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Volatility transmission between oil prices and equity sector returns

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ABSTRACT

This paper employs bivariate GARCH models to simultaneously estimate the mean and conditional variance between five different US sector indexes and oil prices. Since many different financial assets are traded based on these market sector returns, it is important for financial market participants to understand the volatility transmission mechanism over time and across these series in order to make optimal portfolio allocation decisions. We examine weekly returns from January 1, 1992 to April 30, 2008 and find evidence of significant transmission of shocks and volatility between oil prices and some of the examined market sectors. The findings support the idea of cross-market hedging and sharing of common information by investors.

1. Introduction

Changes in the price of oil and its volatility may have significant effects on the economy and the financial markets. Financial market participants need to know how shocks and volatility are transmitted across markets over time. A number of important papers have examined the volatility transmission mechanism across different markets (e.g., Hamao et al., 1990; King and Wadhwani, 1990; Engle and Susmel, 1993; King et al., 1994; Lin et al., 1994; Karolyi, 1995). However, these studies tend to focus on some specific financial market(s) and, to date, no study has examined the volatility transmission mechanism between oil prices and major sector returns.

There are generally two main lines of research in the context of transmission of shocks among financial time series and analysis of volatility or variance. Cointegration analysis is often adopted to study the co-movements between different financial markets over a long period of time. Kasa (1992) was among the first to use this approach to investigate the transmission of shocks among international stock prices and stock returns. The second line of research examines the time path of volatility in financial variables such as stock prices and stock returns. Researchers have commonly used variations of a class of models known as autoregressive conditional heteroscedasticity, or ARCH, to estimate time variant conditional variances. In recent years research has focused more on the persistence and transmission of volatility from one market to another. This paper combines elements of these two lines of research by examining the volatility and shock transmission mechanism between oil prices and five major US sector indexes. Specifically, we focus on the relationship between oil and the financial, industrial, consumer, health, and technology sectors.

In order to examine the relationship between oil and each of these major sectors, we use the bivariate GARCH model. This methodology allows us to simultaneously estimate the mean and conditional variance of returns to oil and each market sector. Our models are estimated using weekly return data from January 1, 1992 to April 30, 2008 and provide evidence of significant volatility transmission between the oil market and some of the examined sectors. Our results are important for building accurate asset pricing models, forecasting volatility in sector returns, and further our understanding of the equity markets. Additionally, since many financial assets are traded based on these sector indexes, it is important for financial market participants to understand the volatility transmission mechanism over time and across these series in order to make optimal portfolio allocation decisions.

2. Literature review

There is a body of literature on how different markets and sectors interact over time. Ewing (2002) used the *generalized* forecast error variance decomposition technique within a vector auto-regression (VAR) framework to analyze the interrelationship among five major sectors, i.e., capital goods, financials, industrials, transportation and utilities. Using monthly data from S&P stock indexes from January 1988 to July 1997, he found that unanticipated 'news' or shocks in one sector had significant impacts on other sector returns. Ewing et al.

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(2003) studied the effects of macroeconomic shocks on five major S&P sector specific stock market indexes for the post-1987 crash period. Using *generalized* impulse response analysis, they showed that individual asset prices were influenced more by unanticipated macroeconomic events than by predictable events. Hassan and Malik (2007) used a multivariate GARCH model to simultaneously estimate the mean and conditional variance among different US sector indexes and found significant transmission of shocks and volatility among different sectors.

A number of papers have explicitly examined the oil markets. Using a vector autoregression (VAR) framework, Sadorsky (1999) has shown that both oil prices and a univariate GARCH measure of oil price volatility play important roles in affecting stock returns. Jones and Kaul (1996) provide evidence that the reaction of the US stock market to oil shocks can be completely accounted for by the impact of these shocks on real cash flows.

Lee and Ni (2002) analyzed the effects of oil price shocks on demand and supply in various industries using VAR models. Their results indicated that for industries with a large cost share of oil, such as petroleum refinery and industrial chemicals, oil price shocks mainly reduce supply. In contrast, for many other industries, such as the automobile industry, oil price shocks mainly reduce demand. Their research suggests that oil price shocks influence economic activities beyond that which is explained by direct input cost effects, for example, by delaying purchasing decisions of durable goods.

Malik and Hammoudeh (2007) examined the volatility and shock transmission mechanism among US equity, Gulf equity and global crude oil markets within a multivariate GARCH framework. They found significant transmission among second moments. They are able to document that Gulf equity markets are the recipients of volatility from the oil market. Additionally, only in the case of Saudi Arabia was there any evidence of a significant volatility spillover from the equity market to the oil market.

Examining foreign exchange markets, Engle et al. (1990) reasoned that volatility in one market is transmitted to other markets like a "meteor shower." Ross (1989) found volatility in asset returns depends upon the rate of information flow. In the context of the present study, differences in market and institutional environments may lead to differences in the rate of information flow across sectors. Moreover, to the extent that the time used in processing information varies with each individual sector, we would expect different volatility patterns across sectors.

The increasing integration of major financial markets has generated a good deal of interest in understanding the volatility spillover effects from one market to another. Two lines of thinking have developed as to why these spillovers exist. First, volatility spillovers may result from cross-market hedging and changes in common information, which may simultaneously alter expectations across markets.[2] A second reason given to explain the mean and volatility spillover effects is that of financial contagion, specifically, a shock to one country's asset market may cause changes in asset prices in another country's financial market. Kodres and Pritsker (2002) developed a multiple asset rational expectations model to explain financial market contagion. Through the channel of cross-market balancing, investors transmit shocks among markets by adjusting their portfolio's exposure to macroeconomic risks. Their results show that the extent of the financial contagion depends upon market sensitivities of shared macroeconomic risk factors and the amount of information asymmetry among markets.

Engle's (1982) ARCH model and the generalized version developed by Bollerslev (1986) are arguably the most popular methods used for modeling volatility of high frequency financial time series data. Multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models have been used to estimate the volatility spillover effects among different markets. For example, Kearney and Patton (2000) used MGARCH to model the volatility transmission mechanism among exchange rates in the European Monetary System. Cappiello, Engle and Sheppard (2006) extend the basic Dynamic Conditional Correlation model of Engle (2002) to study the correlations of global equity and bond returns by allowing for more flexible dynamic dependencies in the correlations and asymmetries, as well as switches, in the correlations across regimes. Ane and Ureche-Rangau (2006) study the dynamics of Asian stock index returns by documenting new characteristics of stock market returns and volatilities through a Regime-Switching Asymmetric Power GARCH model. Brooks (2007) also used the Asymmetric Power GARCH model to examine emerging markets and finds that emerging market behavior is different than developed markets. Recently, Li and Majerowska (2008) examine the linkages between the emerging stock markets and the developed markets using the BEKK parameterization of MGARCH. They find evidence of returns and volatility spillovers from the developed to the emerging markets implying that foreign investors may benefit from risk reduction by adding emerging markets' stocks to their portfolio.[3]

In this paper, we use bivariate GARCH models to simultaneously estimate the mean and conditional variance of oil and sector index returns, thus avoiding the generated regressor problem associated with the two-step estimation process found in many earlier studies (Pagan, 1984).[4] In addition, we employ the BEKK parameterization of the multivariate GARCH model which does not impose the restriction of constant correlation among variables over time. Specifically, we use a bivariate GARCH model which allows us to study the volatility transmission between oil returns and a different market sector simultaneously.[5] Our empirical model is similar to that used by Ewing and Malik (2005) to study the volatility transmission mechanism between large and small capitalization stocks.[6] Thus, the model we use captures all of the fundamental volatility dynamics while still retaining the virtue of being very parsimonious in nature.

3. Methodology

The first step in the bivariate GARCH methodology is to specify the mean equation. Accordingly, the mean equation for each return series is given by:

$$R_{i,t} = \mu_i + \alpha R_{i,t-1} + \varepsilon_{it} \tag{1}$$

where R_{it} is the return on series i between time $t-1$ and t, μ_i is a long-term drift coefficient, and ε_{it} is error term for the return on series i at time t. Keeping in line with the literature on ARCH-class models, Eq. (1) was estimated and the residuals examined for the presence of ARCH effects using the test described in Engle (1982). In our case, each of the estimated series exhibited evidence of ARCH effects.[7]

[2] Fleming et al. (1998) developed a model that demonstrates how cross-market hedging and sharing of common information could lead to transmission of volatility across markets over time.

[3] See Bauwens et al. (2006) for a detailed survey on MGARCH models.

[4] It should be noted that not all models in the literature have the generated regressor problem. For example, Schwert (1989) suffers from this problem while other studies like Kearney (2000) do not.

[5] A model including all variables would be superior since it would capture all the interaction in second moments among all variables simultaneously. Consequently, we attempted to estimate an MGARCH model with all the series included but the model would not converge. Of course, this is hardly surprising as multivariate GARCH models are notorious for convergence problems.

[6] Ewing and Malik (2005) also show that volatility dynamics between large and small capitalization stocks change when endogenously determined structural breaks are incorporated into the bivariate GARCH model. In order to check if our results are robust to structural breaks, we re-estimated our models allowing for structural breaks following their methodology and found that the overall conclusions in this paper remain unchanged. Detailed results are not reported for the sake of brevity but are available on request.

[7] The test statistic is distributed as χ^2 with degrees of freedom equal to the number of restrictions. Each return series exhibited significant ARCH effects which suggest that past values of volatility can be used to predict current volatility.

Table 1
Descriptive statistics.

	Oil	Financials	Consumer	Health	Industrials	Technology
Mean	0.002096	0.001728	0.00139	0.001365	0.001439	0.002074
Median	0.003605	0.003741	0.002923	0.002644	0.002778	0.003243
Maximum	0.150363	0.150566	0.110928	0.126386	0.102055	0.174851
Minimum	−0.23263	−0.10948	−0.11032	−0.09233	−0.12457	−0.21902
Std. dev.	0.046202	0.027454	0.025121	0.023822	0.023995	0.040381
Skewness	−0.31319	−0.20987	−0.18391	−0.0929	−0.31458	−0.36195
Kurtosis	4.153759	5.794862	5.08433	4.605452	5.724803	5.001194
Q(16)	33.39(0.00)	33.56(0.00)	33.32(0.00)	28.61(0.02)	31.52(0.01)	33.07(0.00)

Notes: The sample contains weekly returns from January 1, 1992 to April 30, 2008. The total number of usable observations is 850. Q(16) is the Ljung–Box statistic for serial correlation. The values in parenthesis are the actual probability values.

We next employ a variant of the bivariate GARCH model that is capable of detecting volatility transmission among different series, as well as persistence of volatility within each series. For this purpose, the BEKK parameterization was used for the bivariate GARCH proposed by Engle and Kroner (1995). The model incorporates quadratic forms in such a way to ensure that the covariance matrix will be positive semi-definite, a requirement that is needed so that the estimated variances are non-negative.[8]

The BEKK parameterization for the bivariate GARCH(1,1) model is given by:

$$H_{t+1} = C'C + B'H_tB + A'\varepsilon_t\varepsilon_t'A \tag{2}$$

where H_{t+1} is the conditional variance matrix. Note that for the bivariate case C is a 2×2 lower triangular matrix with three parameters and B is a 2×2 square matrix of parameters which depicts the extent to which current levels of conditional variances are related to past conditional variances. A is a 2×2 square matrix of parameters and measures the extent to which conditional variances are correlated with past squared errors (i.e., deviations from the mean). The elements of A capture the effects of shocks or events on volatility (conditional variance). For the case at hand, the total number of estimated parameters is eleven.

Expanding the conditional variance for each equation in the bivariate GARCH (1,1) model gives:

$$\begin{aligned} h_{11,t+1} = {} & c_{11}^2 + b_{11}^2h_{11,t} + 2b_{11}b_{12}h_{12,t} + b_{21}^2h_{22,t} + a_{11}^2\varepsilon_{1,t}^2 \\ & + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 \end{aligned} \tag{3}$$

$$\begin{aligned} h_{22,t+1} = {} & c_{12}^2 + c_{22}^2 + b_{12}^2h_{11,t} + 2b_{12}b_{22}h_{12,t} + b_{22}^2h_{22,t} \\ & + a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2\varepsilon_{2,t}^2 \end{aligned} \tag{4}$$

Eqs. (3) and (4) reveal how shocks and volatility are transmitted over time and across the two series under investigation.[9]

The following likelihood function is maximized assuming normally distributed errors:

$$L(\theta) = -T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t'H_t^{-1}\varepsilon_t\right) \tag{5}$$

where T is the number of observations and θ represents the parameter vector to be estimated. Numerical maximization techniques were used to maximize this non-linear log likelihood function. As recommended by Engle and Kroner (1995), several iterations were performed with the simplex algorithm to obtain the initial conditions. The BFGS algorithm was then employed to obtain the final estimate of the variance–covariance matrix and corresponding standard errors.[10]

4. Data

Equity market data are obtained from Dow Jones. Weekly returns (Wednesday-close) are calculated from daily price data from January 1, 1992 to April 30, 2008. When a holiday occurs on a Wednesday we use the value on the previous day of trading to calculate the return. The use of weekly returns in the analysis over the use of daily returns eliminates or significantly reduces any potential biases that may arise such as the bid-ask effect, non-trading days, etc. In our analysis, we specifically examine the following sector indexes: financials, industrials, consumer services, health care, and technology. These Dow Jones indexes are commonly used by financial market participants to follow movements of industry groups. Moreover, these indexes are widely used by professionals for measuring market sector performance. These indexes represent a large cross-section of firms and industries in the US. In particular, the financials index includes companies in property and casualty insurance, asset managers, banks, various insurance, REIT, insurance brokers, reinsurance, consumer finance, mortgage finance, investment services, etc. The industrials index is comprised of industrial companies such as 3M, General Electric, Caterpillar, Union Pacific, and others. The consumer services index includes specialty retailers, various retailers, travel and tourism, broadcasting and entertainment, airlines, publishing, restaurants and bars, media, hotels, etc. Examples of these firms include Wal-Mart, SYSCO, Time-Warner, Wendy's, Walt Disney, Target, Papa John's, and Home Depot. Companies in the areas of pharmaceuticals, biotechnology, medical equipment and supplies, as well as health care providers comprise the health care index. Finally, the technology index is made up of firms in telecommunications, software, semiconductors, computer hardware, computer services, internet, electronic office equipment, etc.

We use data for West Texas Intermediate (WTI) as the measure of oil price. WTI is a primary crude stream traded on the domestic spot market at the Cushing, Oklahoma center. Consistent with earlier research, our analysis focuses on returns as the price series were non-stationary in levels (i.e., we were unable to reject the hypothesis that the level of each series contained a unit root). Table 1 provides descriptive statistics for each of the return series.

As reported in Table 1, all of the return series were found to be leptokurtic (i.e., they possess fat tails) which suggests that each of the mean equations should be tested for the existence of autoregressive conditional heteroscedasticity (ARCH). In each case, the mean equation for the return series exhibited evidence of ARCH effects and therefore estimation of a GARCH model is appropriate. Note that the

[8] The BEKK parameterization is more popular in the literature relative to the VECH model introduced by Bollerslev, Engle and Wooldridge (1988) which drastically increases the number of parameters which then must be constrained to be positive in order to guarantee a positive semi-definite covariance matrix.

[9] The coefficient terms in Eqs. (3) and (4) are a non-linear function of the estimated elements from Eq. (2). A first-order Taylor expansion around the mean was used to calculate the standard errors for these coefficient terms as described in Kearney and Patton (2000).

[10] Quasi-maximum likelihood estimation was used and robust standard errors were calculated by the method given by Bollerslev and Wooldridge (1992).

Table 2
Summary of bivariate GARCH results.

Oil and financials sector

$$h_{11,t+1} = \underset{(1.71)}{1.33\times10^{-4}} + \underset{(14.50)}{0.856h_{11,t}} + \underset{(0.86)}{0.059h_{12,t}} + \underset{(0.42)}{0.001h_{22,t}} + \underset{(2.28)}{0.063\varepsilon_{1,t}^2} - \underset{(-2.04)}{0.138\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(1.37)}{0.075\varepsilon_{2,t}^2}$$

$$h_{22,t+1} = \underset{(0.07)}{5.94\times10^{-6}} + \underset{(0.78)}{0.0001h_{11,t}} + \underset{(1.58)}{0.027h_{12,t}} + \underset{(52.69)}{0.941h_{22,t}} + \underset{(0.65)}{0.0007\varepsilon_{1,t}^2} + \underset{(1.40)}{0.011\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(3.49)}{0.045\varepsilon_{2,t}^2}$$

Oil and technology sector

$$h_{11,t+1} = \underset{(2.23)}{0.001} + \underset{(1.43)}{3.362h_{11,t}} - \underset{(-1.93)}{0.402h_{12,t}} + \underset{(1.31)}{0.111h_{22,t}} + \underset{(0.77)}{0.041\varepsilon_{1,t}^2} + \underset{(1.30)}{0.095\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(0.64)}{0.054\varepsilon_{2,t}^2}$$

$$h_{22,t+1} = \underset{(0.01)}{5.25\times10^{-6}} + \underset{(1.75)}{0.071h_{11,t}} + \underset{(4.08)}{0.476h_{12,t}} + \underset{(11.78)}{0.799h_{22,t}} + \underset{(0.95)}{0.003\varepsilon_{1,t}^2} + \underset{(2.04)}{0.027\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(2.31)}{0.060\varepsilon_{2,t}^2}$$

Oil and consumer services sector

$$h_{11,t+1} = \underset{(2.76)}{9.06\times10^{-5}} + \underset{(29.74)}{0.831h_{11,t}} - \underset{(-9.42)}{0.602h_{12,t}} + \underset{(4.45)}{0.109h_{22,t}} + \underset{(2.53)}{0.049\varepsilon_{1,t}^2} - \underset{(-2.43)}{0.106\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(1.56)}{0.057\varepsilon_{2,t}^2}$$

$$h_{22,t+1} = \underset{(0.08)}{2.95\times10^{-6}} + \underset{(3.16)}{0.031h_{11,t}} + \underset{(6.75)}{0.331h_{12,t}} + \underset{(26.11)}{0.860h_{22,t}} + \underset{(0.69)}{0.0008\varepsilon_{1,t}^2} + \underset{(1.43)}{0.015\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(3.36)}{0.078\varepsilon_{2,t}^2}$$

Oil and health care sector

$$h_{11,t+1} = \underset{(1.50)}{3.79\times10^{-5}} + \underset{(18.05)}{0.849h_{11,t}} - \underset{(-2.98)}{0.801h_{12,t}} + \underset{(1.39)}{0.189h_{22,t}} + \underset{(2.79)}{0.038\varepsilon_{1,t}^2} - \underset{(-2.26)}{0.048\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(1.25)}{0.015\varepsilon_{2,t}^2}$$

$$h_{22,t+1} = \underset{(0.41)}{1.03\times10^{-5}} + \underset{(2.69)}{0.032h_{11,t}} + \underset{(6.01)}{0.329h_{12,t}} + \underset{(17.82)}{0.825h_{22,t}} + \underset{(0.17)}{2.43\times10^{-5}\varepsilon_{1,t}^2} - \underset{(-0.35)}{0.003\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(3.78)}{0.094\varepsilon_{2,t}^2}$$

Oil and industrials sector

$$h_{11,t+1} = \underset{(1.74)}{4.34\times10^{-5}} + \underset{(41.61)}{0.937h_{11,t}} - \underset{(-2.51)}{0.198h_{12,t}} + \underset{(1.23)}{0.010h_{22,t}} + \underset{(2.28)}{0.028\varepsilon_{1,t}^2} + \underset{(0.29)}{0.006\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(0.14)}{0.0003\varepsilon_{2,t}^2}$$

$$h_{22,t+1} = \underset{(1.26)}{3.13\times10^{-5}} + \underset{(0.91)}{0.001h_{11,t}} + \underset{(1.90)}{0.069h_{12,t}} + \underset{(13.81)}{0.807h_{22,t}} + \underset{(0.42)}{0.0008\varepsilon_{1,t}^2} - \underset{(0.86)}{0.023\varepsilon_{1,t}\varepsilon_{2,t}} + \underset{(3.92)}{0.166\varepsilon_{2,t}^2}$$

Notes: h_{11} denotes the conditional variance for the oil return series and h_{22} is the conditional variance for the corresponding sector return series. Reported directly below the estimated coefficients are the corresponding *t*-values in parentheses. The mean equations included a constant term and a lagged return term which were significant at conventional levels. Results for the mean equations are not reported for the sake of brevity but are available upon request.

Ljung–Box statistic indicated autocorrelation in all returns. Consistent with casual observation and the public's general impression of stock markets, technology returns were more volatile than the other sectors as measured by standard deviation and also had the highest mean return over the time period examined. The least volatile sector was the health care which also produced the smallest mean return.

5. Empirical results

We focus on the volatility relationships between returns in five sectors and the oil market. Thus, we have estimated five bivariate GARCH models each containing oil returns and the returns on the index for the corresponding sector. Results for each of the variance equations are reported in Table 2.[11] We use $h_{11,t}$ to describe the conditional variance (volatility) for oil at time t and $h_{12,t}$ to describe the conditional covariance between oil returns and those of the corresponding sector. The squared error terms ε_1^2 and ε_2^2 in each model represent the effect of "news" (i.e., an unexpected change or shock) originating in the oil market or the equity market sector, respectively, and may be thought of as direct effects. The cross values of error terms (e.g., $\varepsilon_{1,t}\ \ \varepsilon_{2,t}$) represent the "news" in the oil market and the corresponding equity market sector in time period t and provide information as to the impact of indirect effects of shock transmission.

The results for the oil-financials model reveal that volatility of oil returns is significantly affected by its own news, as evidenced by the significant coefficient on $\varepsilon_{1,t}^2$, and its own past volatility (i.e., significant coefficient on $h_{11,t}$). Additionally, oil return volatility is indirectly affected by news from the financial sector as indicated by the significant coefficient on $\varepsilon_{1,t}\varepsilon_{2,t}$. In fact, it appears that a positive shock in the financials market is associated with a decline in oil return volatility. This might be the case if the better-than-expected performance of financial firms signals less rocky times in the more oil-sensitive sectors of the domestic or world economy. While the volatility of returns in the financials sector is affected by its own news and volatility, no evidence of direct or indirect impacts of oil return volatility is detected. Thus, financial market stability, as measured by conditional variance of returns, is fairly well insulated from oil market shocks. Given the nature of the firms that make up this sector (e.g., insurance, reinsurance, banks, etc.) this finding is consistent with effective risk management strategies with respect to oil concerns. This finding is also consistent with Ewing, et al. (2003) who found financial sector returns to have the least volatile response to macroeconomic shocks such as monetary policy, economic growth, and a measure of the risk premium, than other sectors examined.

From the oil-technology model we see that the volatility of technology returns is directly affected by its own news and volatility, and indirectly affected by shocks and volatility in oil returns. Interestingly, technology is the only sector to have an indirect shock effect from oil returns as exhibited by the significant and positive coefficient on $\varepsilon_{1,t}\ \ \varepsilon_{2,t}$. Thus, when changes in oil returns rise unexpectedly, the performance of technology firms becomes more risky (i.e., volatile) which may be due to greater demand uncertainty associated with IT investment, for example, firms may reduce IT investment when faced with higher energy costs. No significant coefficients, except for the

[11] The Ljung–Box test for serial correlation in the cross product between standardized residuals is a useful diagnostic test for misspecification in the variance equation. The Ljung–Box statistic was found to be insignificant at the conventional level of significance implying that no autocorrelation remains in the residuals of all the reported estimated models. Detailed residual diagnostics are not reported for the sake of brevity but are available on request.

constant term, were found in the equation for oil return volatility. This latter finding is particularly interesting as univariate GARCH estimation was performed separately on all series under investigation and the results (not reported here but available upon request) indicated that both the GARCH and ARCH terms were significant at the 1% level. Thus, the finding of (weak) GARCH effects in the bivariate setting underscores the importance of the role played by the interdependence of different series.

In terms of the oil-consumer services model, our findings suggest that oil return volatility is affected by its own news and volatility, and also by the return volatility of the consumer services sector. There is both a direct and indirect impact of the consumer services sector on oil return volatility which, given that energy related expenditures by households (and many businesses) compete with purchases of retail products, entertainment, dining and the like, is not surprising. What is interesting, however, is the magnitude of association between a shock in consumer services returns and oil return volatility. That is, oil return volatility declines significantly when, for example, demand for these types of consumer products and services is high and consumer services firms are doing well. This observation suggests the existence of a relatively strong mechanism of derived demand for oil stemming from purchases at consumer services firms (recall, that the consumer services sector includes hotels, airlines, travel and tourism, all of which are generally oil price-sensitive). Not surprising is that consumer return volatility is affected by the volatility in the oil sector as increases in either energy price or uncertainty would likely impact demand for goods and services typically purchased by consumers.

The oil-health care model shows that health care return volatility is directly and indirectly affected by volatility in oil returns. Increased volatility in the oil market is often seen as representing greater uncertainty in the aggregate economy. In this sense, this finding provides evidence as to the extent that the health care sector is tied to overall uncertainty in the economy and, accordingly, it appears that firm performance in the health care sector is dependent on oil prices. This may be due to the nature of the competitive environments in which these two sectors operate. Oil underlies much of the production, manufacturing, and transportation activity in the economy while investment (including R&D) in health care firms competes with the purchase of consumer staples (e.g., food and clothing). Health care return volatility is also impacted by its own past volatility and own return shocks. The oil return volatility is found to be indirectly affected by the health care sector, and directly affected by its own news and volatility. The finding of only minor or indirect impact from health care to the oil sector is consistent with the notion that provision of health care services is relatively steady over time. Furthermore, news or volatility in health care returns does not lead to significant changes in energy usage nor does it lead to substitution away from or into health care related products and services.

In the results from the oil-industrials model, we note that oil return volatility is affected indirectly by volatility of the industrials returns, and directly affected by its own news and volatility. This finding is likely due to the amount of oil-related products demanded by firms in the industrials sector. That is, firms in the industrials sector are major demanders and users of oil and petroleum-based products. Somewhat surprisingly, the volatility of returns in the industrials sector is found to only be affected by its own news and volatility. It appears to be insulated from the effects of oil shocks and volatility. However, given the long and established relationship between energy usage (i.e., oil and petroleum products) and this sector, it is likely that these firms have developed strategies for effective mitigation of the impacts of oil return volatility (e.g., futures contracts, derivatives, etc.). Certainly oil prices themselves may affect firm profitability in any particular reporting period, but it appears that the market recognizes the ability of industrials to properly manage their dependence on oil return volatility.

Overall, we find that there is transmission of volatility and shocks between oil and some of the examined sectors. As explained in the introduction to this paper, this volatility transmission is usually attributed to cross-market hedging and changes in common information, which may simultaneously alter expectations across sectors (Fleming et al., 1998). Thus, one might interpret these results as an outcome of cross-market hedging undertaken by financial market participants within these markets or sectors. While the transmission of shocks between oil prices and the stock market has been documented by others, our findings regarding the spillover of shocks between oil and these different sectors' *variance* is novel and comes with its own set of implications.

Financial and strategic decisions regarding asset pricing, risk management and portfolio allocation require accurate estimation of the time-varying covariance matrix. For instance, the issue of hedging option positions when the underlying asset exhibits stochastic volatility like *GARCH* was addressed by Engle and Rosenberg (1995). They estimate hedging parameters using Monte-Carlo simulation of *oil* futures data. Additionally, Cabedo and Moya (2003) proposed using Value at Risk (VaR) for oil price risk quantification because it estimates the maximum oil price change associated with a likelihood level, and can be used for designing risk management strategies. Kroner and Ng (1998) outline the significance of the covariance matrix by calculating the risk minimizing portfolio weights and dynamic hedge ratios.

6. Concluding remarks

This paper examined the transmission of volatility and shocks between oil prices and five major market sectors: financials, industrials, consumer services, health care, and technology. Our analysis used weekly data from January 1, 1992 to April 30, 2008. We provide estimates of the extent to which shocks and volatility are transmitted between oil returns and the returns in different equity market sectors.

Given the popularity of sector index investing and recent events in the oil market, our results are both useful and timely, and highlight reasons why investors should pay attention to how specific sectors behave and interact with the oil market over time. The uncovering of significant interactions between the volatility of returns in the oil market and particular equity market sectors points to the presence of cross-market hedging and sharing of common information by investors. The results underscore the importance of investors keeping a close watch on a variety of different markets since "news" in one sector may impact other markets through a number of interdependencies.

Overall, our results provide important and useful information for building accurate asset pricing models, risk management, and forecasting future sector return volatility. Finally, since many different financial assets are traded based on the indexes examined, it is important for financial market participants to understand the volatility transmission mechanism over time and across series in order to make optimal portfolio allocation decisions.

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