadorsky, 1999; Filis et al., 2011; Arouri and Nguyen, 2010; Lee and Chiou, 2011).

The response of the stock markets to oil price shocks may also differ according to the origin of the shock; a demand-side shock (increase in oil prices), which results from global business fluctuations in the form of an economic expansion, will have a positive effect on stock prices, as suggested by Hamilton (1996), Kilian and Park (2009). A supply-side shock (increase in oil prices) is the result of either the output cutback decisions of OPEC countries or the political tensions such as the US invasion of Iraq. A supply-side shock will lead to a negative effect on stock market returns. Filis et al. (2011) notify three periods; the period 1990-1991, when the precautionary demand for crude oil created a negative correlation between oil prices and stock market returns; early 2000 to mid-2000 period, when the housing market and construction industry boomed as the result of decreasing interest rates worldwide that led to a positive correlation between oil prices and stock market indices, creating an aggregate demand-side oil price shock; and finally the period 2007-2008, when another aggregate demand-side oil price shock took place as the result of the rising demand mainly because of China, which positively affected the stock returns.

Volatility of asset prices is argued to be determined by the flow of information, thus it is assumed that there is a link between the volatility of oil prices and stock prices through the information flow among markets (Clark, 1973; Tauchen and Pitts, 1983; Ross, 1989). Hammoudeh et al. (2004) examine the effect of oil price volatility on the stock return volatility of the S&P oil stock indices, and find out that oil volatility has an echoing effect on the return volatility of the companies in oil exploration and production, with an opposite dampening effect on the stocks of oil and gas refining and marketing companies. Ewing and Thompson (2007) analyze the dynamic co-movements between oil prices and stock markets based on the cyclical components of oil prices and stock prices and come up with the result that crude oil prices are pro-cyclical and lag stock prices by six months.

Some studies claim that at the industry level, oil price shocks constitute a systematic asset pricing risk. Arouri and Nguyen (2010), analyze the impact of oil price volatility on sectoral returns in Europe, using a two-factor GARCH model and evidence sectoral differences in the direction and magnitude of the relationship. Hammoudeh et al. (2010), evidence that rise in oil prices increases the return volatility of the sectors that are intensive oil consumers, while the opposite is true for oil and related sectors by investigating the return volatilities of 27 different sectors in US. Elyasiani et al. (2011) investigate the effect of changes in oil return and oil return volatility on stock returns and stock return volatilities for thirteen industries in US economy and document a significant effect of oil future returns on sector returns in nine of the thirteen sectors. Lee and Chiou (2011), conclude that significant higher fluctuations in oil prices have negative impacts on S&P 500 stock returns, applying a univariate regime-switching GARCH model.Vo (2011), evidence a time-varying correlation between the stock and oil prices which increases with the volatility in the markets, along with a persistent pattern, conditioned on the past volatilities.

In this paper, we investigate the link between gold, oil and ISE (Istanbul Stock Exchange) sector returns in a portfolio context. We assume equal weights of investments in gold, oil and each of 28 sector indices by turn for different portfolio alternatives. We select the sectors from the sub-index classifications of ISE. We analyze the return and volatility relationships simultaneously using an M-GARCH (Multivariate GARCH) model to evaluate constant conditional correlation. The time span of this paper covers the period between September 2002 and July 2012, a highly volatile interval for the world economy, stressed by the 2008 sub-prime mortgage crisis and Euro zone economic crisis. This paper differs from the others in the sense that there is no such an extensive study relating to the conditional correlations among sector returns of ISE, global oil market and gold prices in Turkey. Turkey has imported 1734 tons of gold in the ten year period between 2002 and 2012 and it ranks as the 13th among the countries holding the highest gold reserves in the world[1]. Turkey as an emerging market follows China, Russia and India who hold the 6th, 8th and 11th ranks according to the World Gold Council reports updated in June, 2013. Furthermore, Turkey imports more than 80% of its total crude oil demand annually, which constitutes about 10% of the total imports in US dollars. Between 2002 and 2012, the ratio of net oil imports to foreign trade deficit surge about 25% with peaks at 33% in 2002 and 2009. In this regard, Turkish economy is substantially compelled by the price fluctuations of both oil and gold. As a matter of fact, exploring the association between sector returns and gold and oil prices may enhance investors with a deeper understanding of more effective risk management and hedging strategies.

The empirical results of our research show that oil prices, gold prices and ISE sector returns posit some significant relations. We figure out oil as the most persistent variable in volatility modeling for ISE sectors and gold follows oil in determining the portfolio volatility. The remainder of this paper is organized as follows: Part II describes the data set and explains the methodology; Part III presents the empirical results and discusses the findings; Part IV concludes the paper.

2. Data and Methodology

The data set covers a period from September 2002 to July 2012 using daily intervals of a 5 day week. We study the time series of gold, oil and the ISE sector index returns. The sector index closing price time series are obtained from the ISE database. We use the data for 28 sector indices namely, Banking (XBANK), Electricity (XELKT), Leasing-Factoring (XFINK), Food and Beverages (XGIDA), Real Estate Investment Trusts (XGMYO), Holding (XHOLD), Wood- Paper-Printing (XKAGT), Chemical-Petroleum-Plastic (XKMYA), Basic Metal (XMANA), Metal Products-Machinery (XMESY), Wholesale and Retail Trade (XTCRT), Textile- Leather (XTEKS), Tourism (XTRZM), ISE 100 (XU100), ISE 50 (XU50), ISE 30 (XU30), Information Technologies (XBLSM), Services (XUHIZ), Transportation (XULAS), Industrials (XUSIN), Technology (XUTEK), Insurance (XSGRT), National Whole (XUTUM), Defence (XSVM), Sports (XSPOR), Cement (XTAST), Investment Trusts (XYORT), Communication (XILTM). XU100, XU50 and XU30 are composite indices constructed by the 100, 50 and 30 stocks with the highest trading volumes respectively. Daily free market closing gold prices (TRY/gr) are used in the analysis. As crude oil prices, daily European Brent spot FOB closing prices (USD/Barrel) are obtained from U.S. Energy Information Administration. The gold price per gram is denominated in Turkish Lira and crude oil barrel price is given in US Dollar. Oil prices are converted to Turkish Lira using the daily exchange rate provided by the Turkish Central Bank. Foreign exchange currency rate is indicative USD/TRY selling rates announced by The Central Bank of the Republic of Turkey at 15:30 each day. The variables are expressed in logarithmic returns.

The descriptive statistics for each time series are given in Table 1. We test the stationarity of the series by ADF unit root test. The results are given in Table 2. In the reported statistics, gold shows a higher kurtosis than oil indicating a higher degree of peakedness. Standard deviations of gold and oil are 0.0114 and 0.0258 respectively. The Jarque-Bera (JB) test tells us that normality assumption is not valid for our data. All variable series exceed the critical values of the JB tests which asymptotically follow the Chi-square distribution. These results are supported by the QQ-Plots presented in Figure 1. The plots demonstrate the leptokurtotic behavior of the series in the form of outliers from the diagonal line. Thus, to cope with this typical pattern of financial time series, we prefer utilizing a student's *t*-distribution in our econometric model.

The uprising mortgage crises in 2008 gives reason for fluctuations in gold and oil returns for the period. Figure 2 shows the gold, oil and ISE 100 index log-returns. The increased volatile behavior is observable after May 2007 and prior to June 2008 in all variables.

[1] Istanbul Gold Exchange Database.

Table 1. Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
gold	0.0004	0.0000	0.0819	-0.0926	0.0114	-0.0489	11.2628
oil	0.0004	0.0003	0.1641	-0.1678	0.0258	-0.0945	7.7553
xbank	0.0010	0.0012	0.1559	-0.1452	0.0244	-0.0705	6.3242
xblsm	0.0005	0.0019	0.2936	-0.1228	0.0214	0.4116	22.2971
xelkt	0.0002	0.0000	0.1231	-0.1737	0.0230	-0.2742	8.4743
xfink	0.0007	0.0004	0.1411	-0.1360	0.0246	0.0980	8.0758
xgida	0.0010	0.0010	0.1015	-0.1224	0.0198	-0.3903	7.2881
xgmyo	0.0005	0.0022	0.0849	-0.1223	0.0195	-0.9561	8.0671
xhold	0.0006	0.0020	0.1344	-0.1227	0.0199	-0.5536	7.6115
xiltm	0.0007	0.0000	0.1189	-0.1493	0.0242	-0.0913	6.2138
xkagt	0.0005	0.0008	0.1965	-0.1301	0.0205	-0.1282	9.6772
xkmya	0.0007	0.0009	0.1205	-0.1094	0.0192	-0.3579	6.8371
xmana	0.0006	0.0010	0.1140	-0.1380	0.0194	-0.4250	7.6297
xsgrt	0.0009	0.0011	0.2321	-0.1296	0.0241	0.0107	9.3290
xspor	0.0006	0.0004	0.1517	-0.2035	0.0217	-0.6452	16.0679
xsvm	0.0007	0.0000	0.1793	-0.2468	0.0296	0.0873	10.5119
xtast	0.0006	0.0013	0.0906	-0.1032	0.0151	-0.7205	8.0335
xtcrt	0.0011	0.0010	0.2405	-0.1298	0.0191	0.6955	19.9403
xteks	0.0004	0.0015	0.0900	-0.1461	0.0174	-1.2904	11.2826
xtrzm	0.0005	0.0000	0.1950	-0.1407	0.0262	0.0919	8.3112
xu030	0.0008	0.0011	0.1273	-0.1359	0.0207	-0.1312	6.6632
xu050	0.0008	0.0012	0.1218	-0.1337	0.0199	-0.1971	6.8567
xu100	0.0008	0.0014	0.1213	-0.1335	0.0194	-0.2535	7.1361
xuhiz	0.0008	0.0011	0.0999	-0.1151	0.0166	-0.1504	7.1391
xulas	0.0007	0.0006	0.1191	-0.1217	0.0227	0.0027	6.1340
xulus	-0.0001	0.0008	0.0474	-0.0756	0.0152	-0.9017	6.0372
xusin	0.0007	0.0017	0.1051	-0.1220	0.0163	-0.6642	8.8545
xutek	0.0006	0.0012	0.3034	-0.1616	0.0213	0.7257	26.2496
xutum	0.0008	0.0015	0.1165	-0.1305	0.0187	-0.3177	7.4252
xyort	0.0006	0.0008	0.1392	-0.1191	0.0188	-0.3103	9.8573

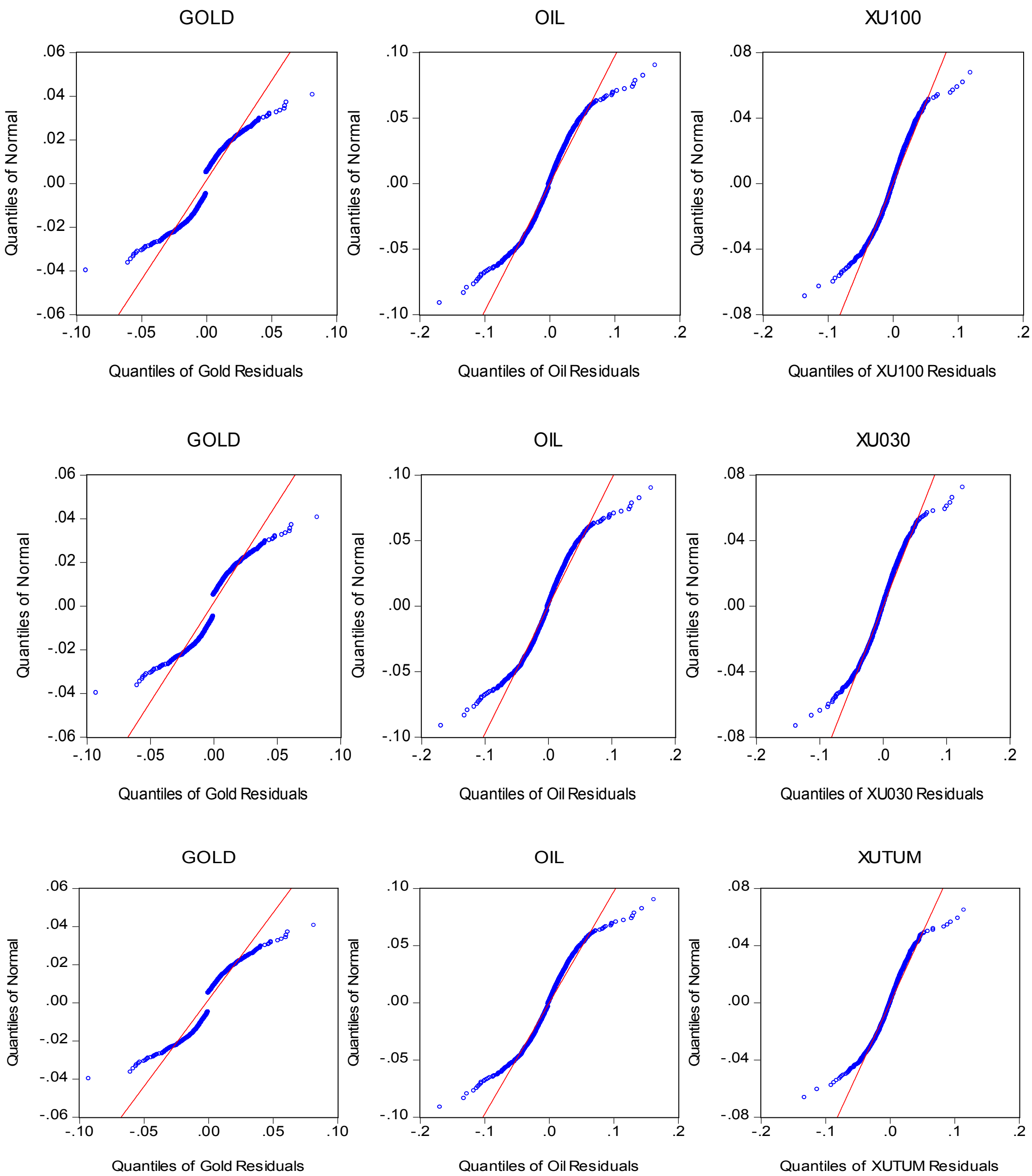
Note: OIL refers to European Brent Spot FOB oil, GOLD to Free Market Closing Gold Prices (TRY/gr) and official abbreviations taken from ISE database. The number of observations is 2334 for gold and 2264 for all other variables.

Table 2. Summary Statistics

	Jarque-Bera	Probability	Sum	Sum Eq.Dev	ADF	Probability
gold	6640.5300	0.0000	0.9278	0.3021	-49.3027	0.0001
oil	2137.5000	0.0000	1.0149	1.5085	-50.2498	0.0001
xbank	1044.2820	0.0000	2.2101	1.3494	-46.9704	0.0001
xblsm	35191.5200	0.0000	1.0250	1.0330	-41.6041	0.0000
xelkt	2855.3540	0.0000	0.3577	1.1996	-44.3218	0.0001
xfink	2433.9990	0.0000	1.6055	1.3711	-43.7329	0.0000
xgida	1792.0450	0.0000	2.2225	0.8882	-36.2509	0.0000
xgmyo	2766.9980	0.0000	1.2247	0.8575	-39.9166	0.0000
xhold	2121.6830	0.0000	1.3891	0.8973	-38.6589	0.0000
xiltm	977.4704	0.0000	1.6182	1.3203	-48.0842	0.0001
xkagt	4212.0340	0.0000	1.2418	0.9500	-45.4504	0.0001
xkmya	1437.2270	0.0000	1.4911	0.8335	-45.6407	0.0001
xmana	2090.1560	0.0000	1.3734	0.8522	-44.4607	0.0001
xsgrt	3778.6680	0.0000	2.0157	1.3153	-44.1164	0.0001
xspor	14067.7300	0.0000	1.2074	0.9175	-37.4405	0.0000
xsvm	4711.9240	0.0000	1.4972	1.7499	-43.4204	0.0000
xtast	2585.8770	0.0000	1.4425	0.5150	-44.1035	0.0001
xtcrt	27253.6600	0.0000	2.4343	0.8292	-47.9713	0.0001

xteks	7099.7270	0.0000	0.9505	0.6873	-45.4545	0.0001
xtrzm	2664.1980	0.0000	1.2034	1.5546	-45.4924	0.0001
xu030	1272.3500	0.0000	1.7931	0.9726	-46.9205	0.0001
xu050	1417.8130	0.0000	1.8064	0.8930	-46.7367	0.0001
xu100	1638.0140	0.0000	1.8120	0.8531	-46.6301	0.0001
xuhiz	1624.6630	0.0000	1.8359	0.6199	-47.8676	0.0001
xulas	926.5145	0.0000	1.6680	1.1699	-44.1466	0.0001
xulus	135.1673	0.0000	-0.0383	0.0598	-15.3329	0.0000
xusin	3399.8180	0.0000	1.6954	0.6028	-44.8776	0.0001
xutek	51189.9000	0.0000	1.2772	1.0226	-45.8753	0.0001
xutum	1885.3280	0.0000	1.8348	0.7880	-46.5850	0.0001
xyort	4472.1070	0.0000	1.3444	0.8018	-45.4564	0.0001

Figure 1. Normal Q-Q plots of the standardized residuals for the CCC (1, 1) MGARCH with the XU100 (first row), XU030 (second row) and XUTUM (third row) variables



Note: Normal Q–Q plots stands for the quantiles of the standardized residuals plotted against the quantities of the normal distribution.

The illustrated dynamics in the models are assumed to be stable over time. We use the CCC as the main model[2]. We compute the log return as variables which have filtered out excessive behavior of the data[3]. The conditional variance-covariance matrix H_t can be specified as :

$$H_t = D_t P D_t \tag{1}$$

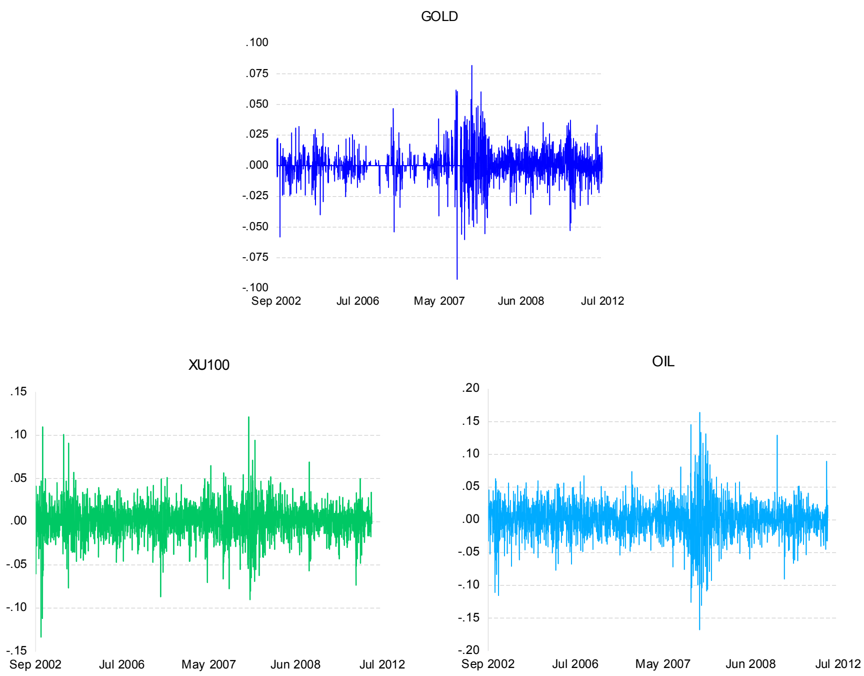
where $D_t = \operatorname{diag}(\sqrt{h_{1t}},\dots,\sqrt{h_{3t}})$, $P = \lfloor \rho_{ij} \rfloor$, with $\rho_{ij} = 1,\ i = 1,\dots,N$.

Off-diagonal elements of the conditional covariance matrix are given as:

$$H_t = \sqrt{h_{it}}\sqrt{h_{jt}}\,\rho_{ij},\ i \neq j \tag{2}$$

where $1 \leq i,\ j \leq N$.

Figure 2. Returns of Gold, Oil, and ISE subindex (IMKB) prices.



Estimated parameters of the CCC-ARCH (Constant Correlation Coefficient) model are given as:

$$y_t = \begin{pmatrix} y_{Gold,t} \\ y_{Oil,t} \\ y_{IMKB,t} \end{pmatrix} = \begin{pmatrix} \beta_{0,1} \\ \beta_{0,2} \\ \beta_{0,3} \end{pmatrix} + \varepsilon_t \tag{3}$$

[2] For the presented MGARCH models we choose AR(1)-CCC (1,1) MGARCH specifications, which are based on well-known tests such as sample cross correlations and Portmanteau tests; for overall goodness of fit we apply the Akaike Information Criterion and the Schwarz Information Criterion.

[3] See the descriptive statistics table. The normality condition is estimated on a high significance level.

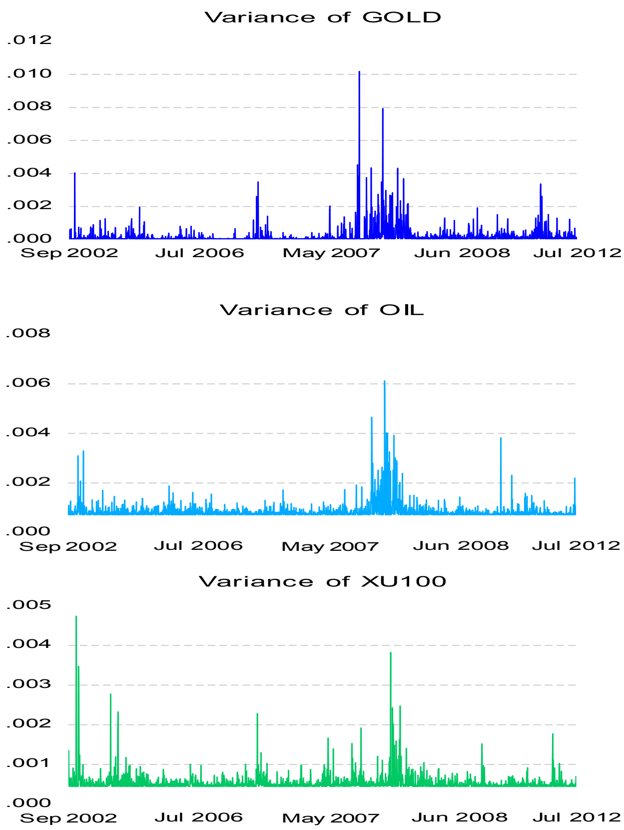
$$(H_t) = \begin{pmatrix} \sigma_{1,t}^2 \\ \sigma_{1,2,t} \\ \sigma_{1,3,t} \\ \sigma_{2,t}^2 \\ \sigma_{2,3,t} \\ \sigma_{3,t}^2 \end{pmatrix} = \begin{pmatrix} a_{1,0} + \alpha_{1,1}\varepsilon_{1,t-1}^2 + \gamma_{1,1}d_{1,t-1}\varepsilon_{1,t-1}^2 + b_{1,1}\sigma_{1,t-1}^2 \\ c_{1,2}\sigma_{1,t}\sigma_{2,t} \\ c_{1,3}\sigma_{1,t}\sigma_{3,t} \\ a_{2,0} + \alpha_{2,1}\varepsilon_{2,t-1}^2 + \gamma_{2,1}d_{2,t-1}\varepsilon_{2,t-1}^2 + b_{2,1}\sigma_{2,t-1}^2 \\ c_{2,3}\sigma_{2,t}\sigma_{3,t} \\ a_{3,0} + \alpha_{3,1}\varepsilon_{3,t-1}^2 + \gamma_{3,1}d_{3,t-1}\varepsilon_{3,t-1}^2 + b_{3,1}\sigma_{3,t-1}^2 \end{pmatrix} \quad (4)$$

The parameter $d(t)$ denotes the variable for diagonal correlation coefficient. Bollerslev (1986) proposes the constant conditional correlations (CCC) model where time-varying covariances are proportional to the conditional standard deviation. In the CCC model the conditional covariance matrix H_t consists of two components that are estimated separately: sample correlations $\rho_{i,j}$ and the diagonal matrix of time-varying volatilities D_t. Then, the covariance estimation is given by the volatility of each asset $\sigma_{i,t}$ follows a GARCH process or any of the univariate models. This model guarantees the positive definiteness of H_t if$\rho_{i,j}$ is positive definite. The CCC is a very simple model and easy to implement. Since matrix D_t has only diagonal elements, we can estimate each volatility separately.

Multivariate GARCH model is estimated by Maximum Likelihood estimator, conditional log-likelihood function (figure 3):

$$\hat{\theta} = \underset{\theta}{max} -\frac{1}{2}\sum_{t=1}^{T}\left(log\,|H_t| + |(\varepsilon_{1t},\varepsilon_{2t},\varepsilon_{3t})' H_t^{-1}(\varepsilon_{1t},\varepsilon_{2t},\varepsilon_{3t})|\right) \quad (5)$$

Figure 3. Time-Varying Variance Estimated from CCC(1,1) MGARCH for the Gold, Oil and Stock Exchange Index Variables



3. Findings

We assume equally-weighted portfolios consisting, gold, oil and each sub-index investment by turn in our models; as an example we construct a portfolio which consists one-third investment in gold, one-third investment in oil and one-third investment in banking sector index. On the total there are 28 different portfolios built by incorporating each sector index by turn along with gold and oil investments. The estimated GARCH models assume a constant correlation coefficient. Table 3 displays that GARCH (β) parameters are significant in all three GARCH equations for each sector index portfolio model examined.

Table 3. Multivariate GARCH results

				Gold		*Oil*		*Index*	
	return gold	return oil	return index	arch1(α_1)	garch 1(β_1)	arch2(α_2)	garch 2(β_2)	arch3(α_3)	garch 3(β_3)
xu100	0.0000	0.0010**	0.0016*	0.1618*	0.8486*	0.0584*	0.9322*	0.1104*	0.8663*
p-value	(0.8889)	(0.0115)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xu050	0.0000	0.0010**	0.0016*	0.1616*	0.8486*	0.0583*	0.9322*	0.1025*	0.8764*
p-value	(0.8270)	(0.0115)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xu030	0.0000	0.0010**	0.0015*	0.1624*	0.8481*	0.0584*	0.9322*	0.0986*	0.8806*
p-value	(0.8905)	0.0116	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xbank	0.0000	0.0016*	0.0014*	0.1759*	0.8334*	0.0579*	0.9315*	0.0901*	0.8871*
p-value	(0.9441)	(0.0001)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xblsm	0.0000	0.0010**	0.0018*	0.1933*	0.8361*	0.0829*	0.9257*	0.2499*	0.6833*
p-value	(0.9528)	(0.0138)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xelkt	0.0000	0.0009**	0.0004	0.2178*	0.8018*	0.0604*	0.9295*	0.2164*	0.7321*
p-value	(0.9692)	(0.0219)	(0.2920)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xfink	0.0000	0.0009**	0.0010*	0.1470*	0.8569*	0.0591*	0.9365*	0.3339*	0.6128*
p-value	(0.8728)	(0.0328)	(0.0040)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xgida	0.0000	0.0009**	0.0015*	0.1671*	0.8449*	0.0624*	0.9286*	0.1350*	0.8170*
p-value	(0.9099)	(0.0222)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xgmyo	0.0000	0.0010*	0.0019*	0.1850*	0.8288*	0.0712*	0.9248*	0.2515	0.7044
p-value	(0.0986)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1357)	(0.5441)
xhold	0.0000	0.0010**	0.0018*	0.1674*	0.8424*	0.0668*	0.9269*	0.1667*	0.8024*
p-value	(0.9162)	(0.0152)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xiltm	0.0000	0.0011***	0.0007***	0.1610*	0.8507*	0.0604*	0.9318*	0.0438*	0.9591*
p-value	(0.8771)	(0.0065)	(0.0666)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xkagt	0.0000	0.0011**	0.0013*	0.1692*	0.8404*	0.0626*	0.9325*	0.2454*	0.6613*
p-value	(0.9224)	(0.0046)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xkmya	0.0000	0.0011*	0.0015*	0.1669*	0.8393*	0.0614*	0.9286*	0.1215*	0.8547*
p-value	(0.9090)	(0.0096)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xmana	0.0000	0.0010**	0.0014*	0.1613*	0.8484*	0.0626*	0.9288*	0.1819*	0.7926*
p-value	(0.8825)	(0.0194)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xsgrt	0.0000	0.0009**	0.0016*	0.1674*	0.8417*	0.0578*	0.9322*	0.1419*	0.8272*
p-value	(0.8264)	(0.0230)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xspor	0.0000	0.0008***	0.0007**	0.1801*	0.8323*	0.0724*	0.9289*	0.4067*	0.6340*
p-value	(0.9271)	(0.0523)	(0.0123)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xsvnm	0.0000	0.0013**	0.0005	0.1712*	0.8302*	0.0634*	0.9324*	0.1823*	0.8116*
p-value	(0.9346)	(0.0029)	(0.2370)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xtast	0.0000	0.0009**	0.0014*	0.1614*	0.8399*	0.0585*	0.9321*	0.2846*	0.6510*
p-value	(0.9016)	(0.0322)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xtcrt	0.0000	0.0010*	0.0014*	0.1731*	0.8449*	0.0723*	0.9240*	0.2187*	0.6360*
p-value	(0.8919)	(0.0150)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

xteks	0.0000	0.0010**	0.0017*	0.1806*	0.8310*	0.0602*	0.9315*	0.1836*	0.7528*
p-value	(0.9249)	(0.0194)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xtrzm	0.0000	0.0013*	0.0003	0.1803*	0.8299*	0.0598*	0.9338*	0.1718*	0.8210*
p-value	(0.9059)	(0.0010)	(0.5158)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xuhiz	0.0000	0.0011*	0.0014*	0.1730*	0.8344*	0.0598*	0.9300*	0.1023*	0.8748*
p-value	(0.9204)	(0.0059)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

				Gold		*Oil*		*Index*	
	return gold	return oil	return index	arch1(α1)	garch 1(β1)	arch2(α2)	garch 2(β2)	arch3(α3)	garch 3(β3)
xulas	0.0000	0.0009**	0.0011*	0.1490*	0.8546*	0.0611*	0.9305*	0.1009*	0.8690*
p-value	(0.8308)	(0.0265)	(0.0047)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xulus	0.0003	-0.0004	-0.0003	0.1013**	0.8657*	0.0222	0.9172*	0.1605*	0.7268*
p-value	(0.7421)	(0.7681)	(0.7850)	(0.0462)	(0.0000)	(0.3347)	(0.0000)	(0.0066)	(0.0000)
xusin	0.0000	0.0007***	0.0018*	0.1672*	0.8390*	0.0599*	0.9301*	0.1518*	0.8228*
p-value	(0.8890)	(0.0973)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xutek	0.0000	0.0011*	0.0013*	0.1812*	0.8332*	0.0678*	0.9296*	0.1932*	0.7687*
p-value	(0.9259)	(0.0085)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xutum	0.0000	0.0010**	0.0018*	0.1733*	0.8333*	0.0578*	0.9316*	0.1189*	0.8561*
p-value	(0.9238)	(0.0143)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
xyort	0.0000	0.0010**	0.0010*	0.1627*	0.8509*	0.0634*	0.9325*	0.1744*	0.8045*
p-value	(0.8667)	(0.0124)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: The results are obtained from the CCC(1,3) M-GARCH model described in Part 3. * denotes significance at 1%, ** denotes significance at 5% and *** denotes significance at 10% respectively.

The sum of α and β coefficients are close to unity, indicating high degree of volatility persistence in the time series. The M-GARCH model assumes a diagonal matrix of time-varying volatilities. Since the conditional co-variance matrix consists of two components that are estimated separately; we observe different parameters for returns and GARCH coefficients for each sector index model. We document positive and significant return coefficients for oil in each portfolio alternative except for the national whole sector index. The return coefficients for sector indices are positive and significant for all the models except the tourism, electricity and national whole portfolios. However, the corresponding return coefficients for gold are insignificant in all the models. In our conditional correlation matrices, we figure out significant results between gold and sector returns in three models. The correlation coefficients between gold and holding, basic metal and commercial indices are all negative and they are listed on Table 4[4].

Table 4. Multivariate GARCH Correlation Coefficients

	Correlation(Gold, Sub-index)
xhold	-0.0472***
p-value	(0.0892)
xmana	-0.0468***
p-value	(0.1006)
xtcrt	-0.0545***
p-value	(0.0581)

Note: The results are obtained from the CCC(1,1) M-GARCH model described in Part 3. *** denotes significance at 10%.

We rank the return coefficients of oil for each portfolio alternative on Table 5. The highest return coefficient for oil is in the banking index portfolio, followed by the tourism and then the defense index portfolios. The oil return coefficients are all positive and this finding can be explained by an attribution to demand side shocks in oil prices. In case of a demand side shock, the rise in oil prices are viewed as an increase in global economic activity promoting economic growth in general. Economic growth boosts corporate earnings and stock prices.

[4] For the sake of brevity, the correlation coefficients for the other models are not listed here, but they are available upon request.

Table 5. Ranking of Oil Return Coefficients from M-GARCH Model

	return oil	garch 2
xbank	0.0016	0.9315
xtrzm	0.0013	0.9337
xsvnm	0.0012	0.9323
xkagt	0.0011	0.9325
xuhiz	0.0011	0.9299
xiltm	0.0011	0.9317
xkmya	0.0010	0.9286
xutex	0.0010	0.9295
xu100	0.0010	0.9322
xu050	0.0010	0.9322

Note: The results are obtained from the CCC(1,1) M-GARCH model described in Part 3.

We list the ranking of the GARCH coefficients for the models on Table 6. Oil GARCH effects are higher than both the sector and gold GARCH effects in all of our portfolios. The highest oil GARCH coefficient is 0.9364 for the leasing index portfolio, while the lowest GARCH coefficient is 0.9171 for the national whole index portfolio. The oil GARCH effects are very similar in magnitude for all of our portfolio alternatives, which minimizes the role of diversification in portfolio investments as the oil price volatility dominates the return volatility of all the sector indices under investigation. Gold GARCH effects are significant in all of our portfolio alternatives with the highest GARCH coefficient of 0.865712 for the national market index and the lowest GARCH coefficient of 0.801756 for the electricity index portfolio. The gold GARCH effects exhibit minor differences in our portfolios, indicating that gold is another strong strong element of the portfolio in determining the volatility of the returns. Only in 9 of our equally weighted portfolios, constructed namely by, XU100, XU50, XU30, banks, communications, chemical-petroleum-plastic, services, transportation and national whole indices, the sector GARCH coefficients are higher than the gold GARCH parameters.

Table 6. Ranking of GARCH Coefficients from M-GARCH Model

Gold		Oil		Sector	
xulus	0.8657	xfink	0.9365	xiltm	0.9591
xfink	0.8569	xtrzm	0.9338	xbank	0.8871
xulas	0.8546	xyort	0.9325	xu030	0.8806
xyort	0.8509	xkagt	0.9325	xu050	0.8764
xiltm	0.8507	xsvnm	0.9324	xuhiz	0.8748
xu050	0.8486	xu030	0.9322	xulas	0.8690
xu100	0.8486	xu100	0.9322	xu100	0.8663
xmana	0.8484	xu050	0.9322	xutux	0.8561
xu030	0.8480	xsgrt	0.9322	xkmya	0.8547
xtcrt	0.8449	xtast	0.9321	xsgrt	0.8272

Note: The results are obtained from the CCC(1,1) M-GARCH model described in Part 3.

The ranking of the return coefficients for the sector indices are listed on Table 7. The highest return coefficient is for the real estate investment trusts, followed by the industrials and holding indices. However, when we check the sector GARCH coefficients we observe that the highest coefficients are for the communication index portfolio, followed by the banking and national 30 index portfolios. The communication and the banking sector indices exhibit a high degree of market concentration while the national 30 index is composed of the 30 stocks with the highest trading volumes. The return volatilities of these portfolios are highly affected by the sectors' own volatilities.

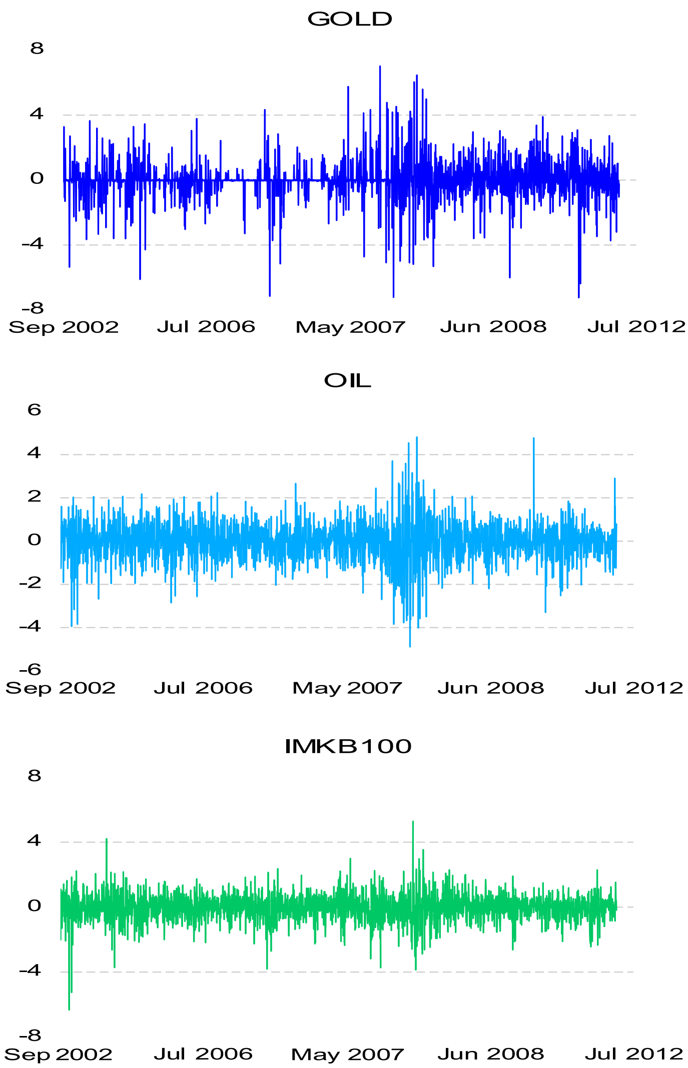
Table 7. Ranking of Index Return Coefficients from M-GARCH Model

	return index	garch 3
xgmyo	0.0019	0.7044
xusin	0.0018	0.8228
xhold	0.0018	0.8024
xutum	0.0018	0.8561
xblsm	0.0018	0.6833
xteks	0.0017	0.7528
xu100	0.0016	0.8663
xsgrt	0.0016	0.8272
xu050	0.0016	0.8764
xgida	0.0015	0.8170

Note: The results are obtained from the CCC(1,1) M-GARCH model described in Part 3.

Figure 4 indicates that the standardized residuals exhibit white noise properties after the modeling. This gives us an insight that CCC (1,1) model is adequate to capture the volatility dynamics of the examined series.

Figure 4. Residuals of square root of correlations



4. Conclusion

In this study, we employ both aggregated and disaggregated data to investigate the effects of oil and gold prices on Istanbul Stock Exchange sector indices. We use 27 industry-level return series along with ISE 100 index and construct equally weighted portfolios of oil, gold and each sector index by turn. We apply a CCC-MGARCH analysis and figure out oil with significantly high GARCH coefficients very close to unity, which are greater than both the sector and gold GARCH effects in all of our portfolios, positioning oil prices as a source of substantial volatility for the portfolios investigated.

In our conditional correlation matrices, we figure out significant results between gold and sector returns in three models. The correlation coefficients between gold and holding, basic metal and commercial indices are all negative. Hence, gold as an investment asset can be used for diversification against the aforementioned three indices. Gold GARCH effects are significant in all of our portfolio alternatives and they exhibit minor differences in our portfolios, implying that gold is an important element of the portfolio in determining the volatility of the portfolio returns. Only in 9 of our equally weighted portfolios, constructed namely by, XU100, XU50, XU30, banks, communications, chemical-petroleum-plastic, services, transportation and national whole indices, the sector GARCH coefficients are higher than the gold GARCH parameters. Thus the own past volatilities of these nine indices have a more pronounced effect on determining the portfolio volatility. Our results are indicative for financial market participants investing in Turkey and portfolio managers regarding risk management and hedging strategies.

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