Oil Prices and the Renewable Energy Sector

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ABSTRACT

Energy security, climate change, and growing energy demand issues are moving up on the global political agenda, and contribute to the rapid growth of the renewable energy sector. In this paper we investigate the effects of oil price shocks, and also of uncertainty about oil prices, on the stock returns of clean energy and technology companies. In doing so, we use monthly data that span the period from May 1983 to December 2016, and a bivariate structural VAR model that is modified to accommodate GARCH-in-mean errors. Moreover, we examine the asymmetry of stock responses to oil price shocks of different sizes, with and without oil price uncertainty. Our evidence indicates that oil price uncertainty has no statistically significant effect on stock returns, and that the relationship between oil prices and stock returns is symmetric. Our results are robust to alternative model specifications and stock prices of clean energy companies.

Keywords: Renewable energy, Transition, Oil prices, Uncertainty, GARCH-in-Mean model, Asymmetric responses

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1. INTRODUCTION

The renewable energy sector has been experiencing remarkable growth over the past decade. Worldwide installations of renewable power capacity reached a new high record of 138.5 GW[1] in 2016 (New Energy Finance, 2017), and expectations for large-scale deployment of renewables have also been raised for years to come. Figure 1 depicts the contribution of each fuel source in electricity generation in OECD countries and highlights the rapid integration of renewables during the recent years.[2] This development, however, is not a result of a single factor or event, but rather a combination of economic and societal concerns associated with the reliability and security of energy supply, the depletion of natural resources, extreme weather events triggered by environmental degradation, and decoupling of economic growth from energy consumption. Moreover, the financial performance of renewable energy companies has a critical influence on the future development of the renewable energy sector, since companies' profitability is positively related to their success in acquiring private capital for infrastructure investments. Therefore, a better understanding of the underlying driving forces is of high interest, not only to investors who need to assess the risk expo-

1. This includes global new investments in wind, solar, biomass and waste-to-energy, geothermal, small hydro and marine sources.

2. Data are obtained from the International Energy Agency (2017) and the World Bank (2018).

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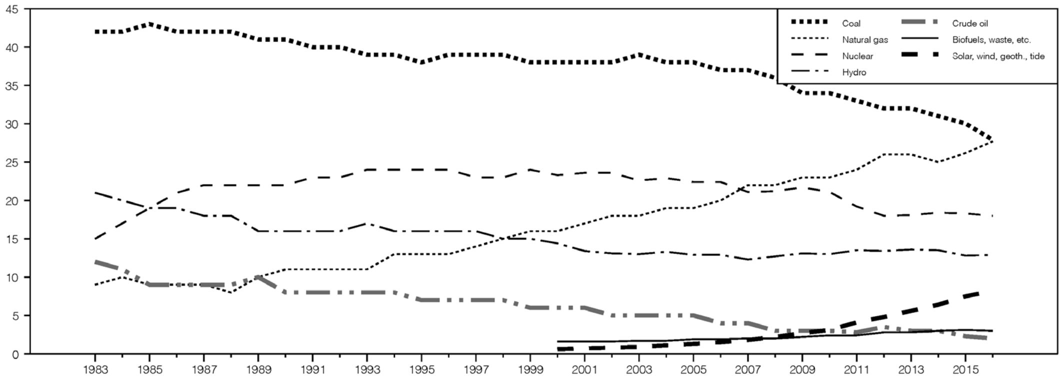
Figure 1: Gross electricity production by source in OECD countries (% share)



sure assumed by their firms, and construct hedge ratios and portfolio weights accordingly, but also to policymakers who must evaluate and adjust the renewable energy policy landscape, in order to facilitate the transition towards a sustainable energy system.

This paper contributes to the literature on the relationship between the price of oil and the stock returns of clean energy and technology companies in several ways. First, we use monthly data over the period from May 1983 to December 2016, and estimate a bivariate GARCH-in-Mean structural VAR model by full information maximum likelihood, thus avoiding Pagan's (1984) generated regressor problems. By doing so, we directly investigate the effect of oil price uncertainty on the response of the renewable energy and technology stock returns. Second, we generate the impulse response functions to assess whether the response of stock returns is symmetric or asymmetric to positive and negative oil price shocks, after accounting for the effect of oil price uncertainty. As an additional contribution to the literature, the use of a test, recently introduced by Kilian and Vigfusson (2011), over the same data set allows us to investigate whether the renewable energy and technology stock returns respond symmetrically or asymmetrically to positive and negative oil price shocks of different magnitude.

Financial performance of renewable energy companies is contingent upon numerous factors, and in fact prices of other energy products that are likely to substitute for renewable energy, for instance, through their positive cross-price elasticities, are considered to be among the most important determinants. Hence, with crude oil being the dominant energy source in the world, accounting for 36.9% of the global primary energy consumption in 2016 (Energy Information Administration, 2017),[3] it is essential to investigate the relationship between the oil price development and the financial performance of the renewable energy sector. Although the contribution of crude oil is decreasing over time in electricity generation, where the majority of renewable energy technologies are predominantly used, other fossil fuels such as coal and natural gas still dominate the electricity supply mix (see Figure 1). In fact, natural gas emerges as a considerable source of the electricity production mix, since it supports the flexible peak-load power generation that complements the intermittent nature of renewables (Kyritsis et al., 2017). Empirical studies, however, investigate the interactions between fuel prices and provide significant evidence of spillovers. In particular, Efimova and Serletis (2014), in a notable study, find unidirectional price spillovers from crude oil to natural gas and electricity markets, thus underlining the importance of crude oil in the U.S. econ-

3. Oil supply of 35.942 quadrillion Btu satisfied 97.394 quadrillion Btu of demand (Energy Information Administration, 2017).

omy. Hence, although crude oil and renewables seem to operate in different markets, they do interact with each other both directly and indirectly through other channels of influence.

Apart from the vast majority of the literature that investigates the effects of oil prices on the economy, the aggregate stock market activity, or even other energy prices such as, for example, the natural gas price, only a few studies pay particular attention to the impact of oil prices on the financial performance of the renewable energy sector; the most noticeable being Henriques and Sadorsky (2008), Kumar et al. (2012), Broadstock et al. (2012), Sadorsky (2012a), Managi and Okimoto (2013), Wen et al. (2014), Inchauspe et al. (2015), and more recently Reboredo et al. (2017). All of these studies, however, ignore the potentially important effect of oil price uncertainty on renewable energy companies, and more particularly on their financial performance.

Since the outset of the global financial crisis in 2008–2009, the crude oil market has experienced dramatic oil price fluctuations, for instance from \$140/barrel in the summer of 2008 to \$60/barrel by the end of 2008, which were followed, after the sharp downturn in the mid-2014, by low and remarkably volatile oil prices (see Figure 2a). Increased oil price volatility translates into significant uncertainty in the crude oil market, and its overall impact should accelerate future transition towards renewable energy. The main argument behind this statement is that with renewable energy considered as a substitute for crude oil, increases in oil price uncertainty should encourage a substitution effect away from crude oil towards renewable energy sources, thus improving the financial performance of renewable energy companies. We read in a press article: "But perhaps the biggest factor is one of the least tangible: uncertainty... people working in renewables say that the volatility in oil is precisely the reason to go green — prices are more stable, with fewer ups and downs" (BBC news, 2015). However, despite some anecdotal evidence that rising oil price uncertainty strengthens the dominance of the renewable energy industry in the global energy scene, and therefore its financial performance, an up-to-date empirical evidence is imperative to confirm or invalidate the hypothesis.

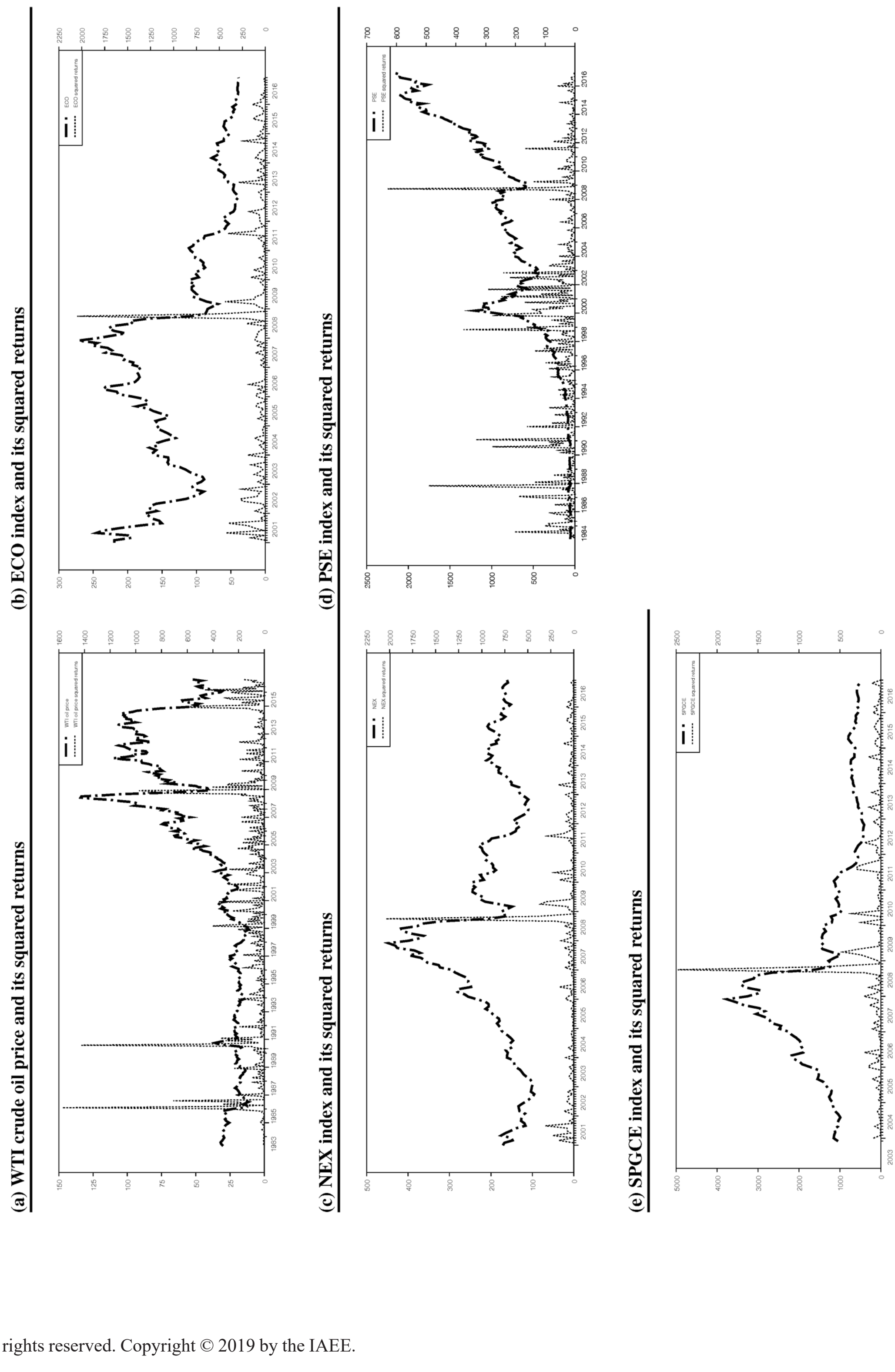
The rest of the paper is structured as follows. In section 2, we review and discuss the empirical literature related to the effects of oil price on the aggregate and industry-specific stock returns, while paying special attention to the relationship between oil prices and stock returns of clean energy and technology companies. Section 3 presents the bivariate GARCH-in-Mean structural VAR model, which is employed to investigate the direct effects of oil price uncertainty on the employed stock returns, as well as the impulse response functions that are employed to evaluate the effect of oil price uncertainty on the response of stock returns to an oil price shock. In Section 4 we present the data and discuss the empirical findings, while in Section 5 we investigate whether the stock returns respond symmetrically or asymmetrically to oil price shocks of different signs and magnitudes, by using a formal symmetry test based on a nonlinear structural VAR model recently proposed by Kilian and Vigfusson (2011). The last section discusses the findings and concludes the paper.

2. REVIEW OF THE LITERATURE

2.1 Oil Prices and Stock Market Activity

Given the indispensable role of crude oil as an energy commodity in the world economy, but also as a financial asset since the early 2000s, there is a substantial and growing body of literature investigating the relationship between oil price shocks and stock market returns. On theoretical grounds, stock prices reflect the value of expected future earnings of companies that contingent on

Figure 2: WTI crude oil price returns and returns of sub-indices



(a) WTI crude oil price and its squared returns

(b) ECO index and its squared returns

(c) NEX index and its squared returns

(d) PSE index and its squared returns

(e) SPGCE index and its squared returns

several factors, such as relative sensitivity to changes in oil prices or dissimilar dependence on the oil industry, might be driven by oil price shocks. In regard to this, Chen et al. (1986) and Hamao (1988) study the effects of oil price changes on the U.S. and Japanese stock markets, respectively, and find no compelling evidence that supports such a relationship. Kling (1985) and Jones and Kaul (1996), in contrast, argue that changes in oil prices have a detrimental effect on stock market returns, while Sadorsky (1999) confirms that oil price fluctuations are imperative for understanding stock market development. Huang et al. (1996), however, find no negative relationship between changes in the price of oil futures and the returns of various stock indices; while Wei (2003) reports that the decline in the U.S. stock market in 1974 cannot be attributed to the 1973–1974 oil price increase. In fact, he suggests other possible factors, including the tightening of monetary policy. This view also receives strong support from Bjørnland (2009), who examines the small and open oil-exporting country of Norway, and argues that oil prices affect stock market returns indirectly, through monetary policy.

A possible explanation for all the aforementioned studies not reaching a general consensus is that none of them, apart from Bjørnland (2009), differentiates oil-exporting from oil-importing countries. Wang et al. (2013) compare the relationship of oil price shocks and stock returns in several countries with different oil-dependence, and find that the explanatory power of oil prices shocks to stock return variations is stronger in oil-exporting than oil-importing countries, as well as the evidence of different magnitudes, durations, and directions of stock response. Arouri and Rault (2012) support this view through their study, with particular reference in the Gulf Corporation Countries, finding a positive relationship between oil price shocks and stock prices. From a similar point of view, Park and Ratti (2008) examine this relationship in the United States and 13 European countries, and report that a positive oil price shock has a statistically significant and negative effect on stock prices of all the oil-importing countries, but positive in the case of the oil-exporting country of Norway.

In a different study, Kilian and Park (2009) follow Kilian's (2009) approach and decompose oil price fluctuations into structural shocks, in order to study their effects on the U.S. stock market returns. In doing so, they treat the price of crude oil as endogenous, and report that the response of stock prices to oil price shocks depends on the nature of oil price shocks. Some notable studies that build upon this framework are Apergis and Miller (2009), Güntner (2014), and Ahmadi et al. (2016). Nor do all the industry sectors respond in a similar way to oil price shocks (see Lee et al. (1995) and Davis and Haltiwanger (2001)), and therefore sectoral-based investigation is imperative for a better understanding of this relationship. The oil and gas sectors, as well as the technology sector, are investigated by Sadorsky (2001, 2003), while a large number of industries in the U.S. and China are explored by Elyasiani et al. (2011) and Caporale et al. (2015), respectively. All their findings underline the necessity of studying the various industries separately, mainly due to their different dependence on the oil industry.

A less extensive yet substantial body of literature investigates the impact of oil price volatility, which is also a measure of uncertainty, on economic activity and stock market returns. Elder and Serletis (2010) were the first to examine the direct effects of oil price uncertainty on real economic activity, and provide evidence of a negative and significant relationship. In addition, they find that increased oil price volatility amplifies the negative response of real economic activity to an unexpected increase in the real price of oil, while diminishing the positive response to an unexpected drop in the real price of oil. Lee et al. (1995) and Ferderer (1996) also underline the important role of oil price volatility in economic activity, while Sadorsky (1999) first explores its impact on the U.S. stock returns, and reports a statistically significant negative association. From a similar point of view, Park and Ratti (2008) show that increased oil price volatility depresses real stock returns in the oil-importing European countries, while they document little evidence of asymmetric effects. Masih et al. (2011) also indicate the dominance of oil price volatility on real stock returns in South Korea, and comment on the need of firms for adjusting their risk management procedures accordingly. Diaz et al. (2016), from an international point of view, examine the relationship between oil price volatility and stock returns in the G7 economies, and provide evidence in favor of a negative association. This negative relationship, however, does not receive support by Alsalman (2016), who reports that uncertainty about the real price of oil has no statistically significant effect on U.S. real stock returns across all the investigated industries, except in the case of the coal sector. Moreover, she finds that aggregate stock returns respond symmetrically to positive and negative oil price shocks, but this symmetry does not hold across all sectors, thus highlighting the importance of studying each sector separately. Alsalman and Herrera (2015) provide further evidence in favor of symmetric response for aggregate stock returns, while Herrera et al. (2015) explain symmetric (asymmetric) responses through the statistically insignificant (significant) effect of oil price uncertainty on investments.

2.2 Oil Prices and the Renewable Energy Sector

Despite the rapid growth of the renewable energy sector over the past decade in the face of rising oil prices and environmental concerns, little attention has been devoted to the relationship between oil prices and stock prices of renewable (or alternative) energy sector.[4] To the best of our knowledge, Henriques and Sadorsky (2008) first discuss this gap in the literature, and investigate the dynamic relationships between alternative energy stock prices, technology stock prices, oil prices, and interest rates, through a four variable vector autoregression model. They find causality effects, in the spirit of Granger, propagating from both technology stock prices and oil prices towards stock prices of alternative energy companies, listed on major U.S. stock exchanges, while the latter stock prices are found to be more strongly correlated with stock prices of technology companies, rather than with oil prices. In fact, they find that oil prices have only a limited impact on renewable energy stock returns. However, Kumar et al. (2012) investigate this relationship, considering also the prices for carbon allowances, and provide evidence that rising oil prices have a significant positive impact on clean energy stock prices, contrary to carbon market prices. Similar to Henriques and Sadorsky (2008), they also support the view that clean energy and technology companies are considered by investors as similar asset classes. Broadstock et al. (2012) adopt time-varying conditional correlation and asset pricing models to explore how the dynamics of international oil prices affect Chinese energy-related stock price returns. Specifically, they study the response of a composite energy index, as well as three sub-indices for oil and natural gas, coal and electricity, and new energy sector, to international oil price shocks, and report that oil price changes are a significant factor in energy-related stock price movements, especially after the 2008 financial crisis, whereas the new energy stocks are found to be the most resilient to oil price shocks.

Building upon the vector autoregressive analysis of Henriques and Sadorsky (2008), Managi and Okimoto (2013) consider a Markov-switching model in order to explore possible structural changes and asymmetric effects among oil prices, technology stock prices, and clean energy stock prices. They provide evidence in favor of a structural change in the market in late 2007, and a positive relationship between oil prices and clean energy prices thereafter. Furthermore, they support

4. The terms alternative energy, clean energy, renewable energy, and sustainable energy are used interchangeably when the discussion comes around to tracking stock indices or investment assets.

the view of Henriques and Sadorsky (2008) and Kumar et al. (2012) for similarity between clean energy stock prices and technology stock prices, by arguing that technologies related to storage and other forms of clean energy benefit from a number of government policies. More recently, Reboredo (2015) investigates the dependence structure and conditional value-at-risk (CoVaR) measure of systemic risk between oil prices and a set of global and sectoral renewable energy indices, through the employment of copulas for the period from December 2005 to December 2013. His empirical findings display that a time-varying average and symmetric tail dependence exists between oil returns and several global and sectoral renewable energy indices, while oil price dynamics contribute around 30% to downside and upside risk of renewable energy companies.

From a different point of view, Inchauspe et al. (2015) examine the dynamics of excess returns for the WilderHill New Energy Global Innovation Index (NEX), which constitutes a major international benchmark index for renewable energy, through the use of a multi-factor asset pricing model with time-varying coefficients. They report a weak influence of oil price, relatively to the MSCI World Index and technology stocks, on NEX returns, although this effect becomes more influential after 2007. In fact, they find that NEX Index yields negative active returns after the financial crisis in 2009, and attribute this poor performance to the increased market uncertainty triggered by low oil price and government subsidy cuts. Bürer and Wüstenhagen (2009) also underline the important contribution of supportive policy environments to renewable energy investments, while Hofman and Huisman (2012) show that, after the financial crisis, 11 out of 12 renewable energy policies decreased significantly in popularity by venture capital and private equity investors. Decreased risk tolerance, higher capital demand and increased borrowing costs are mentioned as some of the contributing factors.

In recent years, a new strand of literature has emerged studying volatility spillovers between oil prices and renewable energy stock prices. Specifically, Sadorsky (2012a) employs different multivariate GARCH models (BEKK, Diagonal, CCC, and DCC) to examine conditional correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. He finds that stock prices of clean energy companies correlate more strongly with technology stock prices than with oil prices, that significant volatility spillovers exist among them, and that oil is a useful hedge for clean energy stocks. Extending this framework to include asymmetric effects, Wen et al. (2014) use a bivariate asymmetric BEKK model to investigate mean and volatility spillover effects between renewable energy and fossil fuel stock prices in China. They provide evidence that negative news about new energy and fossil fuel stock returns lead to larger return changes in their counter assets than positive news, that significant mean and volatility spillovers occur among them, and that new energy stocks are more speculative and riskier than fossil fuel stocks. Sadorsky (2012b) provides a comprehensive study on different factors of renewable energy company risk and highlights that renewable energy companies can be among the riskiest types of companies to invest in. In fact, he shows that oil price increases have a positive effect on company risk, whereas increases in company sales growth reduce systematic risk. Very recently, Reboredo et al. (2017) investigate dependence and causal effects between oil price dynamics and renewable energy returns for the period 2006–2015. Through the use of continuous and discrete wavelets and linear and non-linear Granger causality tests, they find evidence of non-linear causality running from renewable energy indices to oil prices, and mixed evidence of causality propagating from oil prices to renewable energy prices.

Yet, no study has investigated the relationship between oil price uncertainty and the stock prices of renewable energy companies, to the best of our knowledge. The purpose of the paper is to fill this void. A better understanding of the relationship between oil price uncertainty and financial performance of the renewable energy sector is imperative for understanding and foreseeing the evolution of the renewable energy sector in the years to come.

3. THE STRUCTURAL GARCH-IN-MEAN VAR

In this paper we employ a bivariate monthly structural VAR model, modified to accommodate GARCH-in-Mean errors as inElder (2004) and Elder and Serletis (2011), in logarithmic oil price changes and stock returns. See also Elder and Serletis (2011), Chang and Serletis (2018), and Serletis and Mehmandosti (2018). The structural system is represented as follows

$$\boldsymbol{B}\boldsymbol{y}_t = \boldsymbol{\alpha} + \sum_{i=1}^{p} \boldsymbol{\Gamma}_i \boldsymbol{y}_{t-i} + \boldsymbol{\Lambda}\boldsymbol{H}^{1/2}_{\Delta lno_t} + \boldsymbol{\epsilon}_t \tag{1}$$

$$\epsilon_t \,|\, \Omega_{t-1} \sim iid\ N(0, \boldsymbol{H}_t) \tag{2}$$

where the vector $\boldsymbol{y}_t$ includes the change in the price of oil (Δlno_t) and the stock returns (Δlnz_t), $\boldsymbol{\alpha}$ is a parameter vector, $\boldsymbol{B}$ and $\boldsymbol{\Gamma}_i$ are 2×2 matrices representing the contemporaneous and lagged effects, and $\boldsymbol{\epsilon}_t$ denotes a vector of serially and mutually uncorrelated structural shocks. Moreover, $\boldsymbol{\Lambda}$ is a vector of coefficients that measures the effect of oil price volatility on the conditional mean of the employed series, $\boldsymbol{H}^{1/2}_{\Delta lno_t}$ is the conditional standard deviation of oil, Ω_{t-1} denotes the information set at time $t-1$, and $\boldsymbol{H}_t$ is the covariance matrix. The system is identified by assuming that the diagonal elements of $\boldsymbol{B}$ are unity, that $\boldsymbol{B}$ is a lower triangular matrix, and that the structural disturbances, $\boldsymbol{\epsilon}_t$, are contemporaneously uncorrelated.

The conditional variance is modeled as bivariate GARCH

$$diag(\boldsymbol{H}_t) = \boldsymbol{A} + \sum_{j=1}^{s} \boldsymbol{F}_j diag(\boldsymbol{\epsilon}_{t-j}\boldsymbol{\epsilon}'_{t-j}) + \sum_{i=1}^{r} \boldsymbol{G}_i diag(\boldsymbol{H}_{t-i}) \tag{3}$$

where *diag* is the operator that extracts the diagonal from a square matrix. In fact, we assume that the conditional variance of $y_{i,t}$ depends only on its own past squared errors and its own past conditional variances, so that parameter matrices $\boldsymbol{F}_j$ and $\boldsymbol{G}_i$ are also diagonal.[5] Moreover, we estimate the variance equation (3) with $s = r = 1$, since the parsimonious GARCH(1,1) model has been found to outperform other GARCH configurations, under the most general conditions [see Hansen and Lunde (2005)]. Low-order GARCH models, and particularly GARCH (1,1), receive also support by Bollerslev et al. (1992).

We estimate the model by full information maximum likelihood, thus avoiding Pagan's (1984) generated regressor problems associated with estimating the variance function parameters separately from the conditional mean parameters. Consistent with Elder (2004) and Elder and Serletis (2011), we estimate the bivariate GARCH-in-Mean VAR model described by equations (1)–(3), by full information maximum likelihood, and by numerically maximizing the log likelihood function

$$l_t = -\frac{n}{2} ln(2\pi) + \frac{1}{2} ln\,|\boldsymbol{B}|^2 - \frac{1}{2} ln\,|H_t| - \frac{1}{2}(\boldsymbol{\epsilon}'_t \boldsymbol{H}_t^{-1} \boldsymbol{\epsilon}_t) \tag{4}$$

with respect to the structural parameters $\boldsymbol{B}, \alpha, \boldsymbol{\Gamma}, \boldsymbol{\Lambda}, \boldsymbol{A}, \boldsymbol{F}$, and $\boldsymbol{G}$.

5. This assumption can be lifted if the researcher is specifically interested in how the lagged volatility of one variable might relate to the conditional variance of another.

In doing so, we set the pre-sample values of the conditional variance matrix $\boldsymbol{H}_0$ to their unconditional expectation and condition on the pre-sample values of $\boldsymbol{y}_t$. To ensure that $\boldsymbol{H}_t$ is positive definite, we restrict $\boldsymbol{A} > 0$, $\boldsymbol{F} \geq 0$, and $\boldsymbol{G} \geq 0$, as in Engle and Kroner (1995). By satisfying the standard regularity conditions, full information maximum likelihood estimates are asymptotically normal and efficient, with the asymptotic covariance matrix given by the inverse of Fisher's information matrix. For mode details, see Elder (2004) or Elder and Serletis (2011). It is worth mentioning that our model does not capture the time-varying relationships between the employed data series, while a longer analysis period about the performance of the renewable energy sector would benefit such a study.

To evaluate the effect of oil price uncertainty on the response of stock returns to an oil price shock, we generate impulse response functions. These are based on an oil price shock equal to the unconditional standard deviation of the change in the price of oil and are calculated for the GARCH-in-Mean VAR as in Elder (2003)

$$\frac{\partial E(y_{j,t+k} \mid \boldsymbol{\varepsilon}_{i,t}, \Omega_{t-1})}{\partial \boldsymbol{\varepsilon}_{i,t}} = \sum_{\tau=0}^{k-1} [\Theta_\tau \boldsymbol{B}^{-1} \Lambda (\boldsymbol{F} + \boldsymbol{G})^{k-\tau-1} \boldsymbol{F}] \boldsymbol{\iota}_1 + (\Theta_k \boldsymbol{B}^{-1}) \boldsymbol{\iota}_0. \tag{5}$$

where $\boldsymbol{\iota}_1$ denotes $\partial E[vec(\epsilon_t' \epsilon_t) \mid \boldsymbol{\varepsilon}_{i,t}, \Omega_{t-1}] / \partial \boldsymbol{\varepsilon}_{i,t}$, which is an $N^2 \times 1$ vector with $2\boldsymbol{\varepsilon}_{i,t}$ in the $N(i-1)+i$ spot and 0s elsewhere. Moreover, $\boldsymbol{\iota}_0$ denotes $\partial \epsilon_t / \partial \boldsymbol{\varepsilon}_{i,t}$, which is an $N \times 1$ vector with $\boldsymbol{\varepsilon}_{i,t}$ in the ith spot and 0s elsewhere. In fact, Elder (2003) notes that equation (5) is analogous to the impulse response function of an orthogonalized VAR. The second term on the right side of the equation captures the usual direct effect of a shock $\boldsymbol{\varepsilon}_{i,t}$ on the conditional forecast of $y_{j,t+k}$ while the first term captures the effect on the conditional forecast of $y_{j,t+k}$ through the forecasted effect on the conditional variance. It is noteworthy that as the horizon increases the first term shrinks to the zero matrix since the eigenvalues of $\boldsymbol{F} + \boldsymbol{G}$ are constrained to be lower than one. See Elder (2003) for more details.

In particular, the impulse responses are simulated from the maximum likelihood estimates of the model's parameters, while the one-standard error confidence bands are generated by the Monte Carlo method as described in Hamilton (1994, p. 337).[6] The responses are constructed based on parameter values drawn randomly from the sampling distribution of the maximum likelihood parameter estimates, where the covariance matrix of the maximum likelihood estimates is derived from an estimate of Fisher's information matrix. Finally, we plot the impulse responses of stock returns to positive and negative oil price shocks, after accounting for oil price uncertainty, thus gaining a better insight into whether responses are symmetric or asymmetric.

4. THE DATA AND EMPIRICAL EVIDENCE

This study uses monthly closing prices of three clean energy indices, namely, WilderHill Clean Energy Index (ECO), WilderHill New Energy Global Innovation Index (NEX), and S&P Global Clean Energy Index (SPGCE), as well as the technology index, NYSE Arca Technology Index (PSE). Specifically, ECO is a modified equal dollar-weighted index comprised of 52 companies which are active in the renewable energy sector, and whose activities stand to benefit substantially from a societal transition toward the use of cleaner energy and conservation. This index is the oldest index devoted merely to tracking clean (renewable) energy companies, and it is disseminated by the American Stock Exchange (AMEX). NEX is a modified dollar-weighted index comprised of publicly traded companies whose businesses focus on renewable energy and climate change mitigation

6. The confidence intervals are generated by the Monte Carlo method with 1000 simulations.

technologies. Most of the stocks are listed on exchanges outside the United States, and therefore the correlation between the index and ECO is low. NEX constitutes the first and leading global index for clean, alternative, and renewable energy. SPGCE is a weighted index of 30 companies from around the world that are engaged in clean energy production, and clean energy equipment and technology business.

Investments in renewable energy companies, however, may be considered to be similar to those of other high technology companies (Henriques and Sadorsky, 2008). This is an argument actually supported by the stock market behavior in the late 1990s when a large number of fuel cell companies were adversely affected by the technology stock market bubble burst. Furthermore, due to technology innovation, the capital cost of renewable energy sources has declined substantially, thus reducing previous investments barriers and playing an important role in the future development of renewable energy sector. Therefore, we also employ in our analysis the NYSE Arca Technology Index, which is a price weighted index devoted solely to technology, as a proxy for the stock market performance of technology sector. In particular, it is composed of 100 leading technology companies that are active in 15 different industries, including computer hardware, software, data storage and processing, electronics, semiconductors, telecommunications, and biotechnology. Figures 2b–2e illustrate the development of each of the indices alongside with its squared returns. Unlike the PSE index that fully recovers from the losses associated with the global financial crisis in 2008–2009, while exhibiting a clear upward trend for the rest of the investigated period, all three clean energy indices remain at historically low levels. In particular their significant drop in value during the financial crisis is partly reversed in the next year, before another, but smaller, plunge occurs between 2011 and 2012. Since this last decline, only the NEX index rebounds completely and continues fluctuating at the post-financial crisis levels. All stock indices exhibit low price volatility, at least compared to the oil futures price.

In addition, the excess return on the market, which is defined as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks from the Center for Research in Security Prices (CSRP) minus the 1-month Treasury bill rate, is used as a proxy for the aggregate U.S. stock returns. The primary reason for doing so is to examine the effect of oil price uncertainty on the U.S. stock returns at the aggregate level, as well as at the sectoral level of the renewable energy sector. Thereby we are able to gain a better understanding of how differently oil price uncertainty affects the financial performance of the renewable energy sector compared to the aggregate stock market. For the price of oil, we use the nearest futures contract to maturity on the West Texas Intermediate crude oil futures contract, for a number of reasons. Firstly, due to temporary shortages or surpluses, spot prices are more affected by short-run price fluctuations than futures prices (Sadorsky, 2001). Secondly, if a firm engages in hedging, the effectiveness of such hedging activities is evaluated by the variability of futures oil prices (Elyasiani et al., 2011). Lastly, it is the most extensively traded oil futures contract in the world, and therefore constitutes a benchmark for the oil market and commodity portfolio diversification (Sadorsky, 2012b). Our data sample covers the period from May 1983, which coincides with the availability of our proxy for the oil price, to December 2016. For each data series, we calculate the continuously compounded monthly returns as $100 \times ln(p_t / p_{t-1})$, which we employ in the rest of our analysis.

It is worth mentioning here an interesting feature of the data related to the contemporaneous correlation between the different price series. We present these correlations in Table 1 for the first differences of the log levels, since our primary object of interest is stock returns. In order to determine whether these correlations are statistically significant, we follow Pindyck and Rotemberg

Table 1: Contemporaneous Correlations

	First Differences of Log Levels				
Series	**ECO**	**NEX**	**PSE**	**SPGCE**	**WTI**
ECO	1	0.931	0.767	0.907	0.434
NEX	0.931	1	0.798	0.959	0.490
PSE	0.767	0.798	1	0.721	0.328
SPGCE	0.907	0.959	0.721	1	0.440
WTI	0.434	0.490	0.328	0.440	1
	$x^2(10)=939.001$				

Note: Monthly data from 2003:12 to 2016:12.

(1990) and we perform a likelihood ratio test of the hypotheses that the correlation matrices are equal to the identity matrix. The test statistic is

$$-2ln(|R|^{N/2})$$

where $|R|$ is the determinant of the correlation matrix and N is the number of observations. The test statistic is distributed as χ^2 with $q(q-1)/2$ degrees of freedom, where q is the number of series. The test statistic is equal to 939.001 with a p-value of 0.000 for the first differences of the logs, and therefore we can clearly reject the hypothesis that these series are uncorrelated. In addition, we notice that some of the correlation patterns documented in Table 1 also manifest in the graphical presentation of the employed series in the different plots in Figure 2. The four scatterplots between the sub-indices and the WTI crude oil price illustrated in Figure A.9 also provide evidence of correlation between the data series, thus supporting the previous conclusion that the series are correlated. Moreover, we employ two stock indices, namely the Dow Jones Industrial Average (DJIA) and the S&P 500 from Yahoo! Finance, and construct the scatterplots between the renewable sub-indices and each of the stock indices in Figures A.10 and A.11, respectively. The patterns observed between each of the three renewable sub-indices and the Dow Jones Industrial Average (DJIA) are almost identical, displaying a clear positive correlation, in the sense that as one series increases the other one also increases. However, the lower part of the corresponding scatterplots suggests no relationship between the series. This can probably be explained by the fact that none of the renewable sub-indices recovers from the losses associated with the global financial crisis in 2008–2009, and thereby they remain at historically low levels. On the contrary, the PSE technology index recovers fully from the financial crisis and therefore the corresponding scatterplot between the technology index and the Dow Jones Industrial Average (DJIA) displays merely a strong positive correlation. Same conclusions are derived for the case of the S&P 500 index in Figure A.11.

Before we continue to the next step of modeling, we conduct some unit root and stationary tests in each of the employed return series in Table 2, in order to test for the presence of a stochastic trend in the autoregressive representation of the series. All three tests, namely, the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller (1981)], the Dickey-Fuller GLS (DF-GLS) test [see Elliot et al. (1996)] and the KPSS test [see Kwiatkowski et al. (1992)] provide evidence that all return series are stationary, or integrated of order zero, $I(0)$. It should be noted that the Schwarz information criterion (SIC) is used to select the lag length in both the ADF and DF-GLS regressions, assuming a maximum lag length of 4 months for each series, while the Bartlett kernel for the KPSS regressions is determined using the Newey-West bandwidth (NWBW). Moreover, in Table 3 we conduct a series of Ljung-Box (1979) tests for serial correlation, in which the Q-statistics are asymptotically distributed as $\chi^2(4)$ on the null hypothesis of no autocorrelation. Certainly, there is significant serial dependence in the data. In addition, a Ljung-Box test for serial correlation in the

Table 2: Unit Roots and Stationary Tests

Series	ADF	DF-GLS	KPSS	Decision
	Test			
AGG	–18.717*	–5.676*	0.057	$I(0)$
ECO	–10.154*	–10.107*	0.063	$I(0)$
NEX	–9.351*	–9.070*	0.080	$I(0)$
PSE	–14.638*	–13.708*	0.077	$I(0)$
SPGCE	–8.264*	–3.282*	0.182	$I(0)$
WTI	–14.600*	–13.821*	0.075	$I(0)$

Note: An asterisk indicates significance at the 5% level.

Table 3: Tests for Serial Correlation and Conditional Heteroskedasticity

Series	$Q(4)$	$Q^2(4)$	$ARCH(4)$
AGG	2.777 (0.596)	13.527 (0.009)	10.762 (0.029)
ECO	17.059 (0.002)	8.926 (0.063)	10.445 (0.034)
NEX	27.908 (0.000)	9.577 (0.048)	10.718 (0.030)
PSE	37.651 (0.000)	17.017 (0.002)	13.515 (0.009)
SPGCE	25.909 (0.000)	14.220 (0.007)	15.616 (0.004)
WTI	42.656 (0.000)	69.517 (0.000)	52.134 (0.000)

Note: Numbers in parentheses are marginal significance levels.

Table 4: Model Specification Tests with WTI Crude Oil Price

Model	**Homoskedastic VAR**	**Bivariate GARCH-M VAR**
AGG - WTI	5203.715	5143.391
ECO - WTI	2696.742	2704.585
NEX - WTI	2614.204	2615.708
PSE - WTI	5265.364	5208.170
SPGCE - WTI	2191.582	2194.203

Note: This table computes the Schwartz Information Criterion for the conventional homoskedastic VAR and the bivariate GARCH-in-Mean VAR.

squared data provides evidence in favor of conditional heteroscedasticity, which is also confirmed by an ARCH test, distributed as a $\chi^2(4)$ on the null hypothesis of no ARCH effects.

Motivated by the aforementioned discussions and the dynamic properties of the employed data, we estimate the bivariate GARCH-in-Mean structural VAR model given by equations (1)-(3), with one lag as suggested by the Schwarz information criterion (SIC), and using monthly observations on the log change in the price of oil and the log change in the price of each of the indices examined in this paper. To evaluate the efficiency of the model specification in terms of predictability, and its consistency with the data, we calculate and compare the SIC for the GARCH-in-Mean VAR model and the conventional homoskedastic VAR model. Based on the values of the Schwarz information criterion in Table 4, the bivariate GARCH-in-Mean VAR model is preferred over the homoskedastic VAR model in most of the cases.

The parameter estimates of the mean and variance functions, for the different sectors, are reported in Tables 5–6, together with the *t*-statistics. We find statistically significant evidence of ARCH effects in the price of oil and GARCH effects in the stock returns, which provide further support for our proposed model. Specifically, in the case of the bivariate GARCH-in-Mean VAR model for the oil price and aggregate stock returns the coefficients on the lagged squared errors and lagged conditional variance for both the price of oil and stock returns are highly significant, while their sum is equal to (0.268+0.603)=0.871 and (0.118+0.852)=0.970, respectively. These results provide evi-

Table 5: Parameter Estimates for the Variance Function

Equation	Constant	ϵ^2_{t-1}	$\boldsymbol{H}^2_{t-1}$
AGG	0.675 (1.865)	0.118 (3.587)	0.852 (23.804)
ECO	5.295 (1.396)	0.116 (1.817)	0.798 (8.561)
NEX	5.349 (0.914)	0.177 (1.577)	0.694 (2.954)
PSE	1.483 (1.586)	0.156 (2.940)	0.808 (12.720)
SPGCE	4.323 (1.183)	0.086 (1.566)	0.824 (8.172)
WTI	9.119 (2.768)	0.268 (4.509)	0.603 (7.662)

Note: These are the parameter estimates for the free elements in the $\boldsymbol{F}$ and $\boldsymbol{G}$ matrices from the bivariate GARCH-in-Mean structural VAR model given by Equations (1)–(3). Asymptotic *t*-statistics are in parentheses.

Table 6: Coefficient Estimates on Oil Price Volatility

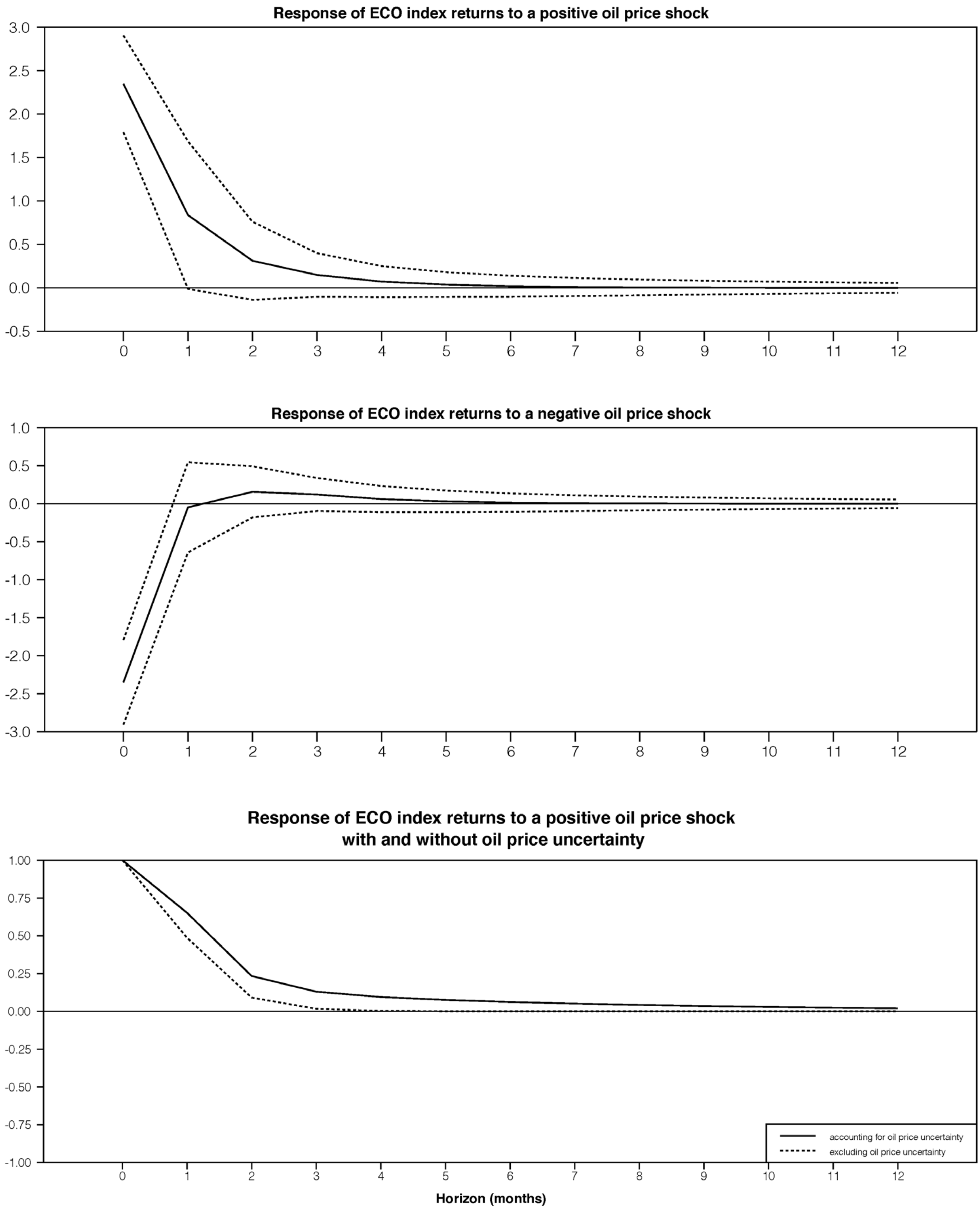
Equation	$\boldsymbol{H}^{1/2}_{\Delta lno_t}$	*t*-statistic
AGG	–0.040	–0.483
ECO	0.154	0.459
NEX	0.341	1.010
PSE	0.002	0.016
SPGCE	0.287	0.940

Note: These are the coefficient estimates for the free elements in the $\boldsymbol{\Lambda}$ vector from the bivariate GARCH-in-Mean structural VAR model. $\boldsymbol{H}^{1/2}_{\Delta lno_t}$ indicates the conditional standard deviation of the log change in the price of oil.

dence that the volatility process for the crude oil price, and also that for the aggregate stock returns, is very persistent. The primary coefficient of interest, however, from the bivariate GARCH-in-Mean VAR relates to the effect of uncertainty about the change in the price of oil on stock returns. This is the coefficient on the conditional standard deviation of the log change in the price of oil in the stock return equation, λ_{21}, and the null hypothesis is that the value of it is equal to zero. The point estimates for the coefficient on oil price uncertainty are reported in Table 6, and show that there is not enough statistical evidence to reject the null hypothesis that the value of λ_{21} is zero.This finding holds across all industry sectors, with the coefficient on oil price uncertainty having a positive but statistically insignificant effect on the renewable and technology industries, and insignificant negative effect on the aggregate stock market. The latter result is consistent with the findings of Alsalman (2016). Furthermore, we investigate the robustness of our results to alternative measures of the oil price. In doing so, we use the composite refiners' acquisition cost of crude oil (RAC), as compiled by the U.S. Department of Energy, and we reach the same conclusion.

In order to investigate the effect of incorporating oil price uncertainty on the dynamic response of stock returns to an oil price shock, we plot the impulse responses for positive and negative oil price shocks in Figures 3–7, over a horizon of twelve months. These are simulated from the maximum likelihood estimates of the model's parameters. Accounting for the effect of oil price uncertainty, we find that a positive shock in oil prices tends to significantly increase the stock returns of the three renewable energy indices, namely ECO, NEX, and SPGCE, immediately, while this positive effect decreases sharply within the first two months (see the first panel of Figures 3, 4, and 6). Specifically, the SPGCE index experiences an increase in its monthly rate of change of about 100 basis point after one month, followed by a decline in the second month by about 50 basis points. It is worth mentioning that the positive effect is quite similar but less prominent for both the NEX and ECO indices. The dynamic effects of the positive oil price shock on the SPGCE and NEX indices are

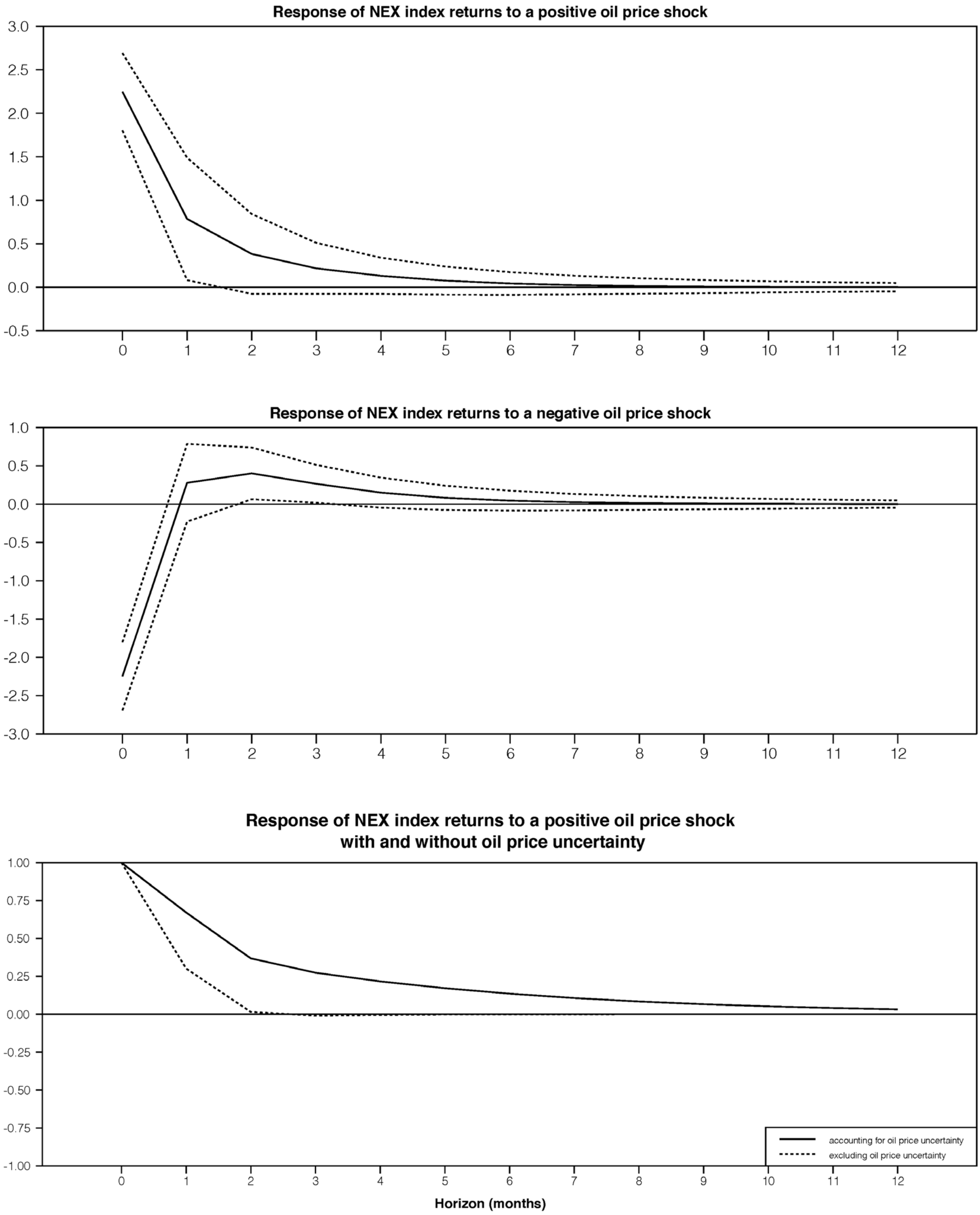
Figure 3: Impulse response functions of the WTI-ECO structural VAR



statistically significant for the first one and a half month, while for the ECO index it is statistically significant only for the first month.

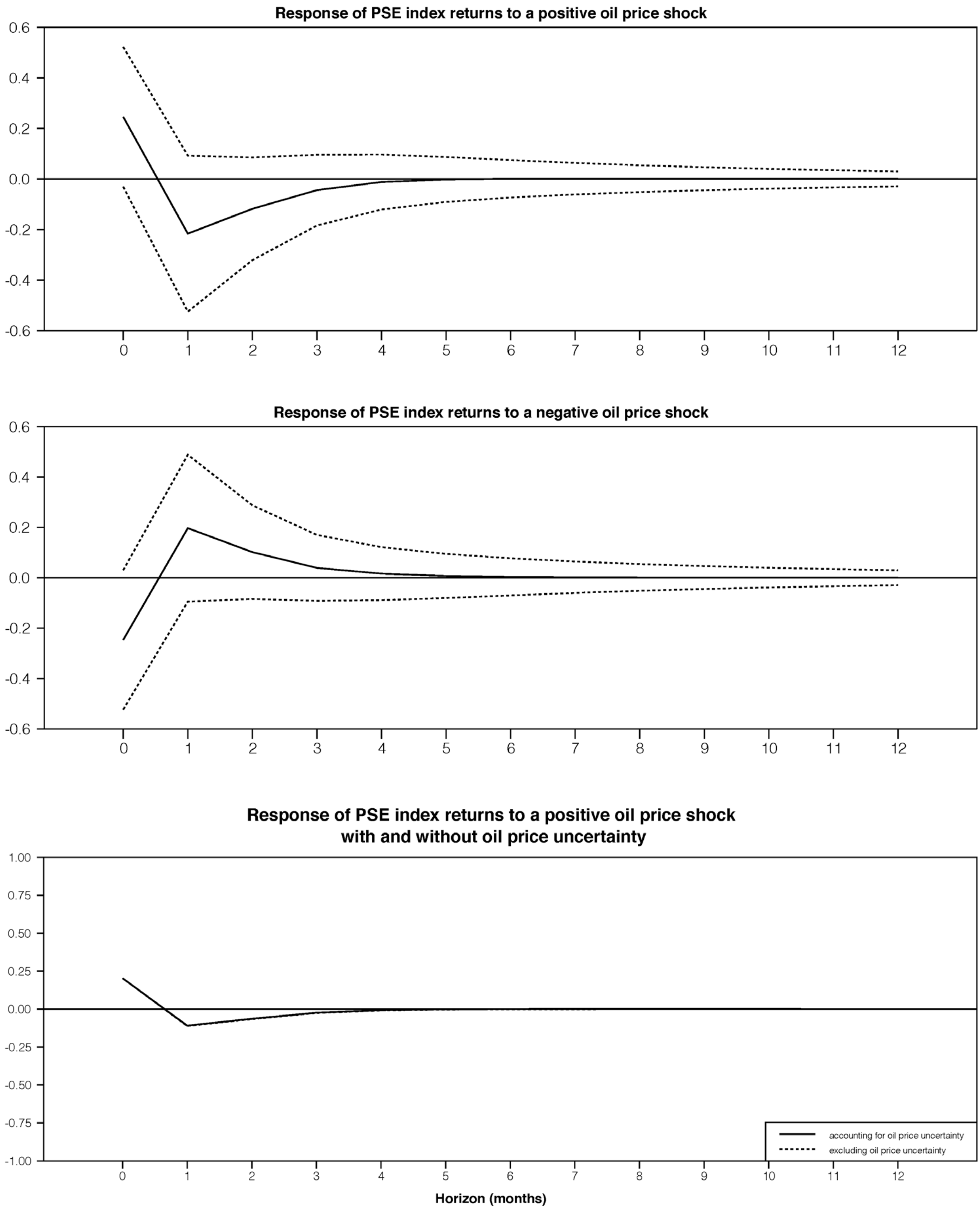
In the second panel of Figures 3, 4, and 6 we report the impulse responses of the same three indices to a negative oil price shock, again accounting for the effects of oil price uncertainty. As can be seen, the dynamic effect of the negative oil price shock on the ECO index is not statistically significantly different from zero after one month. However, a negative oil price shock induces

Figure 4: Impulse response functions of the WTI-NEX structural VAR



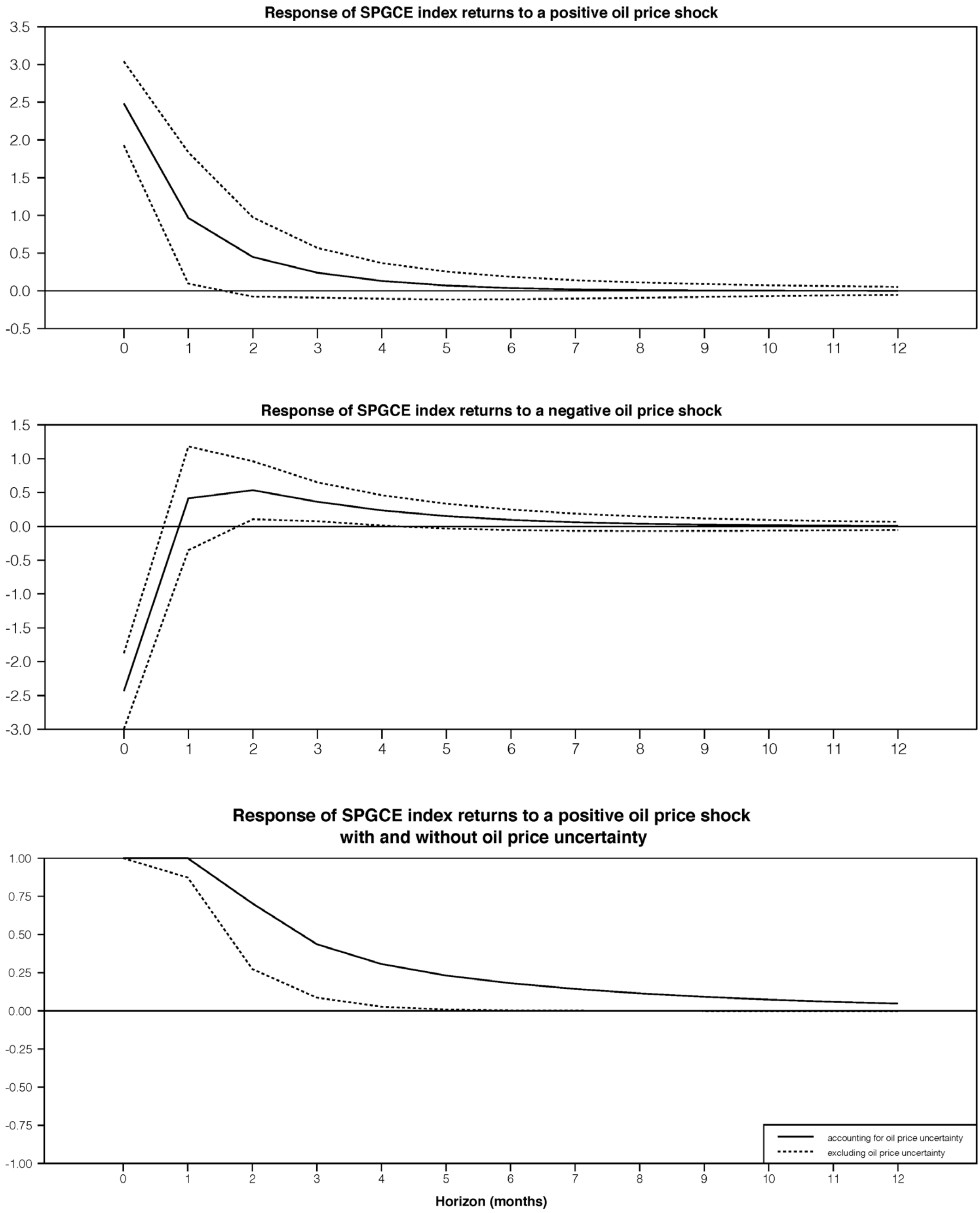
a positive effect on the NEX index of about 25 basis points the first month, followed by a slight increase the second month. In a similar way, the SPGCE index undergoes a jump in its monthly rate of change of about 50 basis points after two months, and decreases slowly towards zero in the following months. Both NEX and SPGCE indices are statistically significantly different from zero for the first three and four months, respectively, since the one-standard error bands lie clearly above the zero line.

Figure 5: Impulse response functions of the WTI-PSE structural VAR



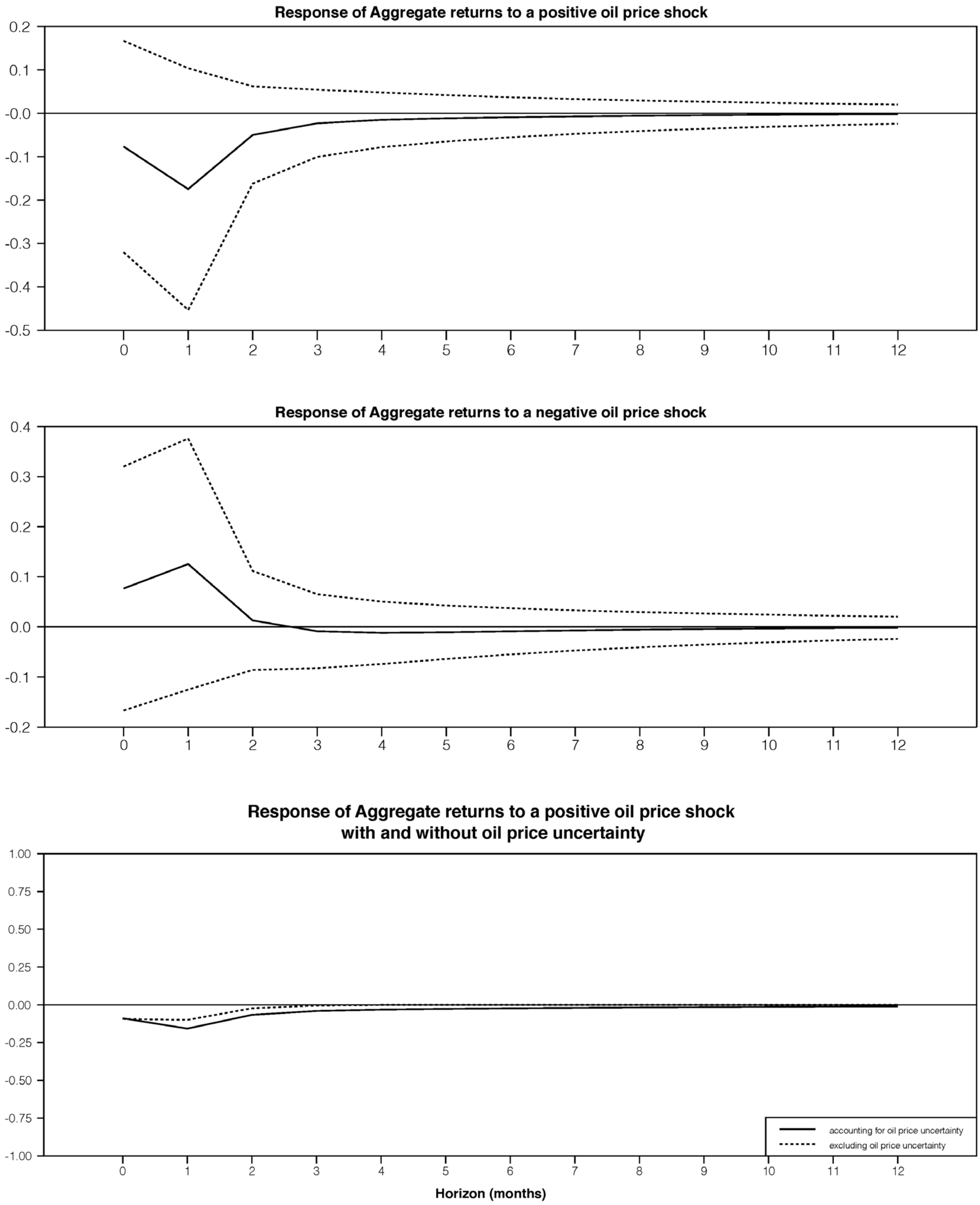
The impulse responses of technology stock returns (PSE), however, are more similar to those of the aggregate stock returns. As can be seen in the first panel of Figures 5 and 7, a positive oil price shock leads to a decline in both stock returns after one month, followed by an increase in the second month. Impulse responses of aggregate stock returns are found to have a more rapid recovery rate than technology stock returns. However, the dynamic effects of the positive oil price shock on both technology and aggregate stock returns are not statistically significant different from

Figure 6: Impulse response functions of the WTI-SPGCE structural VAR



zero at all horizons. In contrast, a negative oil price shock tends to induce a jump in both technology and aggregate stock returns after one month, which is followed by a slow decline (see the second panel of Figures 5 and 7). The dynamic effects of the negative oil price shock on both returns are however not statistically significantly different from zero. Finally, a visual inspection of the impulse responses in Figures 3–7 does not provide clear evidence on whether the responses of the three renewable energy stock market returns to positive and negative oil price shocks are symmetric or

Figure 7: Impulse response functions of the WTI-Aggregate structural VAR



asymmetric, while those of the technology and aggregate returns are more likely to be symmetric. Symmetry in the responses of the aggregate returns to oil price shocks is consistent with the findings of Alsalman (2016).

Next, we compare the impulse responses of the different stock returns to a positive oil price shock as estimated by our model with that from a model in which oil price uncertainty is restricted from entering the stock return equation (that is, $\lambda_{21}=0$). We compare these responses in the third panel of Figures 3–7, with the error bands being suppressed for clarity, and conclude that accounting for oil price uncertainty tends to enhance the positive dynamic responses of the three renewable energy indices to a positive oil price shock, while it amplifies the negative dynamic response of the aggregate returns to a positive oil price shock. Finally, the responses of technology index returns from the two models are found identical, thus providing evidence that uncertainty about the price of oil does not disturb the dynamic response of technology returns to a positive oil price shock.

5. SYMMETRY TEST

We have performed an impulse response analysis to assess whether the relationship between crude oil prices and stock returns of clean energy and technology companies is symmetric or asymmetric, and we have provided evidence in favor of symmetric impulse responses of stock returns to oil price shocks. To investigate the robustness of these results, we employ an impulse response based test, recently introduced by Kilian and Vigfusson (2011).

The Kilian and Vigfusson (2011) symmetry test, based on impulse response functions, involves estimating the following nonlinear structural VAR model

$$\Delta lno_t = \alpha_{10} + \sum_{j=1}^{p} \beta_{11}(j)\Delta lno_{t-j} + \sum_{j=1}^{p} \beta_{12}(j)\Delta lnz_{t-j} + u_{1t} \tag{6}$$

$$\Delta lnz_t = \alpha_{20} + \sum_{j=0}^{p} \beta_{21}(j)\Delta lno_{t-j} + \sum_{j=1}^{p} \beta_{22}(j)\Delta lnz_{t-j} + \sum_{j=0}^{p} \delta_{21}(j)\tilde{o}_{t-j} + u_{2t} \tag{7}$$

where $\tilde{o}_t$ is Hamilton's (2003) net oil price increase over the previous twelve months, defined as

$$\tilde{o}_t = \max[0, lno_t - \max\{lno_{t-1}, lno_{t-2}, ..., lno_{t-12}\}]$$

where o_t denotes the price of oil.

The null hypothesis of symmetric impulse responses of Δlnz_t to positive and negative oil price shocks of the same size is

$$H_0 : I_g(h,\delta) = -I_g(h,-\delta) \quad \text{for} h = 0,1,...,H. \tag{8}$$

It tests whether the responses of Δlnz_t to a positive shock in the oil price growth rate of size δ is equal to the negative of the response of Δlnz_t to a negative shock in the oil price growth rate of the same size, $-\delta$, for horizons $h = 0,1,...,H$. See Kilian and Vigfusson (2011) for a more detailed discussion of the methodology.

Since the Kilian and Vigfusson (2011) test depends on the size of the shock, δ, we illustrate in Figure 8 the empirical responses of the different logarithmic stock returns to one- and two-standard-deviation oil price shocks of positive and negative signs, in a model with one lag and considering the twelve-month net oil price increase. Hence, the figure depicts the response of the logarithmic stock returns to a positive shock $I_g(h,\delta)$, and the negative of the response to a negative shock, $-I_g(h,-\delta)$. The impulse responses are derived for twelve months based on 10,000 simulations and 50 histories.

As can been seen from the different plots in Figure 8, the responses of the different logarithmic stock returns to positive shocks are not significantly different than those to negative shocks, for both small (one-standard-deviation) and big (two-standard-deviation) oil price shocks. In addition, we report the p-values of the null hypothesis (8) in Table 7, for both small shocks ($\delta = \hat{\sigma}$) and large shocks ($\delta = 2\hat{\sigma}$). By looking at the results, we conclude that the null hypothesis of a symmetric

Figure 8: WTI crude oil price returns and returns of sub-indices

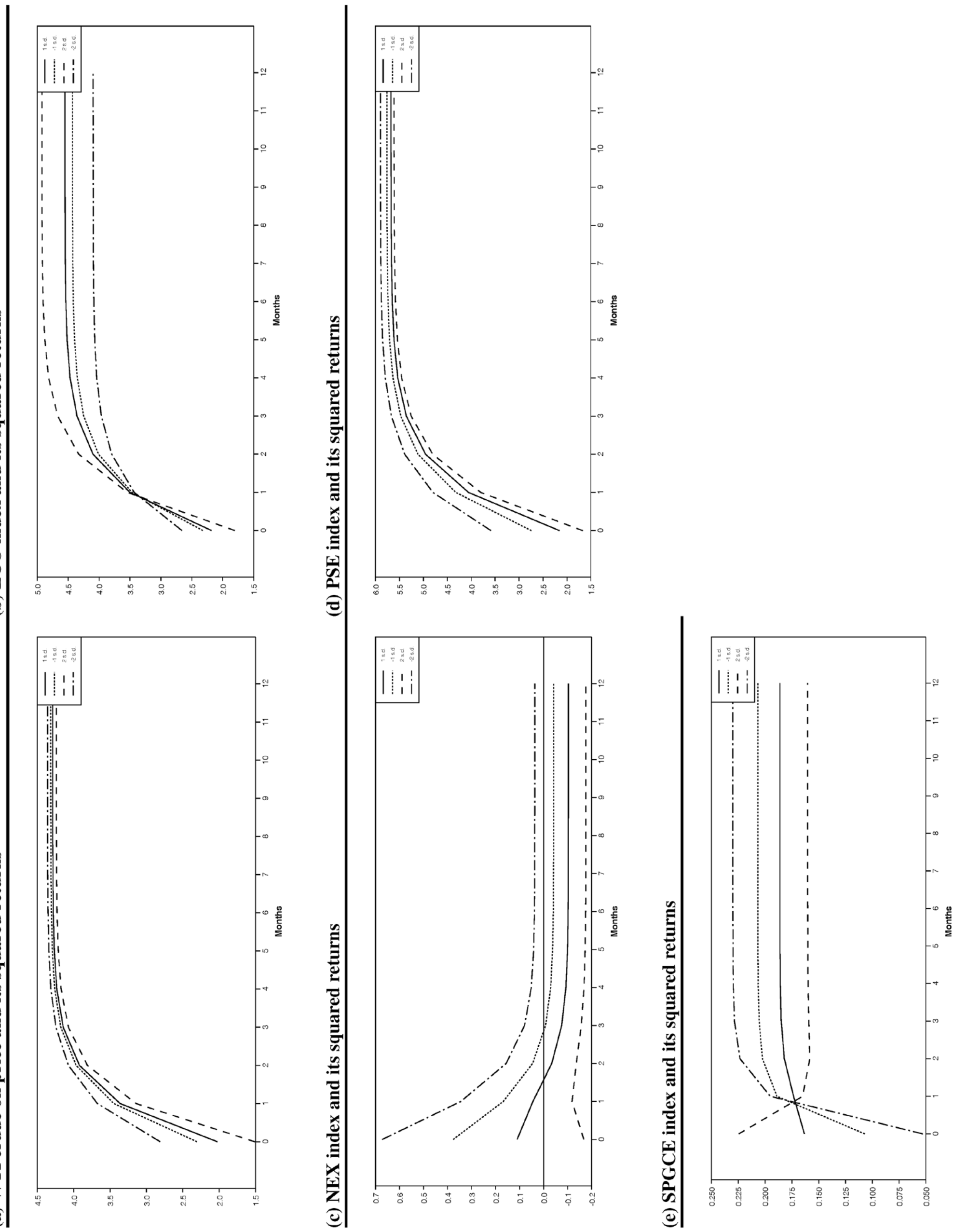


Table 7: *p*-values for $H_0 : I_g(h,\delta) = -I_g(h,-\delta), h = 0,1,...,12$

	ECO		NEX		PSE		SPGCE		AGG	
h	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$
0	0.306	0.299	0.460	0.465	0.221	0.224	0.253	0.250	0.714	0.719
1	0.325	0.310	0.222	0.202	0.089	0.088	0.173	0.155	0.781	0.779
2	0.522	0.505	0.352	0.341	0.183	0.179	0.255	0.240	0.919	0.917
3	0.675	0.656	0.508	0.493	0.205	0.222	0.255	0.249	0.932	0.926
4	0.791	0.781	0.636	0.630	0.314	0.332	0.355	0.345	0.974	0.971
5	0.819	0.827	0.683	0.670	0.368	0.390	0.457	0.444	0.988	0.985
6	0.872	0.880	0.785	0.773	0.433	0.418	0.567	0.556	0.995	0.993
7	0.904	0.907	0.861	0.852	0.541	0.525	0.654	0.645	0.998	0.997
8	0.944	0.946	0.886	0.866	0.632	0.604	0.739	0.736	0.999	0.999
9	0.916	0.949	0.901	0.889	0.721	0.695	0.800	0.804	1.000	1.000
10	0.921	0.971	0.917	0.918	0.772	0.714	0.829	0.841	1.000	1.000
11	0.853	0.885	0.938	0.947	0.835	0.786	0.849	0.876	1.000	1.000
12	0.898	0.923	0.961	0.954	0.884	0.844	0.874	0.866	1.000	1.000

Note: *p*-values are based on the χ^2_{h+1} distribution.

relationship between the oil prices and each of the examined stock returns cannot be rejected at the 5% significance level.

6. CONCLUSION

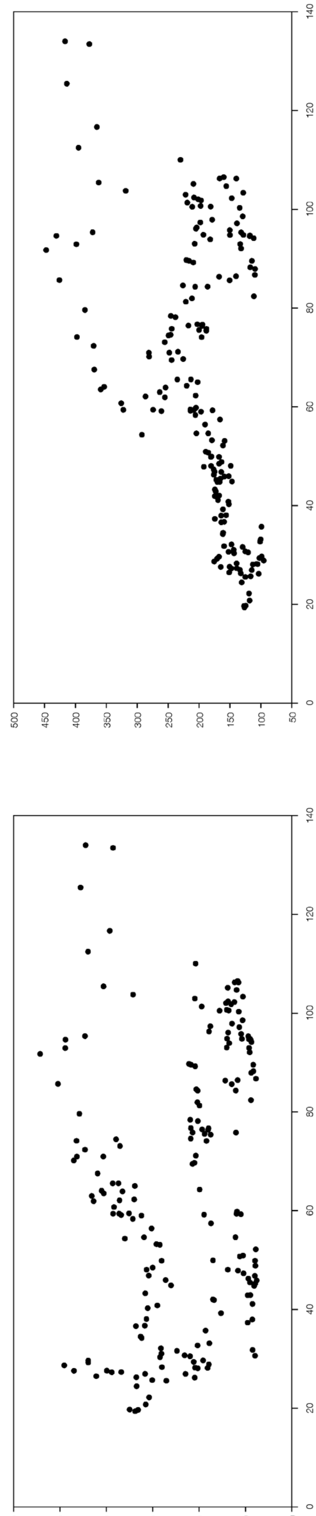
In the context of a bivariate structural VAR model, which is modified to accommodate GARCH-in-Mean errors, we investigate the relationship between oil prices and stock returns of clean energy and technology companies. Specifically, we employ monthly data over the period from May 1983 to December 2016, and estimate the model taking a full information maximum likelihood approach, thus avoiding Pagan's (1984) generated regressor problems. Furthermore, we conduct an impulse response analysis to assess whether the relationship between crude oil prices and stock returns of clean energy and technology companies is symmetric or asymmetric, and provide evidence of symmetric stock responses to oil price shocks. More importantly, we investigate the effects of uncertainty about the change in the price of oil on the employed stock returns, and we find that oil price uncertainty has a positive but statistically insignificant effect on the renewable energy and technology stock returns, and an insignificant negative effect on the aggregate stock returns. Our results are robust to alternative model specifications and stock prices of clean energy companies.

The resilience of renewable energy stock returns to oil price uncertainty effects may stem from the fact that the economics of the renewable energy sector have become very competitive in recent years, and therefore renewables can compete successfully with oil, even when the price of oil fluctuates around the recent low levels. Another possible explanation might be the fact that oil is not predominantly used in electricity generation, while any possible spillover effect from oil to other primary sources of electricity generation such as, for example, coal and gas, seem not to be prominent enough in order to affect renewables indirectly. Furthermore, resilience of renewable energy sector can be explained by the fact that developing countries such as, for instance, China, India, and Middle East countries, experience rapid economic growth that is accompanied by growing energy demand, and finally, severe environmental externalities. Hence, under different pressures of environmental pollution, such as, air pollution and water contamination, they endeavor to reduce fossil fuel consumption and expand their renewable energy industry. Finally, the insignificant effect of oil price uncertainty on the employed stock returns might be a possible explanation for the symmetric stock responses.

APPENDIX

Figure A.9: Scatterplots between sub-indices and WTI crude oil price

(a) ECO index vs WTI crude oil price **(b) NEX index vs WTI crude oil price**



(c) PSE index vs WTI crude oil price **(d) SPGCE index vs WTI crude oil price**

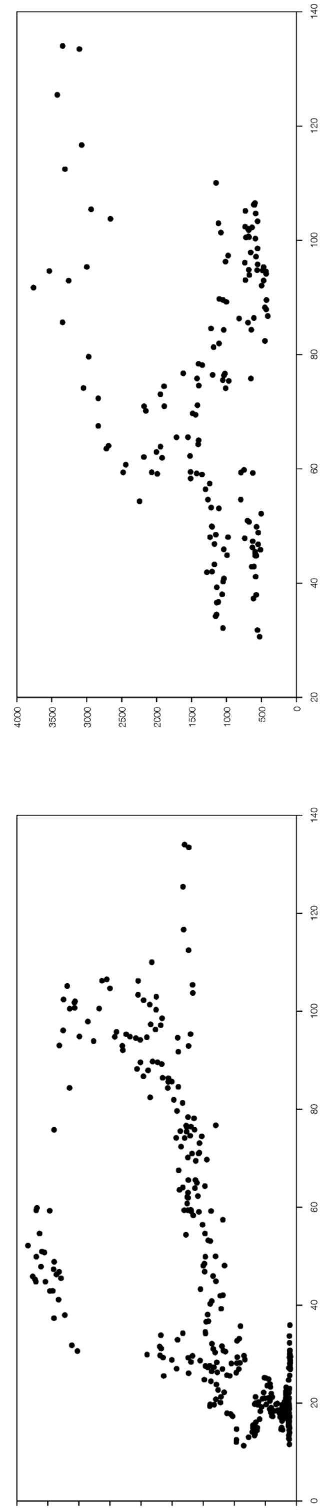


Figure A.10: Scatterplots between sub-indices and DJIA price

(a) ECO index vs DJIA price

(b) NEX index vs DJIA price

(c) PSE index vs DJIA price

(d) SPGCE index vs DJIA price

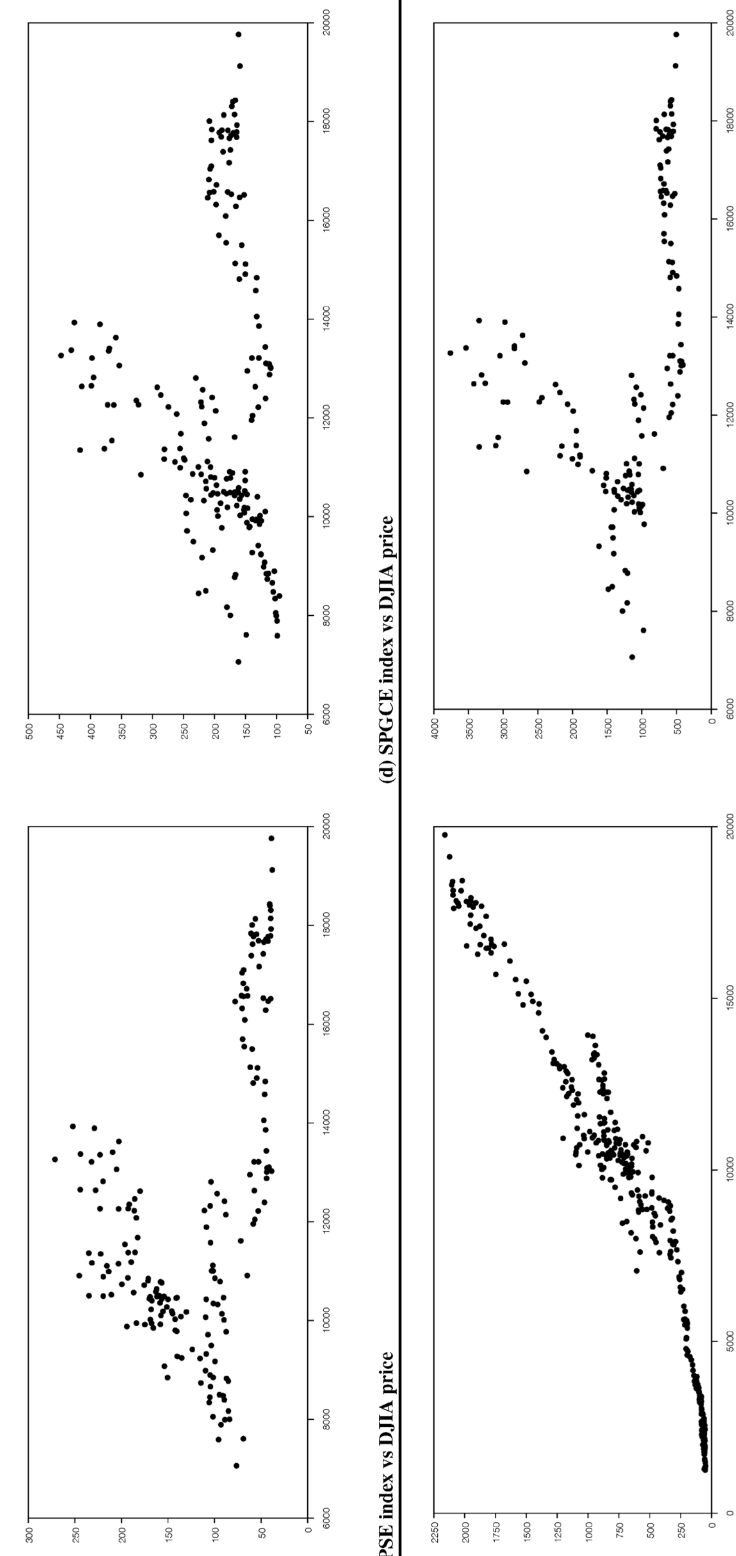
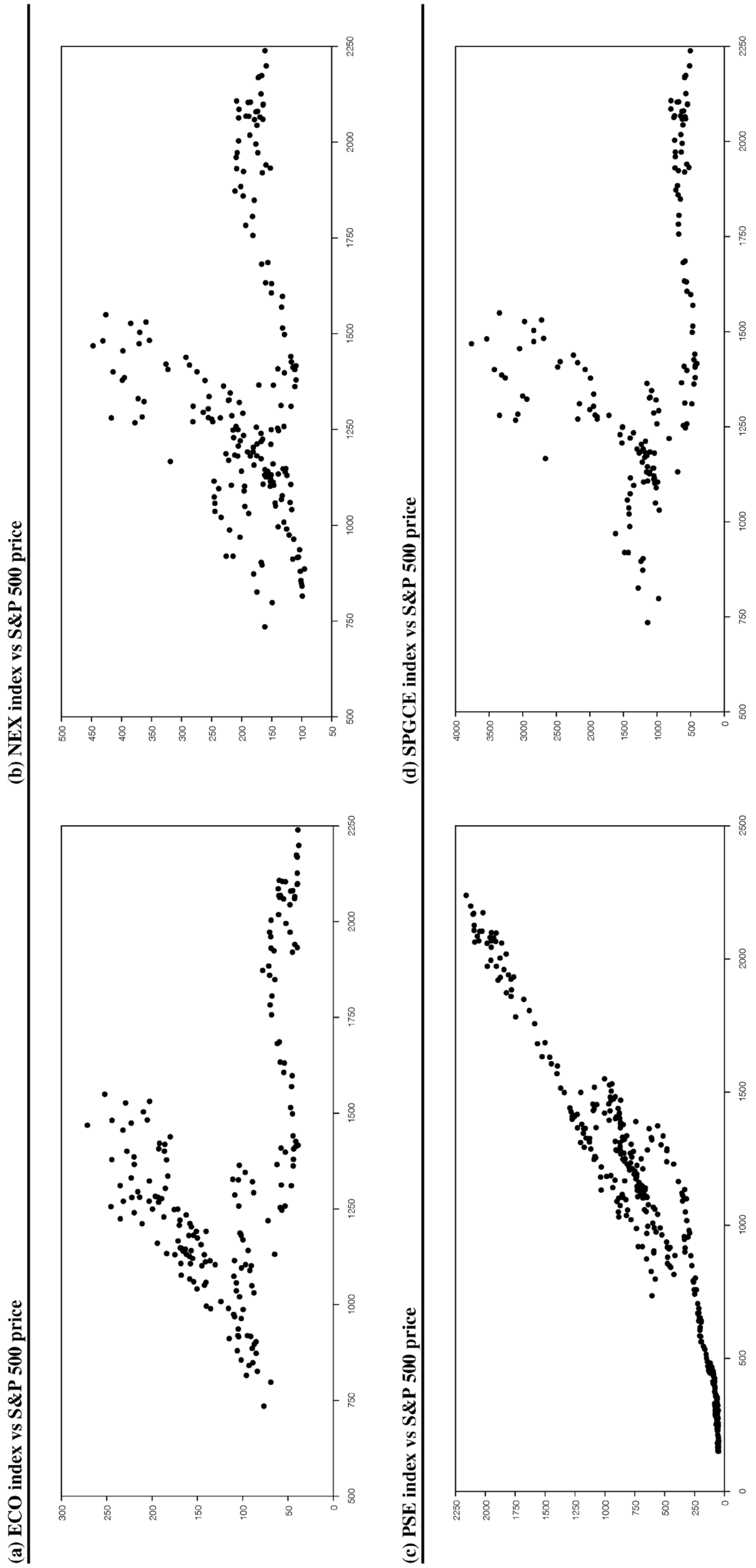


Figure A.11: Scatterplots between sub-indices and S&P 500 price



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