ARTICLE IN PRESS

Economic Modelling xxx (2017) 1–18

Contents lists available at ScienceDirect

Economic Modelling

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

Optimal hedge ratios for clean energy equities

Wasim Ahmad [a,*], Perry Sadorsky [b], Amit Sharma [a]

[a] Department of Economic Sciences, Indian Institute of Technology Kanpur, Kanpur, UP, 208016, India
[b] Schulich School of Business, York University, 4700 Keele Street, Toronto, ON, M3J 1P3, Canada

ARTICLE INFO

JEL Code:
C58
G11
G15
Q43

Keywords:
Clean energy equities
Crude oil
Multivariate GARCH
Optimal hedge ratios
VIX

ABSTRACT

Clean energy equities represent a relatively new class of assets to invest in, and these assets can be very volatile. An understanding of how investors in clean energy stocks can hedge their investment is essential for risk management. In this study, we use daily data covering the period March 03, 2008 to October 31, 2017, to examine how crude oil, US-bonds, gold, VIX, OVX and European carbon prices can be used to hedge an investment in clean energy equities. We apply three variants of multivariate GARCH models (DCC, ADCC and GO-GARCH) to estimate time-varying optimal hedge ratios. The results suggest that VIX is the best asset to hedge clean energy equities followed by crude oil and OVX. This is a new result relative to the existing literature on clean energy stock prices and one that is of interest to current and future investors in clean energy stocks.

1. Introduction

Concerns about climate change, energy security issues, recent developments in clean energy technological innovation and corporate social responsibility have helped clean energy finance become one of the frontier areas of financial research. In response, a body of research literature has developed studying the inter-linkage between clean energy stocks, technology stocks and oil prices along with other factors such as interest rates, global stock market prices, and carbon prices. Some of the notable studies are Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012a; 2012b), Managi and Okimoto (2013), Bohl et al. (2013), Inchauspe et al. (2015), Reboredo (2015), Bondia et al. (2016), Reboredo et al. (2017) and Ahmad (2017). Many of these studies find that technology stocks and oil prices impact clean energy stock prices and that there are volatility spillovers from oil and technology stock prices to clean energy stock prices.

While we have an understanding of how clean energy stocks interact with other assets regarding return correlations and volatility spillovers, what is lacking, however, is a complete understanding of how investors in clean energy stocks can hedge their investments. Clean energy equities represent a relatively new class of assets to invest in, and these assets can be very volatile. An understanding of how investors in clean energy stocks can hedge their investment is essential for risk management. We are aware of only three papers that explicitly calculate hedge ratios for clean energy equities. Sadorsky (2012b), in what is probably the first paper on hedging clean energy equities, finds that clean energy hedge ratios vary considerably across time and that on average a $1 long position in clean energy stocks can be hedged for 20 cents with a short position in the crude oil futures market or a $1.09 short position in technology stocks. Sanchez (2015) finds that, on average, a $1 long position in alternative energy stocks can be hedged for 24 cents in a short position in oil or a $1.01 short position in technology stocks. Ahmad (2017) finds similar results in that, on average, a $1 long position in clean energy equities can be hedged for 32 cents with a short position in crude oil or a $1.29 short position in technology stocks. While, these studies are an important starting point, there is clearly room for more research as important research questions remain. For example, Sadorsky (2012b), Sanchez (2015) and Ahmad (2017) established that there is a considerable time variation in clean energy stock price hedge ratios but they did not, however, compute measures of hedging effectiveness. Neither did any of these studies consider the usefulness of using gold or volatility to hedge clean energy stock prices.

In this paper, we extend the literature on hedging clean energy equities in several ways. First we consider a larger set of possible hedging instruments than what was studied by Sadorsky (2012b), Sanchez (2015), and Ahmad (2017). Specifically, this study examines the possibilities of hedging an investment in clean energy stocks with oil, gold, VIX (the implied volatility of the S&P 500 index options), OVX (oil

* Corresponding author.
E-mail addresses: wasimad@iitk.ac.in (W. Ahmad), psadorsk@schulich.yorku.ca (P. Sadorsky), amitsr@iitk.ac.in (A. Sharma).

https://doi.org/10.1016/j.econmod.2018.02.008
Received 20 September 2017; Received in revised form 27 December 2017; Accepted 11 February 2018
Available online xxxx

Please cite this article in press as: Ahmad, W., et al., Optimal hedge ratios for clean energy equities, Economic Modelling (2017), https://doi.org/10.1016/j.econmod.2018.02.008

implied volatility index), EUA (European Union Allowances (EUA) carbon prices) and the US 10-year Treasury note. Our research builds on the numerous papers investigating the usefulness of using oil (e.g. Arouri and Nguyen, 2010; Arouri et al., 2011a,b; Hammoudeh et al., 2009) or gold (e.g. Baur and Lucey, 2010; Baur and McDermott, 2010; Bekiros et al., 2017; Chkili, 2016; Iqbal, 2017; Jaffe, 1989; Mensi et al., 2013) to hedge equities. This is the first study that analyses clean energy cross-hedge ratios with such a large basket of financial assets.

Second, we compare the hedging performance of different instruments using measures of hedging effectiveness. Sadorsky (2012b), Sanchez (2015), and Ahmad (2017) used GARCH models to calculate in-sample optimal hedge ratios but did not calculate hedging effectiveness.

Third, dynamic conditional correlation (DCC), and generalized orthogonal GARCH (GO-GARCH) are used to calculate optimal hedge ratios. Previous studies of hedging clean energy equities have relied on BEKK, DCC and VARMA-GARCH models to compute hedge ratios. More specifically, we use DCC and GO-GARCH models to estimate hedge ratios because many Multivariate GARCH (MGARCH) models suffer from "The curse of dimensionality".[1] For example, the estimation of BEKK and VARMA-GARCH models becomes difficult even in the trivariate case because of the presence of a vast number of free parameters. The presence of a large number of estimated parameters can create optimisation problems if the likelihood function becomes flat. However, the conditional correlation models are more robust to such estimation issues and allow more variables to be incorporated into the model. Conditional correlation models are easy to estimate and very widely used in the estimation of hedge ratios. Another approach is to use GO-GARCH which has its roots in the factor GARCH literature. Unlike DCC, GO-GARCH captures volatility spillovers which may be an important consideration for the calculation of hedge ratios.[2,3] Which approach, DCC or GO-GARCH works best in practice for hedging clean energy equities is a question that can only be answered through empirical analysis.

Fourth, optimal hedge ratios are calculated using a fixed width rolling window approach. This approach is used to mitigate the effects of changing dynamics, parameter heterogeneity and structural change. Sadorsky (2012b), Sanchez (2015), and Ahmad (2017) all found that clean energy hedge ratios vary considerably over the sample period. Unlike, Sadorsky (2012b), Sanchez (2015), and Ahmad (2017) who calculate in-sample hedge ratios, we calculate the out-of-sample ex-ante hedge ratios from rolling window analysis. For period t, we first use GARCH models to forecast one-step-ahead conditional volatility, and then we use these volatility forecasts to make one-step-ahead hedge ratios.

Our analysis reveals a number of important results that are of interest to investors and others interested in clean energy equities. GARCH models capture all the major turning points including the impacts of the US Fed's tapering and China's economic slowdown. Among the three MGARCH models, we find that the DCCs and ADCCs show a relatively higher level of comovement compared to GO-GARCH. The out-of-sample forecasts of one-period-ahead optimal hedge ratios calculated from rolling window analysis reveal that VIX is the best hedge followed by oil and OVX. The average hedge ratio for VIX is negative while for oil it is positive. This means that an investment in clean energy equity can be hedged by taking long positions is both clean energy and VIX or by taking a long position in clean energy and a short position in oil.

The rest of the paper is structured as follows: Section 2 provides an overview of the current outlook for clean energy investment. Section 3 sums up the review of the literature. Section 4 gives the details about the data. Section 5 provides details on the methodology. Section 6 discusses the empirical results followed by conclusions and discussion in section 7.

2. Current outlook for clean energy investment

According to UNEP-Global Trends in Renewable Energy Investment Report (2016, henceforth, UNEP, 2016), investment in the clean energy sector increased by 5 percent from $273.0 billion in 2014 to $285.9 billion in 2015. The clean energy sector attracted a significant amount of investment despite the upheavals in the exchange rate of US dollar, and sharp fall in crude oil, coal and gas prices. Comparing the clean energy investment figures across countries, it appears that developing countries including Brazil, China, and India have outshined the developed countries. In 2015, China alone accounted for around 36 percent of global clean energy investment. India and Brazil have made investments of $10.2 billion and $7.1 billion, respectively. However, focusing on the investment performance of the clean energy sector, it appears that in 2015, the total public market investment saw a decline of 21 percent which is still higher than its last trough in 2012. Analysing the performance of major clean energy indices in 2015, it appears that the stock prices of clean energy firms have been volatile with a very mild appreciation. The Wilder Hill New Energy Global Innovation Index (NEX) saw a decline of 0.6 percent which was almost equal to the S&P 500 index in 2015. If we compare the performance of NEX vis-à-vis crude oil prices represented by West Texas Intermediate (WTI), we find that during 2014–2015, NEX went down by 6.5 percent while crude oil prices fell by more than 47.5 percent.[4] This implies that the drop in oil prices has had a limited impact on the profitability of NEX stocks though there is some amount of synchronicity. A possible explanation could be that most of the oil importing countries give less emphasis to the development of the clean energy sector when the price of oil goes down. However, analyzing NEX at the individual stock level, it appears that the high volatility has resulted in a substantial rise in the prices of top-performers in the range from 62 percent to 238 percent in 2015. Among different sectors of clean energy, wind power sector has performed better than the rest. Consequently, the NYSE Bloomberg Global Wind Energy Index went up by 27 percent in 2015. A large part of this jump is explained by the better energy generation environment in most of the Western European countries. Besides this, the Paris Climate Change Summit will further boost the investment in the clean energy sector with the ever-increasing role of the private sector (see UNEP, 2016).[5]

3. Related literature

A close appraisal of the existing literature on clean energy finance reveals that no theoretical model has been established to explain the interdependence between crude oil and clean energy stock prices and between clean energy stocks and technology companies' stock prices jointly.[6] Consequently, most studies so far have analyzed the interdependence phenomenon by way of applying a different set of econometric models covering various aspects of macroeconomic and financial implications on clean energy stock price movements. The relevant studies in this field are Henriques and Sadorsky (2008), Kumar et al., (2012), Sadorsky, (2012a,b), Managi and Okimoto (2013), Inchauspe et al.,

[1] Bauwens et al. (2006) provodes a detailed overview of MGARCH models.

[2] It is noteworthy that the GO-GARCH model appeared in the research literature in the same year as DCC (2002) but due to its simple estimation procedure DCC is more popular among researchers than GO-GARCH. However, recent modifications have made GO-GARCH easier to estimate and one of the important GARCH models to explore (see van der Weide, 2002; Boswijk and van de Weide, 2011).

[3] There are a very limited number of studies that have used GO-GARCH to analyze the hedging properties of different assets. Basher and Sadorsky (2016) use this model to analyze the hedging effectiveness of equity and other asset classes.

[4] Authors' own calculation.

[5] The United Nations climate change conference held in Paris in December 2015, also known COP21, has been able to bring together 195 countries to act for zero net emissions in systematic manner by 2050.

[6] The terms alternative energy, renewable energy, and clean energy tend to be used interchangeably although there are differences. Initially, stock analysts and industry analysts used the term alternative energy, before moving on to re-classifications of renewable energy and clean energy.