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# Conditional Jump Dynamics in the Stock Prices of Alternative Energy Companies

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**ABSTRACT:** This paper researches the abnormal information in the WilderHill Clean Energy Index (ECO) and NYSE Arca Technology Index (PSE) by using an autoregressive conditional jump intensity model in Skew Generalized Error Distribution (ARJI-SGED). The research period is from 3 January 2001 to 31 January 2011. We also test the diffusion-jump variance on the PSE and ECO. The empirical result indicates that there are jump phenomena in clean energy and technology companies. The oil price impacts on clean energy and technology companies. Moreover, the PSE has higher levels of volatility clustering than the ECO. These results show that the distributions of PSE return are skewed slightly to the left and fat-tailed. These also mean that jump variance plays a crucial role in market volatility indices.

**Keywords:** Clean Energy; Abnormal Information; ARJI-SGED Model
**JEL Classifications:** C2; G1; Q42

## 1. Introduction

Reacting to climate change concerns, energy security issues, high oil prices and high production costs for industries, renewable energy has developed fast as a result of stimulus, government support and commercialization in recent years. Besides, fossil energy is limited and any mines have already dried up or are approaching exhaustion; thus, inexhaustible renewable energy is sure to be an important alternative. Figure 1 shows the increase in oil price from 1992 to 2012. It also indicates that the cost of production and price levels has risen. Moreover, it is impressive that global investment in renewable energy approached a record high of about $170 billion in 2008, when the financial crisis happened (New Energy Finance, 2010). These developments in clean energy make it an ongoing trend for the foreseeable future, so this study has chosen the WilderHill Clean Energy Index (ECO) as one of its objects. Besides, there has been much discussion surrounding the technology, recently (Tully, 2000). The technology sector is usually referred to as the TMT sector because it is composed of companies in the areas of telecommunications, media and technology. It is also singled out as a very volatile sector for investment (Sadorsky, 2003). Sadorsky (2012) was aware of the importance of the ECO, it already found that oil is a good hedge object for clean energy stock. Besides, Henriques and Sadorsky (2008) indicated that the stock prices of alternative energy companies are impacted by shocks to technology stock prices. Kumar, Managi and Matsuda (2012) showed that oil prices and technology stock prices separately affect the stock prices of clean energy firms. Figure 2 shows the PSE tendency from 1 January 2001 to 15 February 2011: the value increases from 814.43 to 1171.48. It rose by 43.8% in the past decade, and is increasing in substance. All of the above indicate that the importance of technology should not be ignored.

**Figure 1. Oil price for the last twenty years**

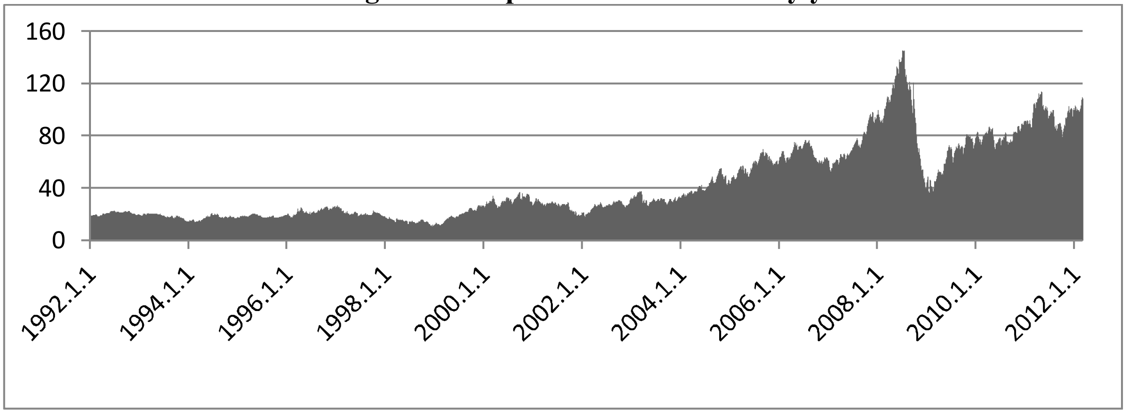
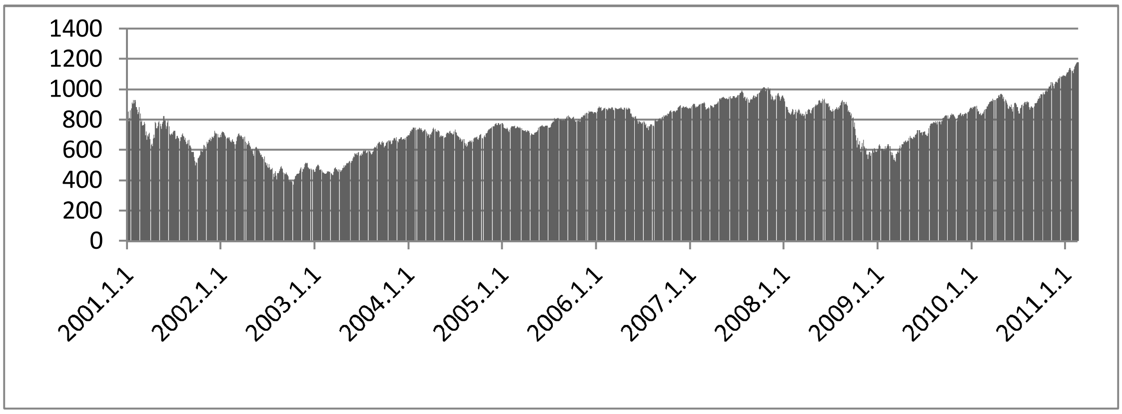



**Figure 2. NYSE Arca Technology Index**




In the volatility process, conditional modeling with asymmetry has been found to be unable to seize the skewness and tail-thickness of financial returns distribution and take advantage of skew-t distribution (Hansen, 1994). After a few years, skew generalized error distribution (SGED) was proposed by Theodossiou (2000) for modelling the empirical distribution of financial asset returns. Later, some scholars applied SGED with another model. Lehnert (2003), for example, combined SGED into the GARCH model to analyse in-sample and out-of-sample option pricing performance using DAX index options. Moreover, the nonlinear dynamics of short-term interest rate volatility were linked with SGED distributions in Bali (2007). Recent studies have mixed diffusion with the jump process. Bakshi, Cao and Chen (1997) and Das and Sundaram (1999) indicated that when governments and investors cannot realize true features, they will make incorrect financial and economic decisions. Zhang and Chen (2011) found that that there are jumps varying in time in China's stock market. Chang, Su and Chiu (2011) also found discontinuous jump behaviour from their in-the-sample biofuel data. Although there has been a large amount of research into the links between stock price and oil price, not all have investigated the feasibility of information quality being a crucial determinant of the degree of abnormal information. To estimate the impact of jump behavior caused by abnormal information, this paper uses the GARCH with autoregressive conditional jump intensity (ARJI) model developed by Chan and Maheu (2002), which takes the gauge of the jump intensity for obeying the ARMA process and joins a GARCH effect. Hence, this paper extends the ARJI with the skew generalized error distribution model (ARJI-SGED) to capture and comprehend the true features for ECO and PSE. The hope is to help governments and investors avoid making incorrect financial and economic decisions.

We hope that our empirical study can contribute to this field of research by using the ARJI-SGED model to investigate the abnormal information between the stock price of clean energy, technology companies and oil price. Furthermore, this paper also explores the diffusion-jump variance on the PSE and ECO. The study shows that the distributions of PSE return series is left-skewed and fat-tailed and the PSE and ECO indices exhibit jump phenomena, implying that the SGED is more appropriate to fit the data. Moreover, there is negative correlation (positive correlation) between PSE (ECO) and oil. These findings are different from some previous research with weekly data frequency. That research also showed that the correlation between oil price and PSE is not significant. Therefore, this study fills a gap in the literature and is hoped to provide valuable information to investors.

The remainder of this paper is organized as follows. The data description is reported in Section 2. Section 3 describes the adopted methodology underlying the ARJI-SGE model. The empirical results are then presented in Section 4. Concluding remarks are presented in the last section.

## 2. Data Description

The data consists of the ECO, PSE and oil prices according to Henriques and Sadorsky (2008) and Sadorsky (2010)[1]. The daily closing prices for ECO, PSE, oil prices and S&P500 were collected from Datastream and interest rate data were obtained from the Federal Reserve Board of St. Louis over the period from 3 January 2001 to 31 January 2011. The continuously compounded daily returns are calculated as the difference in the logarithms of daily ECO, PSE and oil prices and S&P500 multiplied by 100. That is, $R_{i,t} = (\ln S_{i,t} - \ln S_{i,t-1}) \times 100$, where $R_{i,t}$ and $S_{i,t}$ denote the continuously compounded return and price on i asset at time t, respectively.

## 3. Methodology

The purpose of this study applied a multifactor model by Henriques and Sadorsky (2008) incorporated with the abnormal information (jump intensity) by GARJI-SGED model to investigate what relates stock returns on either ECO or PSE to stock market returns and risk factors for oil price returns and interest rate changes. The purpose of this study applied a multifactor model by Henriques and Sadorsky (2008) and incorporated with the abnormal information (jump intensity) by GARJI-SGED model to investigate that relates stock returns on either ECO or PSE to stock market returns and risk factors for the oil price returns and interest rate changes. Thus, the model is described as follows:

$$R_t = \mu_0 + \sum_{s=1}^{n} \mu_s R_{t-s} + \phi_1 Market_t + \phi_2 Oil_t + \phi_3 Rate_t + \varepsilon_{1,t} + \varepsilon_{2,t} \tag{1}$$

$$\varepsilon_{i,t} = \sigma_t z_t \ , \quad z_t \sim NID(0,1)$$

$$\varepsilon_{2,t} = J_t - E\left[J_t \mid \phi_{t-1}\right] = \sum_{k=1}^{n_t} Y_{t,k} - \theta\lambda_t$$

$$J_t = \sum_{k=1}^{n_t} Y_{t,k} \ , \quad Y_{t,k} \sim NID(\theta, \delta^2)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

where $R$ = (ECO and PSE), $Market$, $Oil$ and $Rate$ are returns, S&P 500 returns, oil returns and interest rate change, respectively. $h_t$ represents the conditional heterogeneous variance, $\varepsilon_{t-1}^2$ is the coefficient of lagged residual square and $h_{t-1}$ is the coefficient of the lagged conditional heterogeneous variance. $Y_{t,k}$ is presumed to be independent and normally distributed with mean $\theta$ and variance $\delta^2$. $Z_t$ is a SGED. The density function of the standardized SGED distribution can be expressed as follows:

$$f(z_t \mid \upsilon, \lambda) = C \cdot \exp\left( - \frac{|z_t - \delta|^{\upsilon}}{[1 - sign(z_t - \delta)\lambda]^{\upsilon} \theta^{\upsilon}} \right) \tag{3}$$

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[1]Henriques and Sadorsky (2008) state that ECO was the first index for tracking the stock prices of clean renewable energy companies and has become a benchmark index. PSE is used to measure the stock market performance of technology firms because the Arca represents a pure play on technology.

where, $C = \frac{\upsilon}{2\theta \cdot \Gamma(\frac{1}{\upsilon})}$, the shape parameter $\upsilon$ governs the height and fat-tails of the density function with constraint $\upsilon > 0$. $\theta = \Gamma\left(\frac{1}{\upsilon}\right)^{1/2} \Gamma\left(\frac{3}{\upsilon}\right)^{-1/2} S(\lambda)^{-1}$, $\lambda$ is a skewness parameter of the density with $-1 < \lambda < 1$. $\delta = 2\lambda \cdot A \cdot S(\lambda)^{-1}$ $A = \Gamma\left(\frac{2}{\upsilon}\right)\Gamma\left(\frac{1}{\upsilon}\right)^{-1/2} \Gamma\left(\frac{3}{\upsilon}\right)^{-1/2}$.In the case of positive (negative) skewness, the density function skews toward to the right (left). Sign is the sign function. In particular, the SGED distribution turns out to be the standard normal distribution when $\upsilon = 2$ and $\lambda$ =0.

The jump stochastic process is assumed to be Poisson distribution with a time-varying conditional intensity parameter, $\lambda_t$. The Poisson distribution with parameter $\lambda_t$ conditional on the information set $\Omega_{t-1}$ is assumed to describe the arrival of a discrete number of jumps, where $n_t \in \{0,1,2,\cdots,n\}$ over the interval $[t-1,t]$. The conditional density of $n_t$ is expressed as follows:

$$P(n_t = j \mid \Omega_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^{\,j}}{j!} \qquad \lambda_t > 0, \; j = 0,1,2,\cdots,n \tag{4}$$

The conditional jump intensity $\lambda_t$ is the expected number of jumps conditional on the information set $\Omega_{t-1}$, which is parameterized as:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1} \tag{5}$$

Where $\lambda_t > 0$, and $\lambda_0 > 0$，$\rho \geq \gamma$，$\gamma \geq 0$.

$$\zeta_{t-1} \equiv E[n_{t-1} \mid \Omega_{t-1}] - \lambda_{t-1} = \sum_{j=0}^{\infty} j\, P(n_{t-1} = j \mid \Omega_{t-1}) - \lambda_{t-1} \tag{6}$$

where $P(n_{t-1} = j \mid \Omega_{t-1})$, called the filter, is the ex post inference on $n_{t-1}$ given the information set $\Omega_{t-1}$, $E[n_{t-1} \mid \Omega_{t-1}]$ is the ex post judgment of the expected number of jumps occurred from $t-2$ to $t-1$ and $\lambda_{t-1}$ is the conditional expectation of $n-1$ given the information set $\Omega_{t-2}$. Therefore, $\zeta_{t-1}$ represents the change in the econometrician's conditional forecast of $n_{t-1}$ as the information set is updated. Note from this definition that $\zeta_t$ is a martingale difference sequence with respect to information set $\Omega_{t-1}$. Therefore $E[\zeta_t] = 0$ and $Cov(\zeta_t, \zeta_{t-i}) = 0$, $i$ >0. Hence, the intensity residuals in a specified model should not show any autocorrelation.

The conditional variance of returns is given as:

$$Var(r_t \mid \phi_{t-1}) = Var(\varepsilon_{1,t} \mid \phi_{t-1}) + Var(\varepsilon_{2,t} \mid \phi_{t-1}) \tag{7}$$

The first component of the conditional variance, $\sigma_t^2 \equiv Var(\varepsilon_{1,t} \mid \phi_{t-1})$, is parameterized as a GARCH function of past return innovations.

Given our development of the conditional jump intensity and the jump-size distribution, the conditional variance component associated with the jump innovation is

$$Var(\varepsilon_{2,t} \mid \phi_{t-1}) = (\theta^2 + \delta^2)\lambda_t \tag{8}$$

This contribution to the conditional variance from jumps will vary over time as the conditional intensity $\lambda_t$ varies. In other words, this component can range from being small to large as the expected number of jumps changes over time.

## 4. Empirical Analysis

The descriptive statistics are shown in Table 1. The mean (standard deviation) values run from −23.37% to 4.19% (from 1.3787 to 6.1790) and there is large value in oil returns (interest rate change returns) and small value in interest rate change returns (S&P 500), respectively. Kurtosis of all variables is bigger than three, and all exhibit negative skew except PSE returns. All show non-normal distribution by J-B test. Additionally, each series is characterized by a distribution with tails that are significantly fatter than the normal distribution. Thus, in order to let skewness and tail-thickness in the conditional distribution of returns follow flexible management, this research uses the SGED distribution of Theodossiou (2001). To examine the serial correlation of square returns, the Ljung-Box Q and $Q^2$ test are used. The result shows both statistics with 25 lags are significant at 1% level. All series indicate that all series are autocorrelation, linear dependence and strong ARCH effects.

**Table 1. Descriptive statistics**

| **Items** | **ECO** | **Oil** | **PSE** | **S&P500** | **Rate** |
|---|---|---|---|---|---|
| **Mean** | -0.0220 | 0.0419 | 0.0155 | 0.0010 | -0.2337 |
| **SD** | 2.2317 | 2.2389 | 1.6485 | 1.3787 | 6.1790 |
| **Kurtosis** | 7.6163 | 11.3320 | 6.3948 | 11.1525 | 46.5982 |
| **Skewness** | -0.3958 | -0.0785 | 0.0963 | -0.1871 | -1.0246 |
| **J-B** | 2284.2020*** | 7231.151*** | 1203.853*** | 6935.093*** | 198357.9*** |
| **Q(25)** | 38.959*** | 76.600*** | 41.570*** | 98.845*** | 373.83*** |
| **$Q^2$(25)** | 58617*** | 59048*** | 56887*** | 58409*** | 39196*** |

Notes: 1. *, ** and *** denote significantly at the 10%, 5% and 1% level, respectively. 2. Q(25) and $Q^2(25)$ denote the Ljung-Box Q test for 25th order serial correlation of the returns and squared returns. 3. J-B statistics measure normal distribution for the series.

This research uses the ADF unit root test to examine if stock prices of clean energy, oil price, technology companies, S&P 500 and rate are stationary. The results of the unit root test of the original data and after the first difference data are presented in Table 2. The results show that all original data are not significant at 10% – that is, they are not stationary. However, they are stationary after the first difference of all the data, indicating that they are significant at 1% and stationary. Therefore, this paper uses the returns and interest rate change to conduct the analysis.

**Table 2. Unit roots test**

| ADF | Level | | | 1st | | |
|---|---|---|---|---|---|---|
| | C | C&T | Non | C | C&T | Non |
| ECO | -1.6367 | -1.7192 | -0.5340 | -47.7247*** | -47.7152*** | -47.7299*** |
| OIL | -1.0129 | -2.1582 | 0.9175 | -48.1078*** | -48.0984*** | -48.1031*** |
| PSE | -1.3070 | -2.4570 | 0.4758 | -51.7749*** | -51.7977*** | -51.7821*** |
| S&P500 | -1.8887 | -2.0290 | 0.0042 | -29.2600*** | -29.2691*** | -29.2658*** |
| Rate | -0.1204 | -0.7625 | -0.3372 | -9.0189*** | -9.0462*** | -8.9258*** |

Notes: 1. The null hypothesis is a non-stationary time series.
2. The lag length for the ADF test regressions is determined by the AIC (Akaike information criterion; AIC) criteria.
3. *, ** and *** denote significantly at the 10%, 5% and 1% level, respectively.

The estimates of ARJI with SGED models are listed in Table 3. The diagnostics of the standardized residuals of ARJI-SGED models confirm that the GARCH (1,1) specification in these models is sufficient to correct the serial correlation of these two returns series in the conditional variance equation.[2]

**Table 3. Estimation of the Models ARJI with SGED Model**

| Parameters | PSE | | ECO | |
|---|---|---|---|---|
| | Coefficients | Std Error | Coefficients | Std Error |
| $\mu$ | 0.0209** | 0.0106 | -0.0380 | 0.0252 |
| $\mu_1$ | 0.0354*** | 0.0088 | 0.1024*** | 0.0118 |
| $\mu_2$ | 0.0034 | 0.0082 | 0.0198 | 0.0122 |
| $\phi_1$ | 0.9961*** | 0.0113 | 1.2918*** | 0.0186 |
| $\phi_2$ | -0.0104* | 0.0054 | 0.0699*** | 0.0106 |
| $\phi_3$ | -0.0014 | 0.0018 | -0.0002 | 0.0045 |
| $\omega$ | 0.0013** | 0.0006 | 0.0572** | 0.0276 |
| $\alpha$ | 0.0345*** | 0.0075 | 0.0584*** | 0.0183 |
| $\beta$ | 0.9589*** | 0.0081 | 0.8731*** | 0.0436 |
| $\delta$ | 1.1351*** | 0.2105 | 1.7840*** | 0.2020 |
| $\theta$ | -0.2975* | 0.1734 | 0.1439 | 0.1902 |
| $\upsilon$ | 1.7344*** | 0.0866 | 1.8286 | 0.1082 |
| $\lambda$ | -0.0135 | 0.0293 | -0.0417 | 0.0389 |
| $\lambda_0$ | 0.0012 | 0.0008 | 0.0007 | 0.0005 |
| $\rho$ | 0.6109*** | 0.1638 | 0.8929*** | 0.0037 |
| $\gamma$ | 0.3568** | 0.1566 | 0.1017*** | 0.0027 |
| Function Value | -2322.5745 | | -3919.8395 | |
| Ljung-Box Q(25) | 23.4130 | | 15.4900 | |
| Ljung-Box $Q^2(25)$ | 26.7200 | | 15.0830 | |

Note: 1. Q and $Q^2$ are the Ljung-Box test in the standardized residuals and square standardized residuals. 2. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

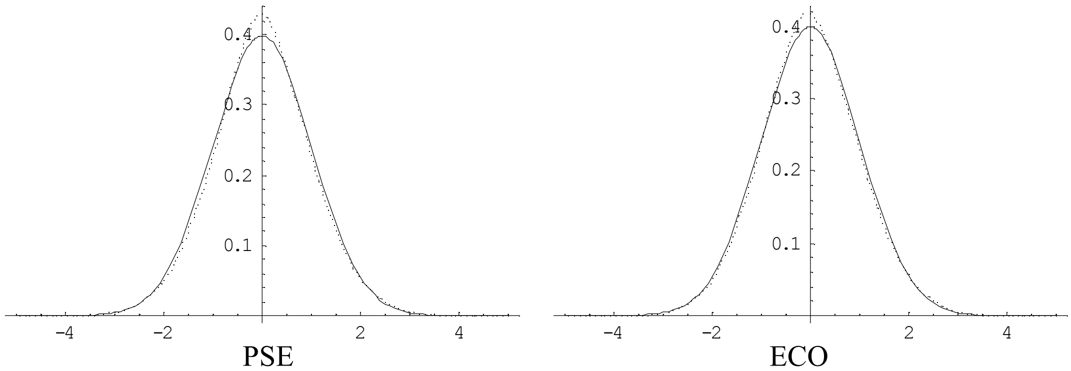
Market risk comparisons are investigated using a multifactor model (Sadorsky, 2001) that relates stock returns on either ECO or PSE to stock market returns (measured by the S&P 500) and risk factors for oil price returns and interest rate changes. These models are estimated using the ARJI-SGED model. The estimated coefficient on the market return indicates that the PSE and ECO indices are 0.9961 and 1.2918 and are positively significant. Oil price return is a negatively (positively) significant risk factor for the PSE (ECO) index at the 10% (1%) level, implying that ifoil returns increase by 1%, then the PSE (ECO) returns will decrease (increase)by approximately 1.04% (6.99%). The driving factors behind oil price movements should help spur greater demand and supply of alternative energy, as indicated byBleischwitz and Fuhrmann (2006), McDowall and Eames (2006) and New Energy Finance (2007). However, the interest rate variable is not a significantly priced risk factor for either the ECO index or the PSE index, indicating that results are consistent with Henriques and Sadorsky (2008).

[2] The estimates are analogous to those of Chan and Maheu (2002), AR(2) model for the condition mean of stock return for all models is necessary, for all models with GARCH(1,1) are appropriate. Misspecified tests based on the modified LB statistic are reported for autocorrelation in the standardized residuals (Q) and the square standardized residuals ($Q^2$) for 25 lags at the bottom of Table 3.

The estimated short-run and long-run ($\alpha$ and $\beta$) persistence of the shocks is positive and significant. The parameter $\beta$ means sensitivity to own past volatility and the volatility sensitivity places PSE and ECO (0.9589 and 0.8731) at a high level of volatility sensitivity. Thesums of parameters $\alpha$ and $\beta$ for the ARJI-SGED model are less than one, and thus ensure that the conditions for stationary covariance hold. The $\alpha+\beta$ are 0.9934 for PSE and 0.9315 for ECO, implying the long memory and high persistence of the conditional variance. This study found that the PSE has higher levels of volatility clustering than the ECO. The jump-size means ($\theta$) is significantly negative, −0.2975, for PSE; however, it is not significantly positive for ECO, implying the jumps' negative impact on the conditional mean of returns for PSE.[3] The $\delta$ for PSE and ECO are significant at the1% level and the jump-size variances for PSE and ECO are 1.2886 and 3.1826.

The parameters $\upsilon$ of the ARJI-SGED model in PSE return are 1.7344 and 1.8286. However, they are significant at the 1% level in PSE. The skewness parameter $\lambda$ for PSE and ECO returns are −0.0135 and −0.0417. The parameters $\upsilon$ and $\lambda$ obey the following constraints: $\upsilon > 0$ and $-1 < \lambda < 1$. The density graphs of SGED[4] distribution (dot) versus normal distribution (line) are illustrated in Figure 3. Each of the SGED distributions is slightly skewed towards the left, and is more leptokurtic and thicker than the normal distribution. These results show that the characteristics of the SGED distribution are consistent with the descriptive statistics of return series reported in Table 1, indicating that the SGED distribution closely approaches the empirical return series. Consequently, the return distributions are not normally distributed and the ARJI-SGED model has better fit to the data.

**Figure 3. The density graphs of Normal and SGED distributions**




As regards jump intensity, the parameters ($\rho$ and $\gamma$) for PSE and ECO are all statistically significant, demonstrating evidence of time-variation in the arrival of jump events. The $\rho$ parameters for the arrival of jump event are 0.6109 and 0.8929 for PSE and ECO, implying that a high probability of many (few) jumps today tends to be followed by a high probability of many (few) jumps tomorrow, as found by Chan and Maheu (2002). The $\gamma$ parameters for the effect of the most recent intensity residual are 0.3568 and 0.1017 for PSE and ECO. The lagged intensity residual and jump clustering of the PSE and ECO are all statistically significant at the 5% level, indicating that the jump frequency within the sample period is not a constant and that the arrival process can systematically deviate from its unconditional mean, as demonstrated by Bates (1996), Chan and Maheu (2002), Maheu and McCurdy (2004), Chiu, Lee and Chen (2005) and Lee and Lee (2009).

[3] The fact that the impact of jumps on the conditional mean of returns tends to be centered around zero on average implies that jumps do affect distribution of returns.

[4] The parameter $(\upsilon,\lambda)$ is obtained from the estimation results of the PSE and ECO indices, respectively.

Table 4 shows the results of the diffusion-jump variance on the PSE and ECO.[5] The variance caused in the jump process of the PSE and ECO contributes 8.55% and 25.05% of the total variance. This study found the importance of jump risks can be determined based on the ratio of the jump variance to the total variance; therefore, the jump variance plays a crucial role and cannot be overlooked. The variance caused in the diffusion process of the PSE and ECO contributes 91.45% and 74.95% of the total variance, indicating that it is important to consider the diffusion risks which can be determined based on the ratio of the diffusion variance to the total variance.

**Table 4. the results of the diffusion-jump variance**

| | PSE | ECO |
|---|---|---|
| Joint Variance | 0.6102 | 1.7105 |
| Jump-induced variance | 0.0855 | 0.2505 |
| Diffusion-induced variance | 0.9145 | 0.7495 |

## 5. Concluding Remarks

We investigated the abnormal information between the stock price of clean energy, technology companies and oil price by using the ARGI-SGED model. The sample period for the data set covers 3 January 2001 to 31 January 2011. We then further explored the diffusion-jump variance on the PSE and ECO.

Empirical results show that when oil returns increase, the PSE (ECO) returns will decrease (increase). Next, the distributions of PSE return series are left-skewed and fat-tailed, indicating the return distributions are not normal distribution. PSE and ECO indices exhibit jump phenomena, and the jump process must match statistical characteristics of the PSE and ECO. These findings imply that the SGED is more appropriate to fit the data. Finally, we also show the result of diffusion-jump variance because jump risks can be determined based on the ratio of the jump variance to the total variance. These empirical results provide valuable information to understand the diffusion-jump process for the change in volatility indices, so that traders can ensure they are using adequate investment strategies.

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[5]Accordingly, this study adopts the model developed by Chan and Maheu (2002), in which the total variance is estimated via $V_t = h_t + \lambda_t(\theta^2 + \delta^2)$, namely the total volatility index variance is divided into the variance caused in the jump process ($\lambda_t(\theta^2 + \delta^2)$) and that caused in the diffusion process($h_t$). Ratio of jump variance to total variance is $[\lambda_t(\theta^2 + \delta^2)]/V_t$.

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