Energy Economics 34 (2012) 248–255

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies

Perry Sadorsky *

Schulich School of Business, York University, 4700 Keele Street, Toronto, Ontario, Canada M3J 1P3

ARTICLE INFO

Article history:
Received 30 April 2010
Received in revised form 22 February 2011
Accepted 9 March 2011
Available online 9 April 2011

JEL classification:
G11
G13
Q42

Keywords:
Renewable energy
Multivariate GARCH
Volatility
Oil prices

ABSTRACT

In this paper, multivariate GARCH models are used to model conditional correlations and to analyze the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. Four different multivariate GARCH models (BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation) are compared and contrasted. The dynamic conditional correlation model is found to fit the data the best and generates results showing that the stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices. On average, a $1 long position in clean energy companies can be hedged for 20 cents with a short position in the crude oil futures market.

1. Introduction

The renewable energy sector has, in the past ten years, become one of the fastest growing segments of the energy industry due primarily to concerns about climate changes, energy security issues and peak oil but also due to new technologies and environmentally conscious consumers. Data released by New Energy Finance (2010) show that global investment in new sustainable energy grew at a compound average annual growth rate of 29% over the period 2004 and 2009.[1] In 2008, global investment in new sustainable energy reached a record high of $173 billion which is impressive given that 2008 was marked by the worst economic downturn since the Great Depression (New Energy Finance, 2010).

The International Energy Agency (IEA) predicts that renewable energy will be the fastest growing component of global energy demand. According to their reference scenario, global demand for renewable energy is expected to grow at a compound average annual growth rate of 7.3% between 2007 and 2030 (International Energy Agency, 2009, p. 74).[2] This compares to a compound average annual growth rate over the same period for world primary energy demand of 1.5%. In the IEA's alternative energy scenario, a scenario in which government policies currently being discussed to address issues of climate change and energy security are actually implemented, the demand for renewable energy is expected to grow by 10.4% per year between 2007 and 2030 (International Energy Agency, 2009, p. 212). Over this same period, world primary energy demand is expected to grow by 0.8% per year. At a growth rate of 10.4% per year, the renewable energy sector will double in approximately 7 years.

Modeling and forecasting volatility lies at the heart of modern finance because good estimates of correlation and volatility are needed for derivative pricing, portfolio optimization, risk management, and hedging. To date, however, very little is known about the volatility dynamics of clean energy stock prices and the possible correlations between clean energy stock prices and other important financial markets like oil prices and technology stock prices. The purpose of this paper is to fill this void. In general, very little is known about the relationship between clean energy stock prices and various other important macroeconomic variables. The paper by Henriques and Sadorsky (2008) is the closest to this present paper. Henriques and Sadorsky (2008), recognizing the importance of the clean energy and alternative energy sectors, use a vector autoregression to study the dynamic relationships between the stock prices of alternative energy companies, oil prices, interest rates, and an index of technology.[3] They do not investigate volatility spillover effects. While conventional

* Tel.: +1 416 736 5067; fax: +1 416 736 5687.
E-mail address: psadorsk@schulich.yorku.ca.

[1] Investment in global sustainable energy includes government and corporate R&D spending and financial (equity, bond and venture capital) investments.

[2] The reference scenario is one in which government policies toward energy are expected to remain unchanged from mid 2007 onwards. Renewables here include wind, wave, tidal, geothermal and solar. Biomass, waste and hydro are excluded from this calculation.

[3] Alternative energy companies include renewable energy companies and some clean burning fossil fuel companies.

0140-9883/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.eneco.2011.03.006

media wisdom is that oil prices are an important driver of movements in the stock prices of alternative energy companies, Henriques and Sadorsky (2008) find that shocks to technology actually have a larger impact on the stock prices of alternative energy companies than do oil prices.[4] While this result may seem somewhat unexpected at first, it actually makes sense within the larger context of alternative energy companies and industry structure. The success or failure of alternative energy companies often depends upon the success or failure of fairly specific technologies. As a result, alternative energy companies often share more in common with technology companies than they do with fossil fuel based energy companies.[5]

As the renewable energy sector expands and more companies go public and the existing publically traded companies become larger in size, it is important to have an understanding of the volatility dynamics of the stock prices of these companies. In this paper, multivariate GARCH models are used to model dynamic correlations and the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. Four multivariate GARCH models (BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation) are compared and contrasted. It is found that the VARMA-GARCH dynamic conditional correlation model fits the data best and this model is then used to construct hedge ratios and optimum portfolio weights.

2. The empirical model

Multivariate GARCH (MGARCH) models have been found to be very useful in studying volatility spillover effects in equity markets (see for example, Booth et al. 1997; Cha and Jithendranathan, 2009; Karolyi, 1995; Karolyi and Stulz, 1996; Koutmos and Booth, 1995; Lin et al, 1994). MGARCH models have been used in the energy economics and finance literature to study oil prices (eg. C.-Y. Chang et al., 2010; Cifarelli and Paladino, 2010; Elder and Serletis 2009; Malik, and Hammoudeh, 2007; Sadorsky, 2006), electricity prices (eg. Higgs, 2009; Worthington et al, 2005) and natural gas prices (eg. Ewing et al, 2002). In this paper, four multivariate GARCH models (BEKK, diagonal, constant conditional correlation, and dynamic conditional correlation) are used to model the volatility dynamics between the stock prices of clean energy companies, oil prices, and technology stock prices.[6] The BEKK model is used as a benchmark. The other models (diagonal, constant conditional correlation, and dynamic conditional correlation) are computationally simpler and can be estimated in two steps. In the first step, univariate GARCH models are used to estimate the variances. In the second step, correlations are modeled based on the standardized residuals from step one.

The econometric specification used in this paper has two components. A vector autoregression (VAR) with one lag is used to model the returns.[7] This allows for autocorrelations and cross-autocorrelations in the returns. A multivariate GARCH model is used to model the time varying variances and covariances. For the diagonal, constant conditional correlation and dynamic conditional correlation models the conditional variance is assumed to be VARMA-GARCH(1,1) (Ling and McAleer, 2003).[8]

$$r_{it} = m_{i0} + \sum_{j=1}^{3} m_{ij} r_{jt-1} + \varepsilon_{it}\,,\ \varepsilon_{it}|I_{it-1} \sim N(0, h_{it})\,,\ i = 1,2,3 \quad (1)$$

$$\varepsilon_{it} = \nu_{it} h_{it}^{1/2},\ \nu_{it} \sim N(0,1) \quad (2)$$

$$h_{it} = c_{ii} + \sum_{j=1}^{3} \alpha_{ij} \varepsilon_{jt-1}^2 + \sum_{j=1}^{3} \beta_{ij} h_{jt-1} \quad (3)$$

In Eq. (1) r_{it} is the return for series i and ε_{it} is random error term with conditional variance h_{it}. The market information available at time $t-1$ is denoted as I_{it-1}. Eq. (2) specifies the relation between the error term ε_{it} and the conditional variance h_{it}. Eq. (3) specifies a GARCH(1,1) process with VARMA terms (Ling and McAleer, 2003). The Ling and McAleer (2003) approach to modeling the conditional variances allows large shocks to one variable to affect the variances of the other variables. This is a convenient specification which allows for volatility spillovers.

The Engle (2002) dynamic conditional correlation (DCC) model is estimated in two steps. In the first step, the GARCH parameters are estimated. In the second step, the correlations are estimated.

$$H_t = D_t R_t D_t \quad (4)$$

In Eq. (4), H_t is the 3×3 conditional covariance matrix, R_t is the conditional correlation matrix, and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag\left(h_{11t}^{1/2}, \ldots h_{33t}^{1/2}\right) \quad (5)$$

$$R_t = diag\left(q_{11t}^{-1/2}, \ldots q_{33t}^{-1/2}\right) Q_t\, diag\left(q_{11t}^{-1/2}, \ldots q_{33t}^{-1/2}\right) \quad (6)$$

Q_t is a symmetric positive definite matrix.

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 \xi_{t-1}\xi'_{t-1} + \theta_2 Q_{t-1} \quad (7)$$

$\overline{Q}$ is the 3×3 unconditional correlation matrix of the standardized residuals ξ_{it}. The parameters θ_1 and θ_2 are non-negative with a sum of less than unity. The correlation estimator is,

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}}$$

For the constant conditional correlation (CCC) case, $R_t = R$ and $R_{ij} = \rho_{ij}$. In the diagonal MGARCH model, $\rho_{ij} = 0$ for all i and j. The diagonal case is very restrictive because it assumes that the dynamic conditional correlations between variables are all zero ($h_{ij} = 0$ for all i not equal to j). The standardized residuals from the MGARCH diagonal model can be used to compute an unconditional covariance matrix.

The MGARCH models are estimated by Quasi-Maximum Likelihood estimation (QMLE) using the BFGS algorithm.[9] T statistics are calculated using a robust estimate of the covariance matrix.

3. Data

The data for this study includes the daily closing prices of the WilderHill Clean Energy Index (ECO), the NYSE Arca Technology Index (PSE) and the nearest contract to maturity on the West Texas Intermediate crude oil futures contract (OIL).[10] The WilderHill Clean Energy Index is a modified dollar weighted index of 54 companies

[4] The technology variable is measured as an orthogonal projection of a technology stock price index on the broad based US market index.

[5] Kumar et al. (in press), find that clean energy stock prices are influenced by technology stock prices and oil prices but not by carbon prices.

[6] There are many popular MGARCH models including diagonal VECH, BEKK and VECH. While, popular, these models do have limitations. In particular, diagonal VECH lacks correlation between the variance terms, BEKK can have a poorly behaved likelihood function (making estimation difficult, especially for models with more than two variables), and VECH has a large number of free parameters (which makes it impractical for models with more than two variables). Restricted correlation models, of the kind used in this paper, are designed to address some of the problems encountered with BEKK and VECH type models and still retain analytical tractability. See the survey by Bauwens et al. (2006) for more details.

[7] As is often the case in applied research, different criterion functions select different lag lengths for the VAR models. SIC chooses 0 lags, AIC chooses 3 lags and HQ chooses 1 lag. Preliminary regression analysis showed very little differences between a VAR with one lag compared to a VAR with three lags. Consequently, in the interest of parsimony, a VAR with one lag is chosen.

[8] Recent examples of the VARMA-GARCH approach include C.L. Chang et al. (2010), Hammoudeh et al. (2009) and Hammoudeh et al. (2010).

[9] All computations are carried out using WinRats 7.0.

[10] The West Texas Intermediate crude oil futures price contract are the most widely traded oil futures contract in the world and used as a benchmark for the oil market and commodity portfolio diversification.

engaged in the clean (renewable) energy business[11,12,13] This is the oldest index devoted solely to tracking clean energy companies. Companies included in this index are engaged in a variety of clean energy areas including battery power, geothermal, hydrogen, solar, wind, and wave. Individuals cannot invest in this index directly but they can invest in the Powershares WilderHill Clean Energy exchange traded fund (ETF) with ticker symbol PBW that tracks this index. The NYSE Arca Technology 100 Index is a price weighted index that consists of the common stocks and ADRs of 100 technology companies.[14] The NYSE Arca Technology 100 Index is one of the oldest US based technology indexes going back to 1982 when it was first initiated by the Pacific Stock Exchange and named the Pacific Technology Index. The index consists of leading companies from several industries, including computer hardware, software, semiconductors, telecommunications, electronics, aerospace and defense, health care equipment, and biotechnology. The index still retains the ticker symbol PSE. There are no companies included in both ECO and PSE.

The sample period for the data set covers January 1, 2001 to December 31, 2010. All of this data is available from Datastream. A plot of the raw data shows that ECO and PSE tend to move together (Fig. 1). The recession of 2008–2009 had a big impact on the stock prices of clean energy companies as the ECO index suffered a huge drop of −123% between September 1, 2008 and March 9, 2009.

For each data series, continuously compounded daily returns are calculated as $100*\ln(p_t/p_{t-1})$ where p_t is the daily closing price. The summary statistics for the returns are shown in Table 1. For each series, the mean and median values are close to zero. For each series the standard deviation is larger than the mean value. For each series, Student *t* statistics indicate that the mean is statistically insignificant from zero. Each series displays a small amount of skewness and a larger amount of kurtosis and the returns are not normally distributed.

Unconditional correlations show that there is a strong positive correlation between ECO and PSE (Table 2). The unconditional correlation between ECO and OIL is positive but the value is about one third of the unconditional correlation between ECO and PSE. The unconditional correlation between OIL and PSE is positive.

Time series graphs of the squared daily returns show how volatility has changed across time. Notice that all three graphs show pronounced volatility clustering between August 2008 and August 2009. In addition, oil shows some big spikes in volatility in September 2001, November 2001 and April 2003. The PSE shows some large spikes in volatility in the first few months of 2001 in response to the bursting of the technology stock market bubble.

The correlations between the squared daily returns show a similar pattern as for the correlations between the returns (Table 3). The correlation between ECO and PSE is positive and larger than the correlation between ECO and OIL. The information presented in Fig. 2 and Table 3 shows volatility clustering and cross-correlations in volatility.

4. Empirical results and discussion

This section reports on the empirical results obtained from estimating multivariate GARCH models. The BEKK model is used as the benchmark and compared to three restricted correlation models (diagonal, constant conditional correlation, and dynamic conditional correlation). The BEKK model is the most computationally intensive of the models studied.

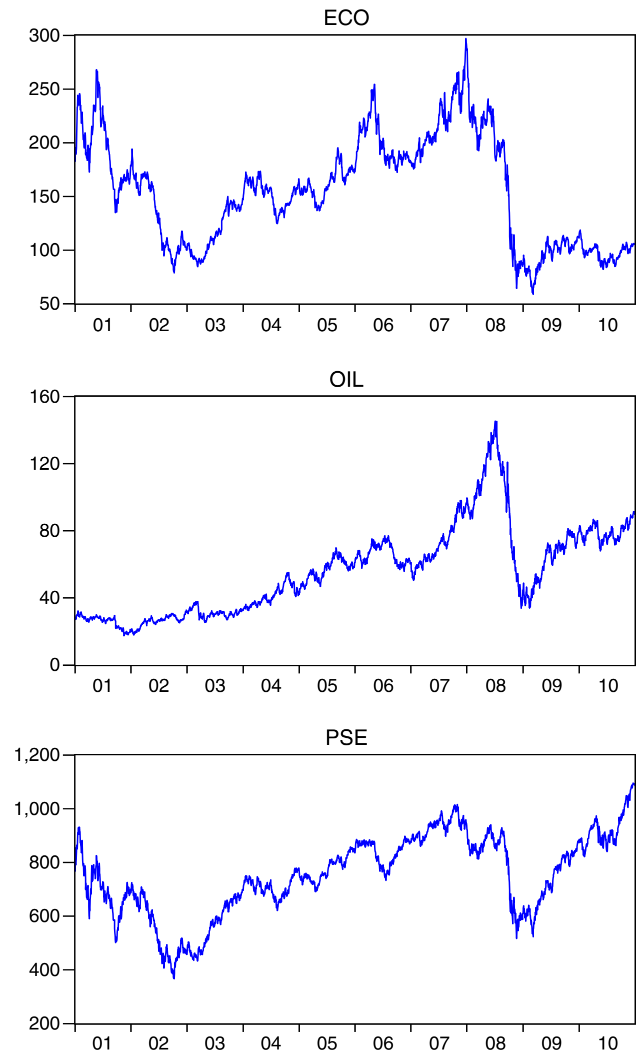

Fig. 1. Time series plots of ECO, OIL and PSE.

4.1. Regression results

Turning first to the VAR for the returns, one of the strongest effects is that a one period lag of PSE positively affects current period ECO (Table 4). The estimated coefficient of PSE in the ECO equation (m_{13}) is positive, of the same order of magnitude and statistically significant at the 10% level for each of the MGARCH models. This result is important in establishing a positive relationship between current period ECO returns

Table 1
Summary statistics for daily returns.

	ECO	OIL	PSE
Mean	−0.023	0.047	0.011
Median	0.000	0.000	0.029
Maximum	14.520	16.410	10.841
Minimum	−14.467	−16.545	−8.121
Std. dev.	2.193	2.504	1.629
Skewness	−0.234	−0.144	0.161
Kurtosis	7.589	7.587	6.812
Student t	−0.539	0.959	0.345
Jarque-Bera	2312.920	2296.485	1590.746
Probability	0.000	0.000	0.000
Observations	2609	2609	2609

[11] http://www.wildershares.com/.
[12] http://www.nyse.com/about/listed/mkt_indexes_other_us.shtml.
[13] The terms clean energy, renewable energy, and sustainable energy tend to get used interchangeably especially when it comes to tracking indices or investment products.
[14] http://www.nyse.com/about/listed/mkt_indexes_nyse.shtml, http://www.nyse.com/about/listed/pse_i.shtml.

Table 2
Correlations between daily returns.

	ECO	OIL	PSE
ECO	1.000	0.238	0.765
OIL	0.238	1.000	0.113
PSE	0.765	0.113	1.000

Table 3
Correlations between squared daily returns.

	ECO	OIL	PSE
ECO	1.000	0.278	0.609
OIL	0.278	1.000	0.172
PSE	0.609	0.172	1.000

and last period PSE returns. In other words, current period ECO returns are influenced by last period PSE returns.[15]

Own conditional GARCH effects (β_{ii}), which measure long-term persistence, are clearly important in explaining conditional volatility (Table 4). The estimated coefficients on the own conditional volatility effects, the β_{ii} terms, are statistically significant at the 1% level in each of the MGARCH models. The coefficient β_{11} refers to the GARCH term in the ECO equation, while β_{22} refers to the GARCH term in the OIL equation and β_{33} refers to the GARCH term in the PSE equations. For a particular i, the estimated coefficients for β_{ii} are remarkably similar across the models. PSE shows the most amount of long-term persistence followed by OIL and ECO.

Own conditional ARCH effects (α_{ii}), which measure short-term persistence, are important in explaining the conditional volatility (Table 4). For each i, the estimated α_{ii} values are smaller than their respective estimated β_{ii} values, indicating that own volatility long-run (GARCH) persistence is larger than short-run (ARCH) persistence.

For the BEKK model there are several instances of significant volatility spillovers. For short-term persistence there is evidence of volatility spillovers between ECO and PSE (α_{13}) and between PSE and ECO (α_{31}). There is also evidence of long-term persistence volatility spillovers between ECO and PSE (β_{13}) and between PSE and ECO (β_{31}).

Looking across the full suite of models, there is some evidence of inter-sector or volatility spillover effects from PSE to ECO (β_{13} in two of the models) and ECO to PSE (β_{31} in three of the models) but the results are somewhat mixed across different models. For example, the estimated coefficient on β_{31} is positive and significant in two of the models but negative and significant in the DCC model. The DCC model also presents evidence of a statistically significant short-term persistence volatility spillover from OIL to ECO (α_{12}). In summary, the strongest evidence for volatility spillovers is found from the estimates of the BEKK model. The restricted correlation models (diagonal, CCC, and DCC) show less evidence of volatility spillovers.

For the CCC model, the correlation between OIL and ECO (ρ_{21}), PSE and ECO (ρ_{31}) and PSE and OIL (ρ_{32}) are each positive and statistically significant at the 1% level. The highest correlation is between PSE and ECO and the second highest correlation is between OIL and ECO. These results for volatility are similar to what Henriques and Sadorsky (2008) found for shocks to stock prices. They found that shocks to technology stock prices have a greater impact on the stock prices of alternative energy companies than does a shock to oil prices. Oil price effects are important, but not as important as technology stock price effects.

For the DCC model, the estimated coefficients on θ_1 and θ_2 are each positive and statistically significant at the 1% level. These estimated coefficients sum to a value which is less than one, meaning that the dynamic conditional correlations are mean reverting.

[15] While not investigated in this paper, this result brings up the possibility of forecasting one period ahead ECO returns using current period PSE returns.

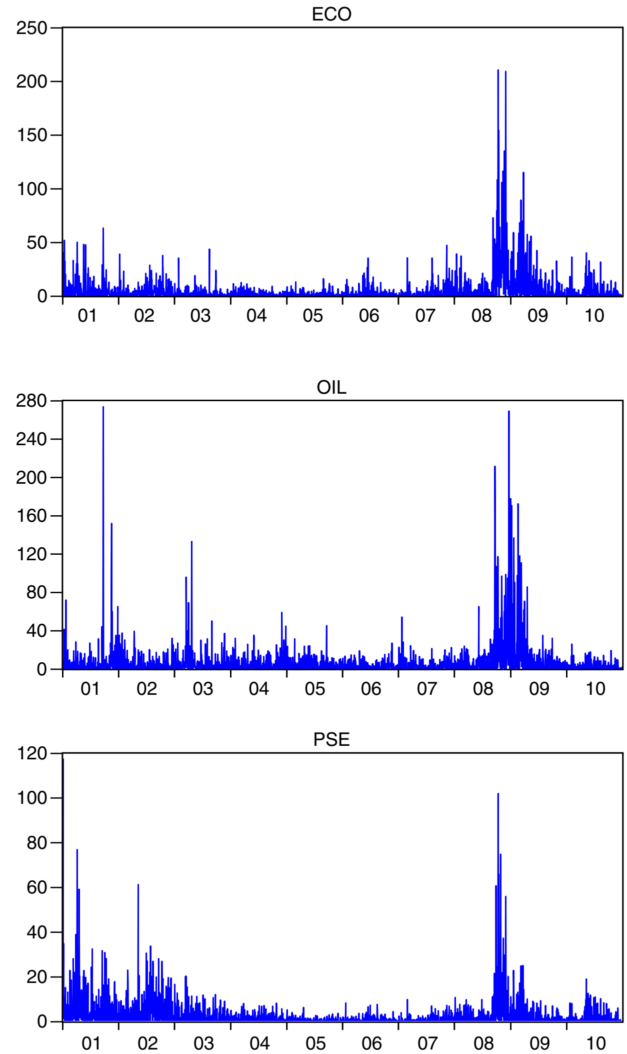

Fig. 2. Squared daily returns.

Both the AIC and SIC criteria show that the DCC model is the best model. The diagnostic tests for the standardized residuals and standardized residuals squared show no evidence of serial correlation at the 1% level in the DCC model (Table 5). It is also worth noting that the AIC and SIC rank the BEKK model as the second best. The BEKK model, although ranked second by both the AIC and SIC, shows more evidence of autocorrelation in the squared standardized residuals. Based on the AIC, SIC and residual diagnostic tests, the DCC model is chosen as the best of the models considered. The DCC model will be used to construct dynamic conditional correlations, optimal hedge ratios and portfolio weights.

4.2. Dynamic conditional correlations

Fig. 3 shows time-varying conditional correlations from the DCC model. Notice that a pattern of volatility clustering is evident for each series. The dynamic conditional correlations can vary a lot from the constant conditional correlations ($\rho_{21}=0.212$, $\rho_{31}=0.760$, and $\rho_{32}=0.078$) emphasizing the need to compute dynamic conditional correlations. Up until 2008 there was no trend in the correlations. After 2008, there is a slight upwards trend in each pair of correlations. Notice that the dynamic conditional correlations between ECO and PSE are all positive and generally larger than 0.5. This indicates that there is little scope for portfolio diversification between these two series. The dynamic conditional correlations between ECO and OIL do alternate in sign and cover a range of values between −0.3 and 0.60. These periods

Table 4
MGARCH parameter estimates.

	BEKK			Diag			CCC			DCC		
	Coeff	*T* stat	Signif	Coeff	*T* stat	Signif	Coeff	*T* stat	Signif	Coeff	*T* stat	Signif
Mean												
m_{10}	0.032	0.718	0.473	0.041	1.073	0.283	0.048	1.442	0.149	0.040	1.085	0.278
m_{11}	0.020	1.533	0.125	0.028	1.281	0.200	0.013	0.434	0.664	0.016	0.464	0.643
m_{12}	0.019	1.291	0.197	0.025	1.338	0.181	0.024	1.725	0.085	0.025	1.333	0.183
m_{13}	0.068	3.288	0.001	0.081	3.003	0.003	0.080	2.175	0.030	0.069	1.668	0.095
m_{20}	0.086	1.767	0.077	0.105	2.674	0.007	0.106	1.992	0.046	0.098	2.129	0.033
m_{21}	−0.012	−0.536	0.592	−0.010	−0.354	0.724	−0.014	−0.448	0.654	−0.014	−0.456	0.648
m_{22}	−0.021	−0.562	0.574	−0.021	−0.973	0.331	−0.014	−0.619	0.536	−0.019	−0.838	0.402
m_{23}	0.060	1.822	0.068	0.056	1.628	0.104	0.057	1.531	0.126	0.053	1.310	0.190
m_{30}	0.062	2.026	0.043	0.059	2.209	0.027	0.059	2.283	0.022	0.061	2.530	0.011
m_{31}	−0.018	−1.444	0.149	−0.017	−0.863	0.388	−0.027	−1.229	0.219	−0.024	−1.052	0.293
m_{32}	0.006	0.455	0.649	−0.005	−0.413	0.679	0.001	0.130	0.897	0.007	0.512	0.609
m_{33}	−0.019	−1.366	0.172	−0.014	−0.503	0.615	−0.014	−0.469	0.639	−0.018	−0.552	0.581
Variance												
c_{11}	0.265	6.055	0.000	0.065	3.192	0.001	0.130	3.018	0.003	0.084	2.920	0.004
c_{21}	0.023	0.350	0.726									
c_{22}	0.193	4.153	0.000	0.089	2.108	0.035	0.069	1.612	0.107	0.102	2.197	0.028
c_{31}	0.082	4.499	0.000									
c_{32}	0.016	1.454	0.146									
c_{33}	0.045	2.498	0.012	0.012	2.102	0.036	0.023	2.951	0.003	0.015	2.998	0.003
α_{11}	0.321	7.171	0.000	0.068	4.484	0.000	0.102	2.670	0.008	0.080	2.587	0.010
α_{12}	−0.007	−0.128	0.898	0.011	1.255	0.209	0.006	0.464	0.643	0.020	1.805	0.071
α_{13}	0.062	3.757	0.000	0.018	1.249	0.212	−0.023	−0.499	0.618	−0.011	−0.256	0.798
α_{21}	−0.021	−1.014	0.310	0.007	0.329	0.742	0.020	0.814	0.415	0.048	1.602	0.109
α_{22}	0.187	6.948	0.000	0.055	3.440	0.001	0.058	3.088	0.002	0.057	3.566	0.000
α_{23}	0.004	0.351	0.726	−0.005	−0.167	0.867	−0.031	−0.763	0.445	−0.010	−0.186	0.853
α_{31}	−0.131	−2.364	0.018	−0.003	−0.375	0.708	−0.001	−0.110	0.913	0.021	1.925	0.054
α_{32}	0.062	1.011	0.312	0.001	0.120	0.904	−0.005	−1.130	0.258	0.005	0.934	0.350
α_{33}	0.128	4.618	0.000	0.059	4.897	0.000	0.052	3.992	0.000	0.026	2.423	0.015
β_{11}	0.934	57.932	0.000	0.903	54.388	0.000	0.780	10.489	0.000	0.864	15.884	0.000
β_{12}	0.000	−0.018	0.986	2.929	1.628	0.104	0.146	1.205	0.228	−0.006	−0.247	0.805
β_{13}	−0.020	−5.082	0.000	1.689	1.953	0.051	0.098	1.304	0.192	0.065	1.003	0.316
β_{21}	0.009	1.278	0.201	1.388	0.739	0.460	−0.033	−0.316	0.752	−0.071	−1.759	0.079
β_{22}	0.979	141.721	0.000	0.927	42.968	0.000	0.914	31.110	0.000	0.930	45.195	0.000
β_{23}	0.002	0.557	0.578	4.973	0.938	0.348	0.421	1.361	0.173	0.009	0.137	0.891
β_{31}	0.039	2.714	0.007	2.179	1.681	0.093	−0.028	−1.179	0.239	−0.034	−2.295	0.022
β_{32}	−0.015	−0.918	0.359	12.248	1.608	0.108	0.061	0.751	0.453	−0.006	−0.546	0.585
β_{33}	0.997	182.825	0.000	0.938	84.876	0.000	0.957	52.216	0.000	0.980	72.821	0.000
ρ_{21}							0.212	9.748	0.000			
ρ_{31}							0.760	83.318	0.000			
ρ_{32}							0.078	3.511	0.000			
θ_1										0.024	4.341	0.000
θ_2										0.972	129.913	0.000
Log L	−14266.6			−15548.2			−14367.7			−14236.4		
AIC	10.968			11.949			11.046			10.944		
SIC	11.049			12.023			11.127			11.023		

Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. Variable order is ECO (1), OIL (2) and PSE (3). In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms. In the mean equation m_{13} represents the effect of a one period lag PSE returns on current period ECO returns. The coefficient α_{13} for example represents the short-term volatility spillover from PSE to ECO while β_{13} represents the long-term volatility spillover from PSE to ECO. There are 2608 observations.

of negative correlation provide an opportunity for meaningful portfolio diversification. The time-varying conditional correlations between OIL and PSE show a similar pattern to that of ECO and OIL.

The dynamic conditional correlation between ECO and Oil reached low values around October 2001 and April 2003. These dynamic conditional correlations surpass the 0.5 value for the first time in December of 2008 before lessening somewhat. By June of 2009, the dynamic conditional correlations are back above 0.5.

The dynamic conditional correlation between ECO and PSE reach low values around October 2003, March 2006 and May 2006. The dynamic conditional correlation between ECO and PSE surpass the 0.9 value for the first time in October of 2008.

The dynamic conditional correlation between OIL and PSE reach low values around April 2003 and August 2008. The dynamic conditional correlation between ECO and PSE surpass the 0.4 value for the first time in November of 2008.

Table 5
Diagnostic tests for standardized residuals.

	BEKK			Diag			CCC			DCC		
	ECO	OIL	PSE	ECO	OIL	PSE	ECO	OIL	PSE	ECO	OIL	PSE
$Q(20)r$	16.580	10.041	19.137	13.532	10.285	18.417	14.487	9.978	19.493	16.444	10.165	18.790
p values	0.680	0.967	0.513	0.853	0.963	0.560	0.805	0.969	0.490	0.689	0.965	0.535
$Q(20)r^2$	34.707	26.834	43.749	20.939	19.045	38.360	41.988	16.563	55.507	23.791	15.216	33.415
p values	0.022	0.140	0.002	0.401	0.519	0.008	0.003	0.681	0.000	0.252	0.764	0.030

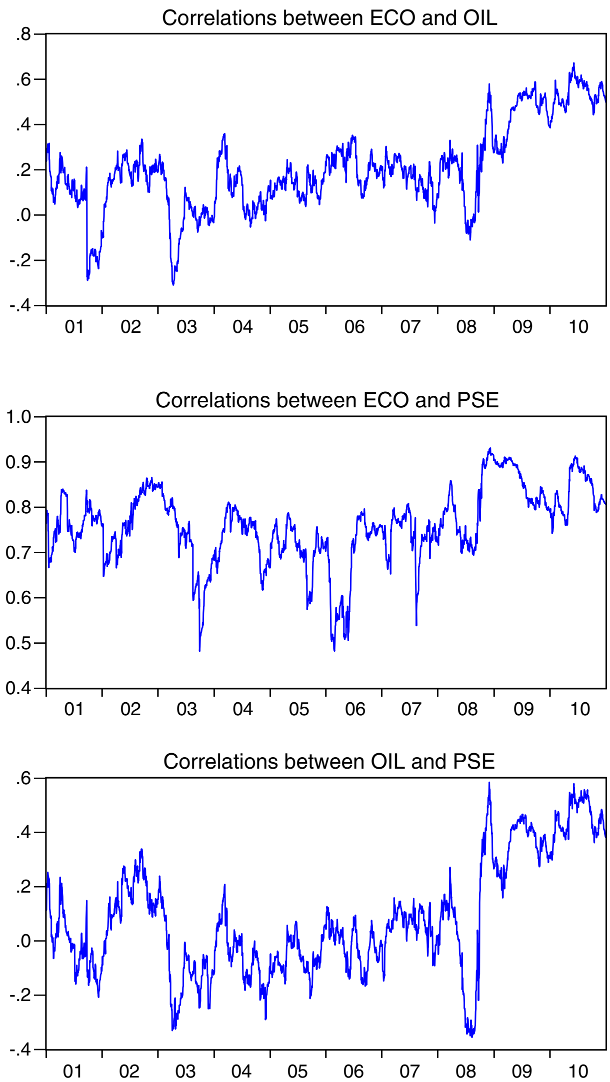

Fig. 3. Time-varying conditional correlations from the DCC model.

These results show that for each pair of series, dynamic conditional correlations reached their highest values in the fall of 2008, as the effects of the greatest economic downturn since the Great Depression of the 1930s were being felt. The time series plots in Fig. 3 show that, for each pair of series, the dynamic conditional correlations provide much more useful information than do the correlations from the constant conditional correlations model. Notice also, that at the onset and duration of the recession of 2008 and 2009, the dynamic conditional correlations were, for each pair of series, much larger than their corresponding values from the constant conditional correlations, illustrating that any calculations done with the correlations from the constant conditional correlation model would have been very miss-leading.

5. Hedging

The conditional volatility estimates can be used to construct hedge ratios (Kroner and Sultan, 1993). A long position in one asset (say asset i) can be hedged with a short position in a second asset (say asset j). The hedge ratio between asset i and asset j is

$$\beta_{ijt} = h_{ijt} / h_{jjt}$$

For most of the hedge ratios, computed from the DCC model, the graphs show considerable variability after August 2008 (Fig. 4). For many of the hedge ratios it is also the case that the maximum value was recorded after August 2008. The exceptions are the PSE/ECO and PSE/OIL hedges where the largest values for these hedge ratios were recorded near the beginning of the sample period.

The average value of the hedge ratio between ECO and OIL is 0.20 while the average value of the hedge ratio between ECO and PSE is 1.09 (Table 6). The average value of the hedge ratio between OIL and PSE is 0.12. These results are important in establishing that a $1 long position in ECO can be hedged for 20 cents with a short position in the oil market. A $1 long position in OIL can be hedged for 12 cents with a short position in the PSE index. As expected from the preceding dynamic conditional correlation analysis, it is not, however, useful to hedge ECO with a short position in PSE. The cheapest hedge is long PSE and short OIL. The most expensive hedge is long ECO and short PSE. Notice that three of the hedge ratios record maximum values in excess of unity.

6. Portfolio weights

The conditional volatilities from MGARCH models can be used to construct optimal portfolio weights (Kroner and Ng, 1998).

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}$$

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \le w_{ij,t} \le 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases}$$

In constructing portfolio weights between two assets, $w_{ij,t}$ is the weight of the first asset in a one dollar portfolio of two assets (asset i, asset j) at time t, $h_{ij,t}$ is the conditional covariance between assets i and j and $h_{jj,t}$ is the conditional variance of asset j. The weight of the second asset is $1 - w_{ij,t}$. Summary statistics for portfolio weights computed from the DCC model are reported in Table 7. The average weight for the ECO/OIL portfolio is 0.60, indicating that for a $1 portfolio, 60 cents should be invested in ECO and 40 cents invested in OIL. The average weight for the ECO/PSE portfolio indicates that 18 cents should be invested in ECO and 82 cents invested in PSE. The average weight for the OIL/PSE portfolio indicates that 26 cents should be invested in OIL and 74 cents invested in PSE.

7. Conclusions

As the amount of money invested in the clean energy sector grows, it is important to have a better understanding of the volatility dynamics of the stock prices of clean energy companies. This paper uses multivariate GARCH models to investigate correlations and the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. Empirical results show that the dynamic conditional correlation MGARCH model is preferred over the other models, although the BEKK is a close second in model choice to the DCC model. The BEKK model also produces more evidence of volatility spillovers than does the DCC model.

For each pair of series, the dynamic conditional correlations vary considerably from their respective constant conditional correlations. For each pair of series, dynamic conditional correlations reached their highest values in the fall of 2008, as the effects of the greatest economic downturn since the Great Depression of the 1930s were being felt. The dynamic conditional correlations between clean energy stock prices and technology stock prices are higher than the dynamic conditional correlations between clean energy stock prices and oil prices. These results are important in establishing that clean energy companies have more in common (correlate more closely) with technology companies than they do with the oil markets.

The conditional volatilities from the DCC model can be used to estimate dynamic hedge ratios. On average, a $1 long position in oil can

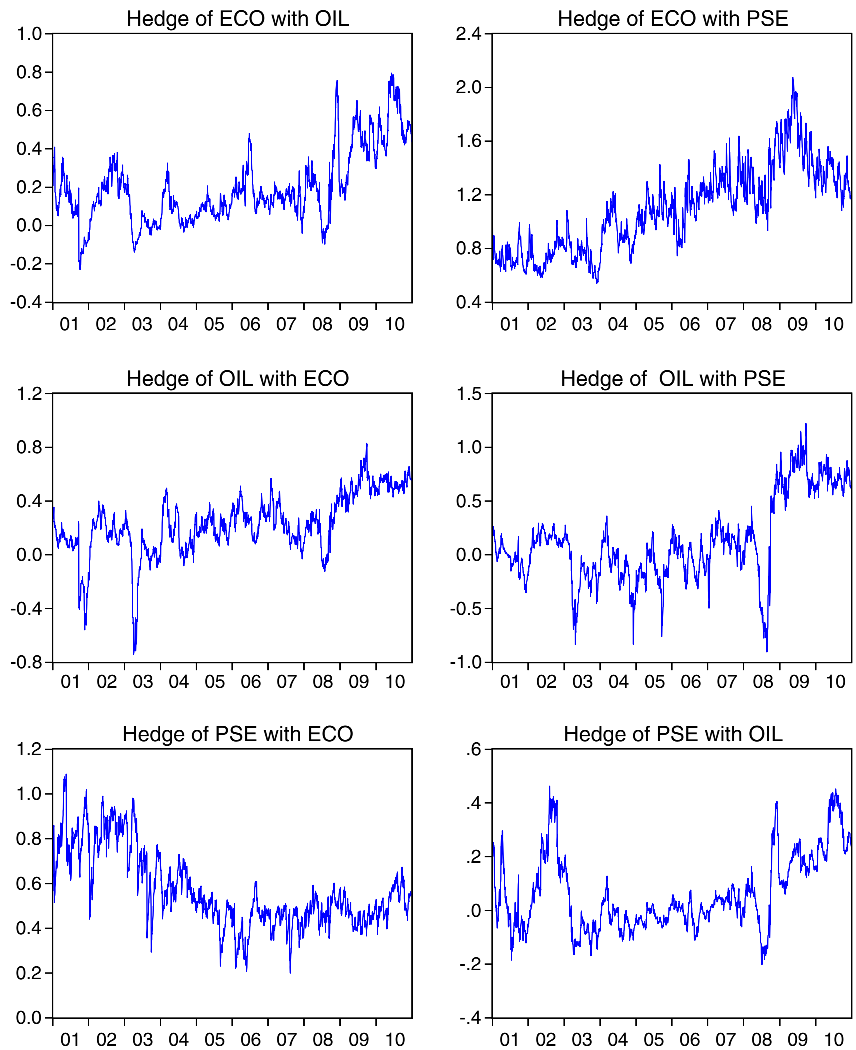

Fig. 4. Time-varying hedge ratios computed from the DCC model.

be hedged for 12 cents with a short position in the technology stock price index. On average, a \$1 long position in clean energy companies can be hedged for 20 cents with a short position in the crude oil futures market. It is not, however, useful to hedge an investment in clean energy companies with a short position in technology companies as these two data series are very highly positively correlated.

The conditional variances and covariances from the DCC model can be used to construct optimal two asset portfolios. The average weight for the ECO/OIL portfolio is 0.60, indicating that for a \$1 portfolio, 60 cents should be invested in ECO and 40 cents invested in OIL. The average weight for the ECO/PSE portfolio indicates that 18 cents should be invested in ECO and 82 cents invested in PSE.

The results of this paper on dynamic conditional correlations, hedging and portfolios show that the stock prices of clean energy companies correlates fairly highly with the stock prices of technology companies. Technology stocks are not a good hedge for clean energy stocks and an optimal portfolio between technology stocks and clean energy stocks is heavily weighted to technology stocks. Oil is a useful hedge for clean energy stocks and a clean energy and oil portfolio is weighted 60% to clean energy stocks.

The results of this paper show that a portfolio of clean energy stocks and oil futures can be built and that oil futures can be used to hedge an investment in clean energy stock prices. The high correlation between the stock prices of clean energy companies and technology companies, however, may create a dilemma for investors. If the stock prices of clean energy companies correlate highly with the stock prices of technology companies and clean energy companies are riskier than technology companies, then why invest in clean energy stocks? The problem is that many technology companies specialize in bringing new consumer products to market while clean energy companies specialize in bringing new or improved energy source products to market. Energy source products are a basic input (need) to economic activity while new consumer products often first appear as a new want. Yet with a new

Table 6
Hedge ratio (long/short) summary statistics.

	Mean	St. dev.	Min	Max
ECO/OIL	0.20	0.19	−0.23	0.79
ECO/PSE	1.09	0.31	0.54	2.08
OIL/ECO	0.23	0.23	−0.74	0.83
OIL/PSE	0.12	0.39	−0.90	1.22
PSE/ECO	0.57	0.17	0.20	1.09
PSE/OIL	0.06	0.14	−0.20	0.46

Table 7
Portfolio weights summary statistics.

	Mean	St. Dev	Min	Max
ECO/OIL	0.60	0.16	0.13	0.90
ECO/PSE	0.18	0.28	0.00	1.00
OIL/PSE	0.26	0.17	0.00	0.84

consumer electronics product, a want soon becomes rationalized as a need and this easily increases sales for these products (new mobile smart phones for example). For clean energy companies it becomes important to avoid the "Valley of Death" which is the gap between innovation, adoption and diffusion of new energy technologies (Burer and Wustenhagen, 2009; Weyant, 2010). Government policy aimed at 1) reducing greenhouse gas (GHG) emissions by putting a price on emissions, 2) increasing the amount of innovative activity in technologies that reduce GHG emissions, and 3) educating the public regarding investment opportunities to reduce GHG emissions can together create a better investment environment for clean energy companies (Weyant, 2010).

Acknowledgements

I would like to thank an anonymous reviewer for helpful comments.

References

Bauwens, L., Laurent, S., Rombouts, J.V.K., 2006. Multivariate GARCH models: a survey. Journal of Applied Econometrics 21, 79–109.

Booth, G.G., Martikainen, T., Tse, Y., 1997. Price and volatility spillovers in Scandinavian stock markets. Journal of Banking and Finance 21, 811–823.

Burer, M.J., Wustenhagen, R., 2009. Which renewable energy policy is a venture capitalist's best friend? Empirical evidence from a survey of international cleantech investors. Energy Policy 37, 4997–5006.

Cha, H.-J., Jithendranathan, T., 2009. Time-varying correlations and optimal allocation in emerging market equities for the US investor. International Journal of Finance and Economics 14, 172–187.

Chang, C.-L., McAleer, M., Tansuchat, R., 2010a. Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. Energy Economics 32, 1445–1455.

Chang, C.-Y., Lai, J.-L., Chuang, I.-Y., 2010b. Futures hedging effectiveness under the segmentation of bear/bull energy markets. Energy Economics 32, 442–449.

Cifarelli, G., Paladino, G., 2010. Oil price dynamics and speculation: a multivariate financial approach. Energy Economics 32, 363–372.

Elder, J., Serletis, A., 2009. Oil price uncertainty in Canada. Energy Economics 31, 852–856.

Engle, R.F., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20, 339–350.

Ewing, B.T., Malik, F., Ozfidan, O., 2002. Volatility transmission in the oil and natural gas markets. Energy Economics 24, 525–538.

Hammoudeh, S., Yuan, Y., McAleer, M., 2009. Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets. The Quarterly Review of Economics and Finance 49, 829–842.

Hammoudeh, S., Yuan, Y., McAleer, M., Thompson, M., 2010. Precious metals-exchange rate volatility transmissions and hedging strategies. International Review of Economics and Finance 19, 633–647.

Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Economics 30, 998–1010.

Higgs, H., 2009. Modelling price and volatility inter-relationships in the Australian wholesale spot electricity markets. Energy Economics 31, 748–756.

International Energy Agency, 2009. World Energy Outlook. IEA, Paris.

Karolyi, G.A., 1995. A multivariate GARCH model of International Transmissions of stock returns and volatility: the case of the US and Canada. Journal of Business and Economic Statistics 13, 11–25.

Karolyi, G.A., Stulz, R., 1996. Why do markets move together? An investigation of US–Japan stock return comovements. Journal of Finance 50, 951–986.

Koutmos, G., Booth, G., 1995. Asymmetric volatility transmission in international stock markets. Journal of International Money and Finance 14, 747–762.

Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric movements of asset prices. Review of Financial Studies 11, 817–844.

Kroner, K.F., Sultan, J., 1993. Time dynamic varying distributions and dynamic hedging with foreign currency futures. Journal of Financial and Quantitative Analysis 28, 535–551.

Kumar, S., Managi, S., Matsuda, A., in press. Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Economics doi:10.1016/j.eneco.2011.03.002.

Lin, W., Engle, R., Ito, T., 1994. Do Bulls and Bears move across borders? International transmission of stock returns and volatility. Review of Financial Studies 7, 507–538.

Ling, S., McAleer, M., 2003. Asymptotic theory for a vector ARMA-GARCH model. Econometric Theory 19, 278–308.

Malik, S., Hammoudeh, S., 2007. Shock and volatility transmission in the oil, US and Gulf equity markets. International Review of Economics and Finance 17, 357–368.

New Energy Finance, 2010. Global Trends in Sustainable Energy Investment 2010. United Nations Environment Program and New Energy Finance, 2010.

Sadorsky, P., 2006. Modeling and forecasting petroleum futures volatility. Energy Economics 28, 467–488.

Weyant, J.P., 2010. Accelerating the development and diffusion of new energy technologies: beyond the "valley of death". Energy Economics doi:10.1016/j.eneco.2010.08.008.

Worthington, A., Kay-Spratley, A., Higgs, H., 2005. Transmission of prices and price volatility in Australian electricity spot markets: a multivariate GARCH analysis. Energy Economics 27, 337–350.