2020 Doctor's Thesis

Stock Returns of Clean Energy Companies and Macroeconomic Influences

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1 Introduction

1.1 Background of clean energy sector

Clean energy is the energy that has a clean production process without greenhouse gas and other kinds of pollutants released. Renewable energy generated from renewable sources, such as sunlight, wind, tides, is often referred to as the main component of clean energy[1]. In this century, technological development in the clean energy sector has accelerated the transformation from natural sources into viable energy for daily life. Moreover, in this decade, innovations in this sector have focused on reducing the cost of clean energy production and improving energy efficiency by using clean energy. Figure 1.1 displays the share of renewable energy in the global energy consumption surged since 2000, which expanded quickly after the 2008-09 Global Financial Crisis. From the perspective of the region, energy transition from fossil fuels to clean energy does not just concentrate on industrialized countries and newly industrializing countries. Emerging countries also take chances to employ the latest advanced technologies for developing clean energy and taking the place of traditional fossil fuels (Figure A1.1 In appendix).

Renewable energy-related companies are the main participants in the clean energy sector, classified by energy sources, including solar power, solar heating, wind power, hydropower, biomass, geothermal, et cetera. Figure 1.2 shows an absolute advantage of hydropower and the outstanding performance of the wind and solar as two rising stars in the clean energy sector.

[1] The definition of clean energy is not clear-cut. In this study, when considering the sources of energy, the terms "clean energy", "green energy", "sustainable energy" and "renewable energy" are used interchangeably. In fact, some kinds of renewable energy generate in an inappropriate process also causing air pollution. However, the current development of renewable energy is aimed to use renewable energy in a clean way.

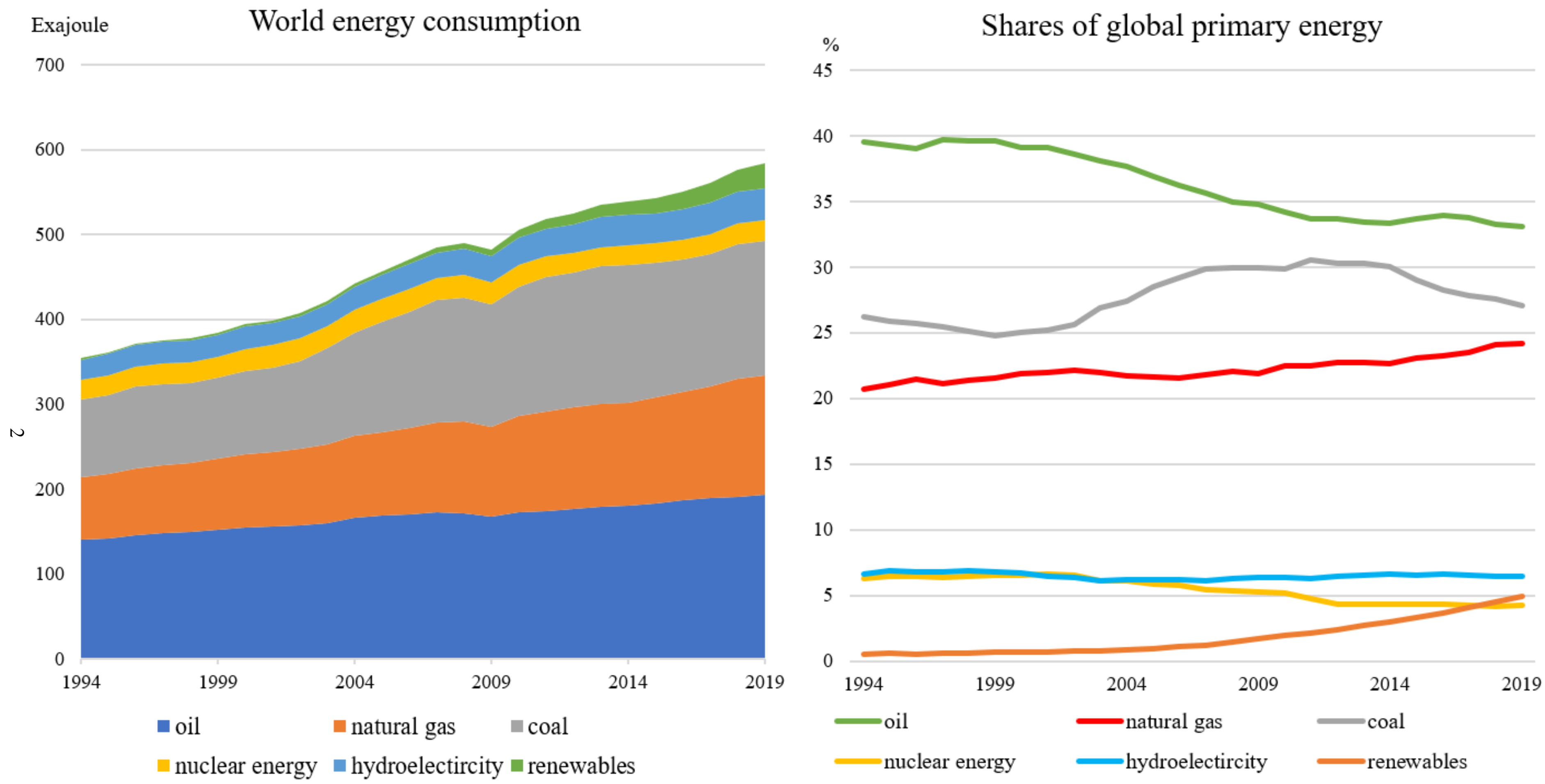

Figure 1.1 World energy consumption and shares of global primary energy: 1994-2019.

Notes: Data source is the BP Statistical Review of World Energy 2020. 1 Exajoule is equal to 10^{18} joules.

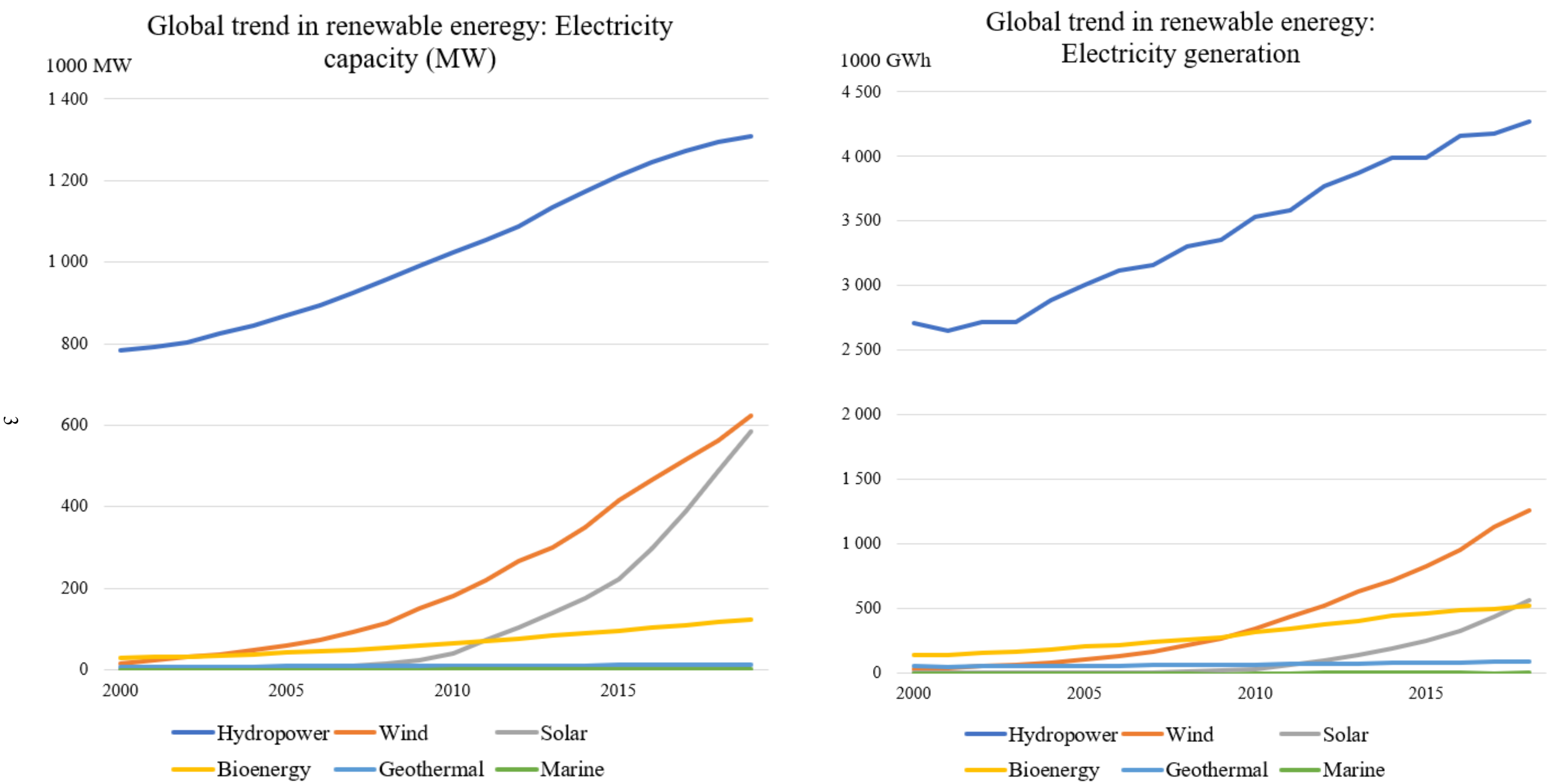

Figure 1.2 Electricity capacity shares and Electricity generation shares of global renewable energy: 2000-2019.

Notes: Data source is the International renewable energy agency (IRENA). MW means megawatt. GWh means Gigawatt-hour.

The clean energy sector also includes non-renewable but zero-emission energy, namely, nuclear energy, which maintains a relatively stable amount of production in the observed period (Left subplot of Fig 1.1). However, the share of nuclear slowly is in a falling trend and exceeded by renewable energy in 2018 (Right subplot of Fig 1.1). Furthermore, the clean energy sector also consists of the companies providing ancillary services in power generation, air and water heating or cooling process, and transportation with various clean natural sources as energy inputs.

Two reasons mainly drive the development of the clean energy sector. First is the urgency of governments to achieve the goal of preventing climate change. The urgent attention of governments to deal with climate changes have a long history. At the Earth Summit in Rio de Janeiro 1992, 154 nations signed the United Nations Framework Convention on Climate Change (UNFCCC), which marks a launch of the worldwide efforts of governments to realize "stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (UNFCCC Article 2). After that, this international environmental treaty has gone through the Kyoto Protocol (1997)[2], the Bali Action Plan (2007)[3], the Copenhagen Accord (2009)[4], and the Paris Agreement (2015) to deal with greenhouse gas emission and climate change with 197 parties.

The Paris Agreement decided the long-term temperature goal to limit the increase in average global temperatures to well below 2 °C, and ideally to limit the increase to 1.5 °C. After

[2] The Kyoto Protocol was concluded and established legally binding obligations under international law, for developed countries to reduce their greenhouse gas emissions in the period 2008–2012.

[3] The Bali Action Plan made decision recognized that there was a need for "deep cuts in global emissions" (several countries proposed 100% reductions by 2050) and that "developed country emissions must fall 10-40% by 2020".

[4] The Copenhagen Accord states that global warming should be limited to below 2.0 °C. This may be strengthened in 2015 with a target to limit warming to below 1.5 °C.

that, governments around the world, as the UNFCCC parties, have committed to achieving this goal by proposing Nationally Determined Contributions (NDCs) to significantly lower their country-level CO2 emissions. The main ways to achieve the goals of NDCs have reached an agreement that is encouraging the acceleration of energy transformation to clean energy and upgrading of the existing energy efficiency all around the world.

Second is energy security issues that partially force traditional energy users to seek alternatives having fewer security risks. Energy security is of importance to maintain the normal operation of society. Due to the uneven distribution of traditional energy (fossil fuels), countries with fewer energy reserves suffer more from energy vulnerabilities. Globalization further raises the position of energy and energy security issues on national security and the whole economy. From a micro perspective, the unbalance of supply and demand for traditional energy hurts energy users by disturbing their production plans by affecting their costs. From a macro perspective, energy-exporting countries (oil-rich nations) could manipulate energy supply to dampen energy-importing countries (oil-poor nations) by attacking the industries regarding energy as input and harming their overall economic systems in the long-run. Therefore, it is valuable to increase the level of energy autonomy in any country.

In the context of climate change and energy security, energy supply is the key point of utmost importance. Renewable resources have fewer limits in different geographical areas. Therefore, renewable energy suffers less from the supply-side threat from energy-rich countries. As long as energy technology processes, every country can choose suitable energy sources to keep their energy supply stable on their own sources and realize less carbon emission if they choose clean energy sources.

1.2 Green investment

Under pressure from climate change and energy insecurity, money started to flow into the clean energy sector at a rapid rate. From 2004 to 2018, total climate finance flow increased more than five times, from 61.7 billion US dollars to 332.1 billion US dollars (Figure 1.3). This upward trend will not diminish in the next 30 years. To reach the goals of the Paris Agreement (NDCs targets), the international renewable energy agency (IRENA) estimates 27 trillion US dollars is necessary to invest in the renewable energy sector for the period from 2016 to 2050[5]. It implies a considerable investment potential for investment activity in clean energy sectors, compared to the current investment situation.

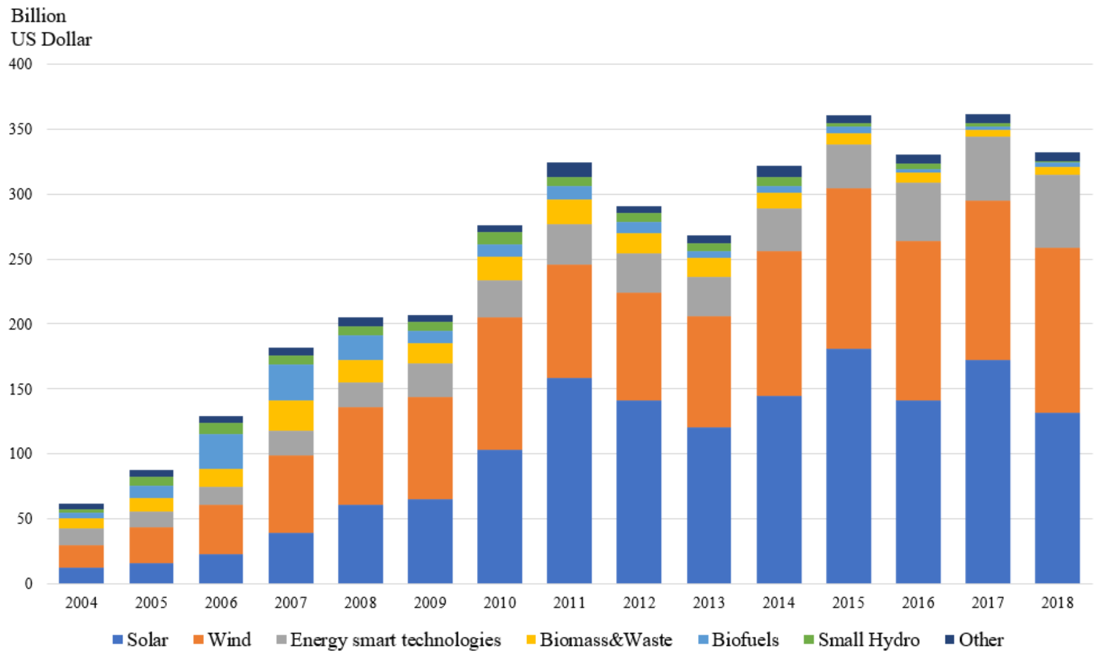

Figure 1.3 Global new investment in clean energy: 2004-2018.

Notes: Data source is the Research company BloombergNewEnergyFinance (BNEF).

[5] Estimation is from Global energy transformation: A roadmap to 2050 (2019 edition).

Green investments are the investment activities that use various financial tools such as stocks, exchange-traded funds, mutual funds, and bonds to invest in the underlying projects aiming to promote a green energy transformation toward a sustainable energy system[6]. For instance, the projects related to air pollution reduction, carbon emission reduction, fossil fuel reduction, generation of alternative energy sources, waste management, and other actions to improve the environment are all regarded as the target projects of green investments.

The green investments involve two different types of green financing methods showing in Figure 1.4. One is targeted green financing, in a narrow sense, that represents the investment used to support the specific implementation of green technologies and activities in project forms or specialist clean energy-related companies. Targeted green financing is usually provided by financial instruction with the selected use of proceeds in the public market, such as green bonds and loans. Moreover, common equity investment is also of importance for specialist clean energy-related companies. With a broader approach, the investment for companies of any sector aiming to manage and improve their environmentally friendly roles is also important to promote the development of clean energy. Therefore, it is defined as untargeted green financing.

In addition, the classification principles of green investments are numerous. Based on the sources of organizations and capital intermediaries, money for green investments can be from government budgets, development finance institutions, commercial financial institutions, corporate actors, households, et cetera. Various financial instruments are used in green investment, such as grants, low-cost project debt, project-level market rate debt, project-level

[6] The definition of green investment is not clear-cut. In this study, when considering the investment in clean energy sector, the terms “green investment”, “climate investment”, “green financing” and “renewable energy investment” are used interchangeably.

equity, and balance sheet financing. According to the types of activities, two types can be financed. One is to adapt to climate change, and another is to mitigate the damage of climate change. Based on sector segments, green investments can flow to low-carbon transport, renewable energy generation, energy efficiency, et cetera.

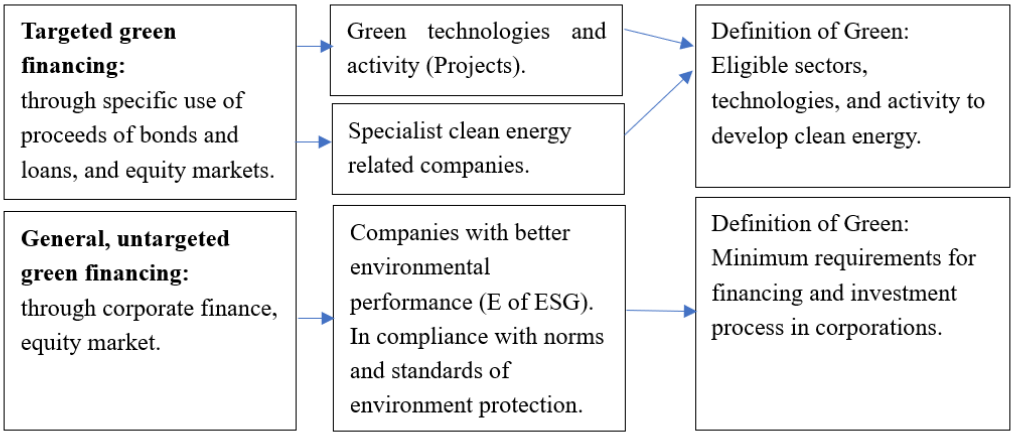

Figure 1.4 Two types of financing methods in green investment.

Notes: figure source is in the research of Kahlenborn et al. (2017).

For investors who invest in environmental-friendly projects and for environmental-friendly companies/projects who raise funds through green investment tools, green investment is a double-edged sword. The advantages of green investments include that i) creating a convenient environment for the sustainability-related companies/projects to get money; ii) giving the general public a chance to understand the development status of clean energy companies, which would reversely give more recognition to these companies for their innovative efforts; iii) providing tax exemption and personal satisfaction to investors. The main limitations and drawbacks of green investments are from the features of this sector. First, clean energy companies have a higher-risk as an emerging sector and are exposed to extra climate risk. Second, the small size of the green investment market makes investors withdraw hard.

Green investments are not equally applied to all financing methods. Investments using equities have a long history and amount the biggest share in ESG investing. In recent years, bonds, loans, and climate change-related overall asset allocation process also make significant progress, with their own advantages. This study narrows the research target to focus on targeted green financing. And the next subsection introduces the global open market finance status of clean energy equity and green bond in detail.

1.2.1 Investing in clean energy equity

More than 500 companies get involved in the leading edge of the clean energy sector in the stock markets. Stock markets give the listed clean energy companies one more channel to raise money and give the investors who concern about climate change one additional way to achieve their sustainability objectives by investing in this field. This public market financing method is essential for the advancement of the clean energy sector. The companies from various sectors can be included in the selection universe if companies contribute to clean energy development. For example, the companies focus on R&D and product greener utilities in improving the performance of photovoltaic panels, keeping the stability and efficiency of the wind power, off-grid solar system, and electric vehicle charging infrastructure. The manufacturers provide services to construct photovoltaic generation stations, wind farms, and other infrastructure-related clean energy. The companies whose main businesses are about energy storage and conservation or power delivery and conservation are also regarded as clean energy-related companies.

This thesis uses clean energy stock indices to understand green financing. As a primary investment tool, investment participants view indices as a reference to guide their investment decisions. It is more transparent to compare the indices among different sectors to reveal the characteristic of clean energy sectors. So far, the main index providers have developed more than 20 indices to identify and track the clean energy stocks' performances. Table 1.1 displays an overview of the main indices related to global clean energy stocks. The clean energy indices can choose stocks listed in one exchange or cover important clean energy companies from any stock exchanges worldwide as a global index. Regarding the market capitalizations of the clean energy index, S&P/TSX Renewable Energy and Clean Technology Index has the least amount with 2,748.46 million Canadian Dollars. Some indices are composed of the listed companies from a relatively narrow sectoral range, e.g., on clean energy or renewable energy. Others cover a broader range of green activities by including energy efficiency-related companies. Furthermore, many sustainability-related indices also include clean energy stocks as one kind of choice, such as Socially Responsible Investing (SRI) indices, Environmental, Social and Governance (ESG) indices, and environmental change indices.

The WilderHill Clean Energy Index represents the development of the clean energy sector in Chapter 2. It is widely used in academic research, and investment managers refer it to make clean energy-related investment decisions. At least three funds are based on this index. This index provider selects the companies listed in major US exchanges whose main businesses benefit from an energy transition to adapt to clean energy, less carbon emission, and conservation. Specifically, this index is comprised of stocks of 40 listed companies in the following six areas: i) renewable energy supplies – harvesting, ii) energy storage, iii) energy

Table 1.1 Summary of clean energy indices

No.	Index Name	Exchanges	Launch date	Market cap.	Index-tracking ETF and fund
1	Ardour Global Alternative Energy Indexes	Global	Jan. 1, 2000		VanEck Vectors Low Carbon Energy ETF Ardour Global Alternative Energy Portfolio
2	WilderHill Clean Energy Index	US	Aug. 16, 2004		Invesco WilderHill Clean Energy ETF PowerShares WilderHill Clean Energy Portfolio
3	European Renewable Energy Index (ERIX)	European	Oct. 13, 2005		
4	ISE Clean Edge Global Wind Energy Index	Global	Dec. 16, 2005		First Trust Global Wind Energy ETF
5	RENIXX Renewable Energy Industrial Index World	Germany	May 1, 2006		
6	WilderHill New Energy Global Innovation Index	Global	Oct. 1, 2006		Invesco Global Clean Energy ETF PowerShares Global Clean Energy Portfolio PowerShares Global Clean Energy Fund
7	Nasdaq Clean Edge Green Energy Index	US	Nov.17, 2006		First Trust Nasdaq Clean Edge Green Energy Index Fund
8	S&P Global Clean Energy Index	Global	Feb. 22, 2007	USD 5,332.86	iShares Global Clean Energy ETF iShares Global Clean Energy ETF USD Dist
9	MAC Solar Index	Global	Mar. 31, 2008	USD 2,200.00	Invesco Solar ETF
10	MSCI Global Alternative Energy Index	Global	Jan. 20, 2009	USD 2,109.56	
11	S&P/TSX Renewable Energy and Clean Technology Index	Canada	Mar. 25, 2010	CAD 2,748.46	
12	S&P Kensho Clean Power Index	US	Dec. 1, 2016	USD 24,750.87	SPDR® Kensho Clean Power ETF
13	CIBC Atlas Clean Energy Index	US/Canada	Nov. 13, 2017	CAD 17,830.32	ALPS Clean Energy ETF

Notes: This table shows the main clean energy indices, not covering all indices represent this sector. The information is collected from the homepage of each index. Market cap. indicates the mean value of the market capitalization, and the units of market capitalization are in millions.

conversion, iv) power delivery and conservation, v) greener utilities, vi) cleaner fuels.

The WilderHill New Energy Global Innovation Index is used in Chapter 3 to represent the development of the global clean energy sector. To reflect the global situations of this emerging lower-carbon sector, the WilderHill New Energy Global Innovation Index selects more than half of the companies listed on exchanges outside America. This index is comprised of 87 companies listed in various exchanges around the world covering the following two strands: one is related to energy conversion, energy efficiency, or energy storage; another is related to various renewable energy sources, such as wind, solar, biofuels & biomass, and others.

1.2.2 Investing in green bonds

Green Bond Principles (GBP) defines green bonds as “any type of bond instrument where the proceeds will be exclusively applied to finance or refinance new or existing eligible green projects.” As fixed-income securities, they are usually issued by governments, multinational institutions for raising money to finance some themed projects whose objectives are related to clean energy, decarbonization, and energy efficiency. The advantage of the green bond market is that it provides an additional source of green financing for long-term green projects in some areas with limited bank loan supply for long-term green projects.

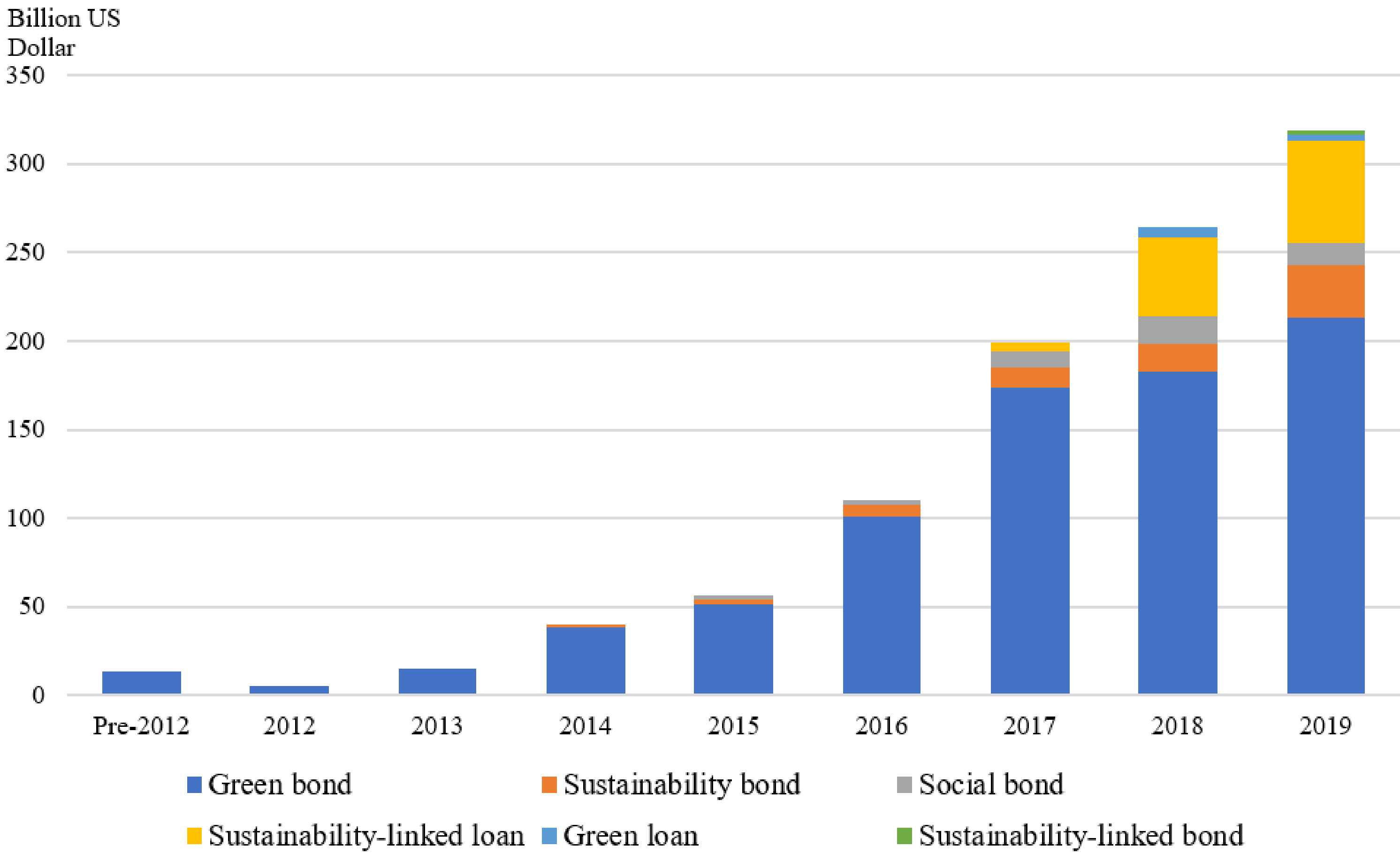

Figure 1.5 Sustainable debt issued by instrument type: Until 2019.

Notes: Data source is the Research company BloombergNEF (BNEF).

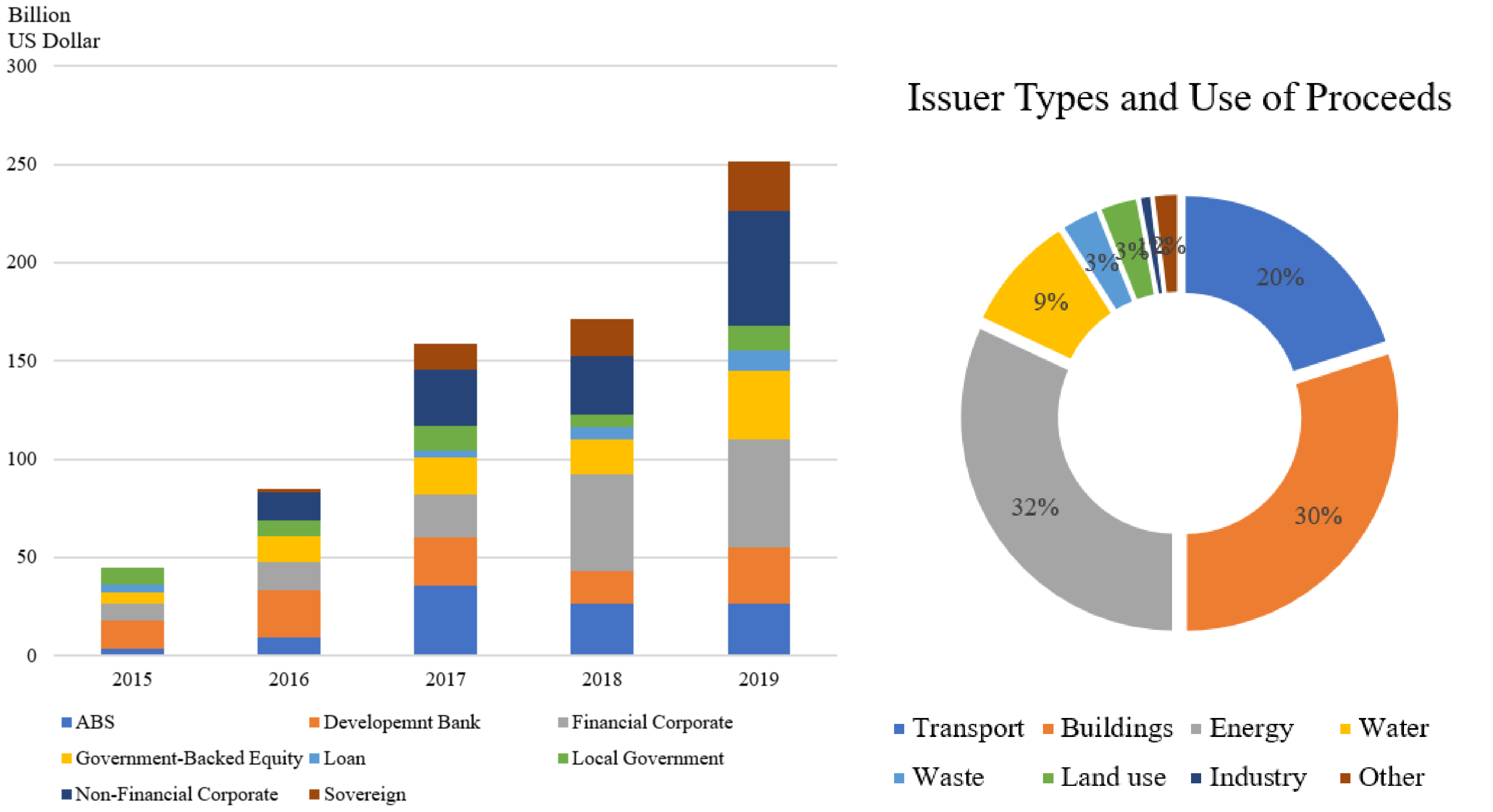

Figure 1.6 Global green bond market by issuer types: 2015-2019 and the use of proceeds in 2019.

Notes: Data source is the Climate Bonds Initiative.

According to the BloombergNewEnergyFinance, the green bond market shows an exponential growth among various types of sustainable debt, increasing from 5.1 billion US dollars in 2012 to 271 billion US dollars in 2019 in Figure 1.5. In addition, Figure 1.6 introduces the issuer types and use of proceeds of the green bonds, displaying that the main issuers of the green bonds were financial corporate and non-financial corporate in 2019. The public sector issuance also rose significantly, with almost types of issuers reaching record volumes. The use of proceeds in the green bonds indicates that energy, buildings, and transport sectors have a substantial amount of insurance, accounting for over 82% of the green bonds in 2019.

In debt markets, investors gradually pay more attention to the dual social and green benefits. It makes the green bond market more enthralling in the last few years. Given the huge amount of the global bond market, the green bond market has great potential to attract more investment. However, this novel market still faces various risks due to relatively low liquidity and yields, lack of a clear definition of "greenness," and additional costs for defining the green criteria to decide the eligibility of projects.

1.2.3 Other investments

Figure 1.7 indicates that a variety of financing vehicles are used in green investments. Equity is the leading channel for the private sector to provide green investments, followed by corporate bonds in the green bond market (in Figure A1.2). In Figure 1.6, we can see that public sectors also play a critical role as issuers in the global green bond market. Public investment flows are critical to the clean energy sector at the beginning stage by injecting initial capital. Furthermore, governments help this sector to establish an enabling investment environment for enhancing the risk-return profiles of green financial planning, thereby attracting more interests of private financial flows into clean and sustainable growth. Currently, government and national or international development finance institutions started to launch government-backed environmental funds and green funds of Public-Private Partnership, which mainly invest in the unlisted green companies and green infrastructure projects.

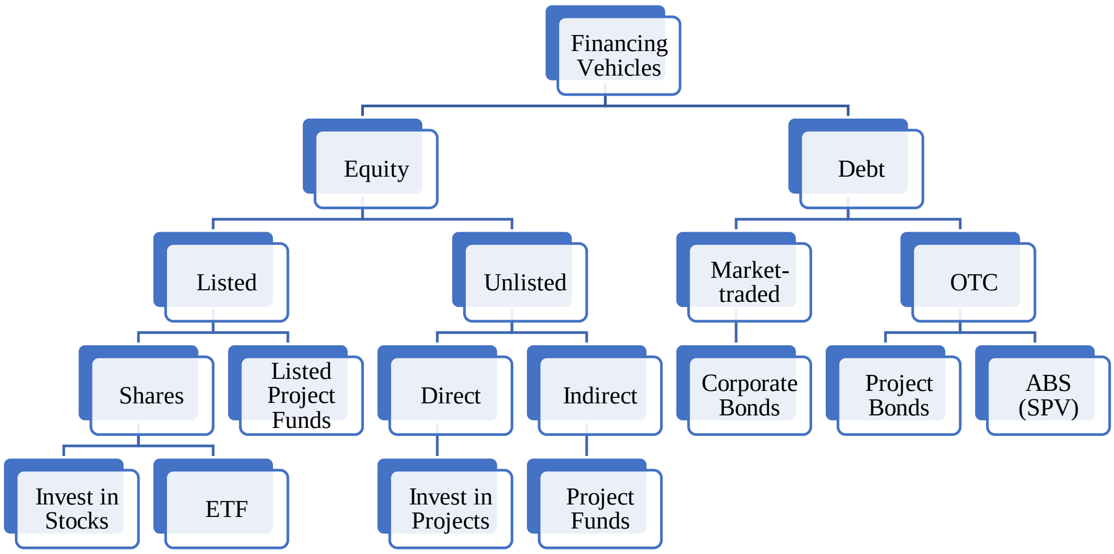

Figure 1.7 Main investors' financing vehicles for green investment.
Notes: Figure is designed by Kaminker and Stewart (2012).

1.3 Literature review

1.3.1 Clean energy stocks

This subsection introduces the existing literature regarding what roles macroeconomic variables play in the clean energy stock market. Theoretically, these macroeconomic influences affect clean energy stocks through various channels. However, empirical studies show that the results of some variables are unclear about their impacts on this tiny energy segment.

i) Oil prices

Oil has a dominant position in the energy industry. Oil prices also play an important role in the macroeconomy by directly affecting energy supply and demand and indirectly affecting inflation and industrial production. Oil prices also have been proven to affect the stock market from various channels. As for the clean energy sector, oil prices can directly affect the demand for clean energy. Based on the substitution effect among different energy sources, oil price increases make the demand for clean energy products increase. The surge of the demand for the outputs of clean energy companies increases their profits, and the expected returns on clean energy stocks also rise. Therefore, oil prices are always one of the main factors in the research on the clean energy stock market.

However, in the existing literature, the empirical evidence shows that the impact of oil prices on clean energy stocks is not consistent. With a multifactor model and the Granger causality test, Henriques and Sadorsky (2008) report that oil price returns indicate a statistically significant impact and are Granger causes of the US clean energy index. However, when they examine the dynamic relationship, impulse response functions show that oil price shocks have no statistically significant impact on clean energy stock prices. Kumar et al. (2012) also report a partially significant impact of oil prices consistent with the results from Henriques and Sadorsky (2008).

Managi and Okimoto (2013) concern that the impact of oil prices is time-varying and thus use a Markov-switching vector autoregressive model to extend the research of Henriques and Sadorsky (2008). They also extend the sample period to 2010 and find a positive relationship between oil prices and clean energy prices after 2007. Based on the time-varying method, they conclude that the impact of oil prices is more important on clean energy stocks in the increased economic feasibility period of the clean energy, financial crisis, and oil prices increase after 2007. Inchauspe et al. (2015) report a similar time-varying impact of oil prices and attribute clean energy stock returns to oil price surge and government policy incentives from 2007 onwards.

Reboredo (2015) examines tail dependence and possible systemic impact of oil price changes on clean energy stocks, indicating that oil prices significantly affect the systemic risk of clean energy companies. Bondia et al. (2016) employ a Vector Error Correction Model to report oil prices Granger cause clean energy stock prices in the short run. Gupta (2017) shows that an increase in oil prices is positively related to clean energy stock prices. Considering different time scales, Reboredo et al. (2017) show that the dynamic interaction between oil prices and renewable energy returns is weak in the short run but gradually rising over the long run.

Ahmad (2017) examines clean energy-related variables under directional return and volatility spillover frameworks. The spillover shows that crude oil exhibits a limited interdependence with the clean energy index, implying a possible portfolio combining the oil index and the clean energy index. Ahmad et al. (2018) show that oil prices have high hedging effectiveness for clean energy stocks. Paiva et al. (2018) investigate the inter-influence of oil prices and renewable energy sources. They use a Detrended Cross-Correlation Analysis to show that the relationship between oil prices and clean energy index is overwhelmingly uncorrelated, except during the financial crisis from 2008 to 2012. Ferrer et al. (2018) mention that oil prices are not a key driver of the stock market performance of clean energy companies, indicating a decoupling of the alternative energy segments from the traditional energy market. Reboredo and Ugolini (2018a) report that oil prices are major contributors to the dynamics of clean energy stock returns, followed by other energy prices.

Bouri et al. (2019) examine the tail dependence among various variables with the clean energy index and find that oil prices are a good safe-haven asset to the clean energy index. Kocaarslan and Soytas (2019a) show that oil prices significantly-positively impact clean energy stock prices in the short-run. However, the impact of oil prices becomes negative in the long-run. They think that the short-run positive impact is from speculative investments, and the long-run negative impact is from the overall economic condition. Maghyereh et al. (2019) find significant bidirectional return and risk transfers from the oil market to the clean energy market. Pham (2019) finds that the relationships between oil prices and clean energy stock sub-sectors vary across the sub-sectors. Specifically, the stock prices of biofuel and energy management companies are highly connected to oil prices. Uddin et al. (2019) find that clean energy stock returns significantly positively depend on oil price changes, with a cross-quantile dependence method. Xia et al. (2019) show that the fossil fuel-renewable energy network system has a relatively high interdependence level. However, Kyritsis and Serletis (2019) indicate that oil prices have no statistically significant impact on stock returns of clean energy companies in a long sample period from May 1983 to December 2016. Lv et al. (2019) prove that the relationship between oil prices and clean energy stock prices is significant before the oil price decline in 2014 and then became insignificant after the decline.

Kanamura (2020) shows that the correlations between clean energy and oil prices are positive and an increasing function of the corresponding energy prices. Nasreen et al. (2020)

employ spillover analysis to explain that the correlation between oil price and clean energy index is significantly high from 2006 to 2011 but only at low frequencies. The study of Zhang et al. (2020) is the closest research to this study, focusing on the impact of exogenous structural shocks of oil prices on clean energy stocks. They use the wavelet-based quantile-on-quantile and Granger causality-in-quantiles methods to find that the impact of oil supply shock on clean energy is strong in the short-term and long-term. The impact of oil aggregate demand shocks is quite positive at higher and lower quantiles of clean energy stocks in the middle-term. The impact of oil-specific demand shocks on stocks is asymmetric at the higher quantiles of clean energy stock returns in the long-term.

ii) Technology stock prices

Technological breakthroughs in the clean energy sector make renewable energy sources eligible for daily life. In the late 1990s, a large number of fuel cell companies were affected by the bubble burst in the technology stocks. To survive in this sector, clean energy companies are committed to making more technological innovations and improving their R & D capabilities to reduce their costs. So, the changes in clean energy stock prices heavily rely on the technology development trend (Kyritsis and Serletis 2019).

Starting from the research of Henriques and Sadorsky (2008), the existing literature reaches a consistent conclusion on technology stock prices as an essential factor affecting clean energy stock prices. Sadorsky (2012) finds that clean energy stock prices correlate more highly with technology stock prices than with oil prices in a dynamic conditional correlation model. Similar results of the impact of technology stock prices are reported in Kumar et al. (2012) and

Managi and Okimoto (2013). Kumar et al. (2012) mention that investors might see clean energy stocks similar to other technological stocks. Managi and Okimoto (2013) show that fuel cell companies also experienced increases when the boom for high-technology firms happened in the stock market.

Bohl et al. (2015) find the region-specific impact of technology stocks, which shows a stronger impact on the US index than the indices composed of the stocks listed in the global and European markets. Using excess returns of high-technology stocks, Inchauspe et al. (2015) show that the influence of technology stocks is in line with previous studies. They also explain that technology stock prices are important pricing signals for clean energy stocks because they compete for the same technology-related inputs. Bondia et al. (2016) also document a significant impact of technology stocks, providing empirical support to the argument given in existing literature. Gupta (2017) uses firm-level data to show that clean energy stock returns increase with the advancement of country-level technology and innovation. Using various methodologies and including more variables, the impact of technology on clean energy stocks is always significant. Ahmad (2017) document that technology stocks play a vital role in return and volatility spillovers of renewable energy stocks and crude oil prices. Ferrer et al. (2018) document a significant pairwise connectedness between clean energy and technology stock prices, implying that investors perceive these two types of stocks as similar assets. Kocaarslan and Soytas (2019a) use a NARDL model to show a significant relationship between stock prices of clean energy and technology firms in both the short-run and the long-run. Sun et al. (2019) use the stock index in China to show consistent results of technology stocks also in an emerging country. Nasreen et al. (2020) make a phase differences study to indicate that technology stock returns lead to clean energy stock returns. The volatility spillover network reflects that technology stocks are a net transmitter to clean energy stocks at all frequencies and over the whole period.

iii) Interest rates

The business cycle research indicates the importance of interest rates in the stock market. Higher interest rates reflect an expanding economy that motivates a portfolio adjustment to invest more in the sectors that benefit from this circumstance. The green investments can be viewed as an important contributor to positive economic trends in the expansion stage of the business cycle (Kocaarslan and Soytas 2019a).

Henriques and Sadorsky (2008) find that interest rates are not a significant risk factor for clean energy stock prices. However, interest rates are a Granger Cause of clean energy stock prices. The impulse response function results show that interest rate shocks have a significantly positive impact on clean energy stock prices in the first two weeks. Then the impact quickly becomes insignificant once and turns significantly positive after ten weeks. Kumar et al. (2012) use a multifactor model to show that interest rates are a significant risk factor for the clean energy stock index. Moreover, the bilateral Granger causality results report contrast results to the findings of Henriques and Sadorsky (2008), implying that movements in interest rates are affected not only by inflation and economic cycle but also by financial markets. Lee and Baek (2018) believe that economic booms make interest rates and stock prices increase, reflecting a positive effect of changes in interest rates on clean energy stock prices. Kocaarslan and Soytas (2019b) use the federal funds rates to represent the effect of monetary conditions and find that they have a significant impact on the dynamic correlations between stock returns of clean energy and technology companies.

The research mentioned above regards interest rates as one indicator of the business cycles, implying that the macroeconomic environment impacts the clean energy stock companies. Furthermore, other research views interest rates as bond yields to analyze their impact on the relationship between the stock market and the bond market.

Bondia et al. (2016) explain the relationship between interest rates and clean energy stock prices by the relationship between stocks and bonds, implying the investment alternatives between each other for investors. Ahmad et al. (2018) use the continuous futures settlement price of the 10-year US Treasury note to represent the bond market. The generalized orthogonal-generalized autoregressive conditional heteroskedasticity (GO-GARCH) model results reveal that bond prices have negative dynamic dependence with clean energy stock prices. Ferrer et al. (2018) find that the US 10-year Treasury bond yields are net recipients in connectedness between renewable energy stocks and crude oil prices. Lundgren et al. (2018) find a consistent net recipient role of bond yields in a connectedness network with clean energy stocks. And they also find significant bilateral Granger causality relationships between the bond market and clean energy indices from various regions.

iv) Other variables in bond market

Besides interest rates, other financial variables from the bond market are also used to examine their impacts on clean energy stock prices.

Ferrer et al. (2018) include the US default spread and the volatility of the US government bond markets in the connectedness network with clean energy stocks. They use the difference between Moody's seasoned yields on Baa and Aaa corporate bonds to represent the default spread, demonstrating the effect of business cycle movements on the aggregate credit or the default risk in the economy. They also use the implied volatility of the US Treasury bond markets to examine the impact of uncertainty of interest rates on clean energy stock prices. However, based on the connectedness network, these variables are all net receivers of return and volatility spillovers from other variables in the networks.

Kocaarslan and Soytas (2019a) examine the impact of business cycles and monetary policy on the dynamic correlations between oil prices, stock prices of technology companies, and stock prices of clean energy companies. Because the business cycle fluctuations have a strong linkage with the changes in the oil market and stock markets (Fama and French 1989, Mork et al. 1994). Specifically, the default spread (the difference between the yields on the 10-year Treasury bond and the 3-month Treasury bill), the term spread (the difference between the yields on the BAA-rated and AAA-rated corporate bond), and TED spread (the difference between 3-Month LIBOR and 3-Month Treasury Bill) are included in their examination. They find positive impacts of these spread variables on the dynamic correlations, implying that worse business conditions lead to dynamic correlations between oil prices and stock prices of technology and clean energy companies increase.

v) Exchange rate

Uddin et al. (2019) identify foreign exchange rates as a potential driver of clean energy stock prices because of the multinational setting of many clean energy companies. The changes in exchange rates affect the cost of foreign inputs and revenue from overseas, thus affecting the profits and the expected value of multinational clean energy companies. The empirical examinations confirm that clean energy stock returns have a positive dependence on exchange rates. Sadorsky (2012) reports the dynamic correlations between the stock prices of clean energy and technology companies and oil prices. Kocaarslan and Soytas (2019b) find that the impact of US dollar changes is the main driver of this time-dependent relationship due to its role as the invoicing currency of the global crude oil trade.

vi) Stock market index

Gupta (2017) uses the local market return series to measure the impact of overall stock markets. They argue that the country-specific institutional quality makes clean energy stock returns highly correlated with the local stock market. They use firm-level panel data to examine that the local stock market returns are a critical determinant of clean energy stock returns. Inchauspe et al. (2015) find that the MSCI world stock market index is highly correlated with the clean energy stock index, indicating a key role as a pricing factor of the stock market index for the clean energy stock companies. Lundgren et al. (2018) use the US and European stock market indices to explain the significant impact of big markets with large corporations and capital investments on the smaller clean energy sector. Reboredo and Ugolini (2018a) also report a significantly positive impact of the stock market index on clean energy stock returns in a GARCH model.

vii) Market volatility index (VIX)

VIX is a measure of the expected volatility of the S&P 500 stock index, reflecting the investors' risk aversion in the stock market. As a fear indicator, the VIX increase means a sign of greater uncertainty and induce investors to adjust their portfolios. As one sector in the stock market, clean energy stocks are affected by the overall stock market uncertainty.

Ahmad et al. (2018) find that VIX is the best asset to hedge clean energy stock returns. Ferrer et al. (2018) document that stock prices of clean energy companies and VIX are both the net transmitters of return and volatility connectedness among various financial indicators. Ji et al. (2018) report that clean energy stock prices have the largest dynamic dependence on VIX than other energy prices. Lundgren et al. (2018) report a similar role as a net transmitter of VIX in a network with other uncertainty variables, financial variables, and clean energy stock prices. Uddin et al. (2019) use VIX to represent the financial uncertainty and find that the VIX does not affect the dependence of clean energy stock prices on other asset classes.

viii) Crude oil volatility index (OVX)

To extend the research on the impact of oil prices, Dutta (2017) firstly extends to examine the fluctuations in oil price. The uncertainty in the oil market could affect the policy in renewable energy sectors worldwide. The oil price implied volatility index (OVX), referred to as an oil market uncertainty indicator, affects the financial market performance of clean energy stocks significantly.

Ahmad et al. (2018) report a negative dynamic correlation between clean energy stock prices and OVX, and the OVX has high hedging effectiveness among other considered variables. Ji et al. (2018) examine that the Kendall dependency between clean energy price returns and OVX is significantly negative, implying that the increase of oil market uncertainty leads to a fall in clean energy price returns. Dutta et al. (2020) investigate different kinds of commodity market volatility indices of the crude oil, gold, and silver market. They find negative relationships of clean energy stock prices with three commodity market volatility indices in the dynamic conditional correlation model. And the implied volatility index of crude oil has the highest hedging effectiveness, among other effective tools, followed by gold and silver indices.

ix) Policy uncertainty

As the policy-supported sector, Lundgren et al. (2018) also include the economic policy uncertainty into a connectedness network to analyze its impact on clean energy stock prices. However, they find that policy uncertainties in the US and Europe are relatively isolated from the other variables in their network setting. Uddin et al. (2019) mention that equity and other asset prices are sensitive to policy uncertainty, but they cannot find a significant impact of policy uncertainty on the relationships between clean energy and other asset classes.

x) Carbon emission allowance prices

As we all know, climate change is one reason for the development of clean energy to reduce carbon emissions. There are other methods to prevent climate change, such as pricing the right for carbon emissions. Higher carbon permit prices may make the cost of energy users increase and induce energy transition to less-polluting clean energy.

Kumar et al. (2012) report an insignificant relationship between carbon allowance prices and clean energy stock prices. They think that the regional carbon system and lower carbon prices make carbon prices cannot affect the clean energy stock market. Dutta (2017) reports that the volatility of carbon prices is also statistically insignificant to affect the volatility of clean energy stock returns. Dutta et al. (2018) document a consistent insignificant result of carbon prices to affect clean energy stock returns with Kumar et al. (2012). And they also document that significant volatility linkage exists only in the European market, implying that emission prices have country-specific or region-specific features. Ahmad et al. (2018) use multivariate GARCH models to prove that carbon prices have significant persistence in clean energy returns in the short-term and the long-term. Moreover, the impact of carbon prices is asymmetric, meaning that positive news of climate change concerns make volatility increase higher. Sun et al. (2019) also confirm no significant positive relationship between clean energy stock prices and carbon futures prices. They believe a low carbon price level cannot achieve the substitution effect due to the external cost of carbon emission from fossil fuels. Xia et al. (2019) report that the carbon market becomes a main transmitter in different energy markets in a dynamic Value at Risk (VaR) connectedness network, showing the critical impact of carbon prices in the VaR network.

xi) Commodity prices

Apart from the main energy commodity oil, prices of other kinds of energy also may have a substitution effect on clean energy. Therefore, some studies also include main commodity prices to examine their impacts on clean energy stocks.

Reboredo and Ugolini (2018a) use a multivariate vine-copula dependence model to investigate the impact of prices of oil, gas, coal, and electricity on clean energy stock returns. They find that oil prices and electricity prices are essential factors to affect clean energy stock returns in the US and European stock markets. Song et al. (2019) report consistent results that oil prices are closely related to clean energy stock prices, while natural gas prices and coal prices have a weak connection with clean energy stock prices. Xia et al. (2019) confirm that fossil fuels and clean energy have a high level of interdependence in a network approach. They find that electricity price changes are a major contributor to clean energy stock returns in the return connectedness network, and oil and coal show more impacts in the VaR connectedness network. Kanamura (2020) shows that the correlations between clean energy stocks and oil or natural gas prices are significantly positive.

xii) Gold Prices

As a safe-haven asset, gold is an effective hedge against the stock market risk. If gold also plays a good role as a safe-haven to clean energy stock indices, investors would adjust their portfolios to lower their risk by involving more golds.

Ahmad et al. (2018) conclude that gold is not the best hedge tool for clean energy stock prices. Consistently, Elie et al. (2019) report that gold is just a weak safe-haven asset for clean energy indices. Uddin et al. (2019) find that a positive impact of gold price changes on clean energy stock returns is only significant during extreme market conditions. Focusing on the implied volatility index, Dutta et al. (2020) indicate that the implied volatility index of crude oil is also most effective than the implied volatility index of gold.

xiii) Cultural dimensions indicators

To investigate the financial performance of clean energy companies, Gupta (2017) examined the influence of societal factors. By using firm-level panel data, he includes cultural dimensions indicators in regression. The results show that clean energy stock returns are significantly high in societies with low scores in the uncertainty avoidance index and indulgence index and a high score in the long-term orientation index.

xiv) Investor sentiment indicators

With the development of behavioral finance, more research focuses on investor sentiment, which affects stock returns, liquidity, and volatility of the stock market. To research the investor sentiment in clean energy stocks, Reboredo and Ugolini (2018b) examine the impacts of the Twitter sentiment index and sentiment divergence. However, the results show that Twitter sentiment cannot convey useful information in clean energy sectors. Song et al. (2019) use the Google search volume index (GSVI) and find that investor sentiment towards clean energy is time-varying and more critical in the short-run.

xv) Other indicators

Besides the above-mentioned variables, some novel factors are discussed, like Bitcoin prices and rare earth prices. Because bitcoin mining needs a huge electricity demand, and the rare earth is one of the clean energy production inputs. Symitsi and Chalvatzis (2018) find significant risk spillovers between Bitcoin prices and clean energy stock indices. Moreover, Baldi et al. (2014) find a negative impact by raising rare earth prices on clean energy indices.

1.3.2 Green bonds

Research on the green bond market started over the last five years. So far, green bonds play a novel role in the bond market and have a relatively weak relationship with other macroeconomic factors. Moreover, research on this field is partially focusing on the relationship between green bonds and conventional bonds.

Pham (2016) is the first research to investigate volatility spillover between the green bond market and the overall conventional bond market. Hachenberg and Schiereck (2018) find that green bonds trade marginally tighter than non-green bonds of the same issuers. Karpf and Mandel (2018) report that green bonds have been traded at lower prices and higher yields, underperformed than their credit profiles. However, the credit quality of municipal green bonds shows a rising tendency, and premium became positive in recent years. Reboredo (2018) examines that the co-movement between green bonds and corporate and treasury bonds is higher than between green bonds and stocks and energy commodity prices. Moreover, green bonds are affected by the spillovers from bond markets, but the impact of stocks and energy markets is negligible. Flammer (2020) shows that corporate green bonds are an effective tool to improve the environmental footprint of the companies and contribute to the long-term value of companies. Nanayakkara and Colombage (2019) find that investors pay a premium in green bonds than general corporate bonds. However, Zerbib (2019) reports that green bond yields are lower than conventional bonds. Broadstock and Cheng (2019) find that financial market volatility, economic policy uncertainty, daily economic activity, oil prices, and sentiment indicator towards green bonds have significant impacts on correlations between green bonds and black bonds. Hyun et al. (2020) find no robust and significant yield premium or discount on green bonds compared with conventional bonds.

1.4 Motivation

Based on the above sections, we have understood the rapid development of the clean energy sector and explained the reason why it can attract capital to flow in this sector. As this sector expands, the influence of macroeconomic variables gradually penetrates, promoting or hindering the development of the clean energy sector. The clean energy stock markets as one way to reflect the status of the clean energy sector are also affected by the macroeconomic influences. Section 1.3.1 has introduced the impact of macroeconomic variables on clean energy stock returns involved in the existing literature. Previous literature fails to reach a consensus about the impact of oil prices. Depending on different methodologies and stock markets in different countries, some studies report a substitution effect between these two energies, finding a significant positive impact of oil price changes on clean energy stock returns (Managi and Okimoto 2013, Inchauspe et al. 2015). In comparison, others indicate no significant impact of oil price changes on clean energy stock returns, showing that the clean energy sector is closer to the high technology industry (Kyritsis and Serletis 2019).

Oil prices can affect cost, discount rates, and aggerated demand of almost any company. Then company profits will be further affected, followed by stock prices. As for clean energy companies, considering the substitution effect, oil prices can directly affect the demand for clean energy-related products. Therefore, the impact of oil prices relies on the substitution effect. If an energy transition happened, the substitution effect affects the clean energy stock returns. While oil users reject the energy transition, no substitution effect implies a low-level impact on the clean energy stock returns. Based on the underlying sources of oil price changes, this study examines three kinds of oil price shocks: oil supply shocks, aggregate demand shocks, and oil-specific demand shocks, distinguished by Kilian (2009).

Moreover, the impacts of some variables have not been examined in detail or have been ignored. After the Global Financial Crisis, uncertainty has played a fundamental role in influencing energy prices (Ji et al. 2018). The contagious uncertainty affects the energy market by rendering the price changes in traditional energy and the stock returns of clean energy higher. Therefore, it is necessary to examine the impact of uncertainty on clean energy stock returns with appropriate uncertainty measures identifying the uncertainty from different sources (Baker et al. 2016, Jurado et al. 2015, Ludvigson et al. 2015, Caldara and Iacoviello 2018). Existing literature has reported the significant impacts of policy uncertainty, oil price uncertainty, and financial uncertainty on the fluctuation of clean energy stocks (Ji et al. 2018, Ferrer et al. 2018, Lundgren et al. 2018).

However, the impacts of two kinds of uncertainty have not been examined on clean energy stock returns. First, strongly correlated with the above-mentioned uncertainty proxies, the uncertainty of the macroeconomic environment can affect any participants in the economy and force investors to adjust their decision under this background. A stable macroeconomic environment is more conducive to the development of emerging industries, such as the clean energy sector. However, a turbulent macroeconomic environment will lead to a decline in green investment. Second, oil supply disruptions usually follow geopolitical crises. Geopolitical risk evaluates the uncertainty level of the geopolitical events, which affects the supply of fossil fuels and the demand for clean energy. Therefore, this study extends the research on the impact of different kinds of uncertainty on clean energy stocks and examines the impacts of macroeconomic uncertainty and geopolitical risk on the clean energy stocks market.

In a nutshell, this study extends the empirical research about the impact of macroeconomic influences on green investment, especially on clean energy stocks, by including the oil price changes and uncertainty related variables with appropriate empirical models.

1.5 Thesis structure

This doctoral thesis has four chapters to investigate stock returns of clean energy companies and macroeconomic influences. Chapter 1 introduces the development status of the clean energy sector and green investment trends, showing a background of the investment in the clean energy sector. The existing literature in subsection 1.3 elaborates on the impact of various macroeconomic influences on green investment. Furthermore, the motivation and the structure of this thesis are also introduced in this chapter. Chapter 2 reports an empirical study introducing how macroeconomic influences affect clean energy stock returns by examining the impact directions, channels of transmission, and lasting times of the examined macroeconomic influences. Stock returns are one of the most critical indicators to represent the fluctuations in the stock market. In addition, the volatility of returns is also a critical indicator to reveal the risk of stocks. Plenty of financial market-related studies start to analyze the return and volatility of the stocks from numerous directions. Most of the previous studies about the clean energy stock market also use these two variables to represent clean energy stocks. Therefore, Chapter 3 further focuses on the volatility of clean energy stock returns, investigating the impacts of oil price shocks, macroeconomic uncertainty, and geopolitical risk on the long-run variances of clean energy index, and making a comparison study by including the volatility of the global oil and gas index to investigate the exposed risks of different energy-related stocks. Chapter 4 concludes this study and discusses some remaining questions and future tasks about green investments in the clean energy stock market or other financial instruments.

Appendix 1

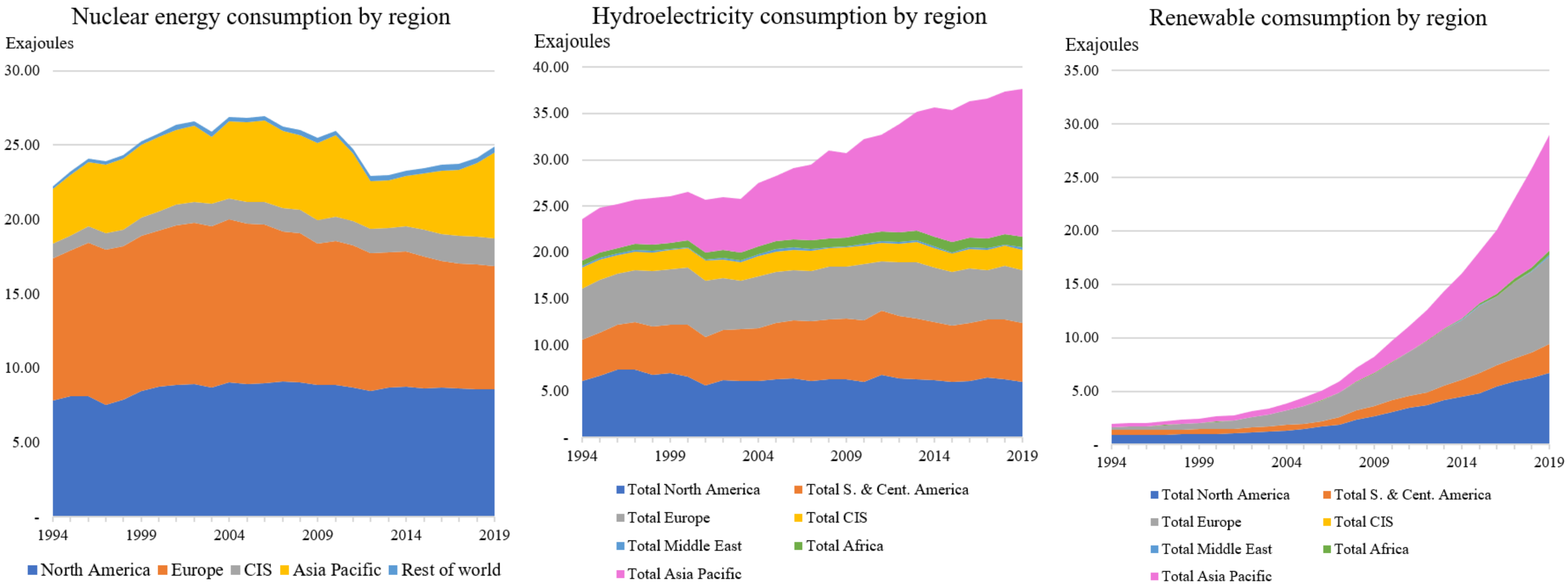

Figure A1.1 World energy consumption of hydroelectricity, renewable, and nuclear by region: 1994-2019.

Notes: Data source is the BP Statistical Review of World Energy 2020.

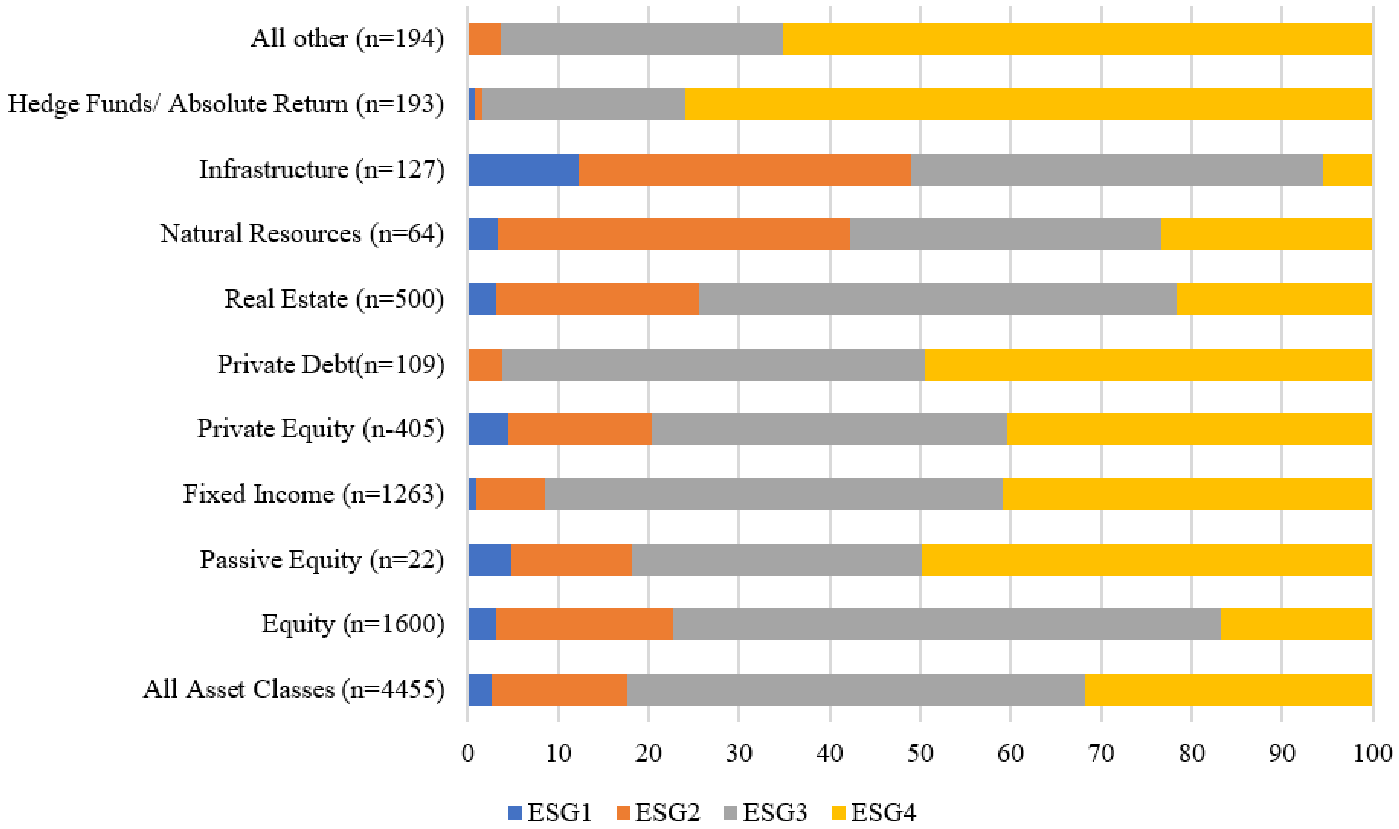

Figure A1.2 Distribution of Mercer ESG ratings.

Notes: Ranking ESG is based on the investment manager strategies about ESG factors and active ownership. From ESG1 to ESG4, the integration level of ESG factors or active ownership falls. n is the number of strategies evaluated. The data source is the Mercer's global manager research team.

2 Do Oil Price Shocks and Policy Uncertainty Affect Clean Energy Stock Returns?

In chapter 1, we already have a preliminary understanding of the clean energy sector and clean energy stock markets. In this chapter, an empirical study is made to elaborate on how clean energy stock returns would respond to the impacts of oil price shocks and policy uncertainty.

2.1 Introduction

With the global pressure caused by climate change and air pollution, traditional energy users are considering the possibility of using clean energy alternatives such as solar, wind, and hydropower. The uncertainties in the oil market, such as unpredicted increases in oil prices, stress the need for energy substitution and may accelerate the energy transition. Although the oil price changes are often considered a crucial factor for the development of clean energy, there is no consensus among economists about the relation between stock prices of clean energy and prices of oil. Therefore, to shed light on the link between oil prices and clean energy stock prices, a more detailed analysis is necessary.

Kilian (2009) argues that, historically, oil price shocks have mainly been driven by a combination of global aggregate demand shocks and precautionary demand shocks, rather than by oil supply shocks. The author attributes fluctuations in the real prices of oil to three structural shocks in the oil market. Using the oil price decomposition method proposed by Kilian (2009), Kang, Ratti, et al. (2017) investigate the effects of oil price shocks and economic policy uncertainty on the stock returns of oil and gas companies. They find that, on average, a demand-side oil shock has a positive effect on the returns of oil and gas companies, whereas shocks to policy uncertainty have a negative effect on stock returns. Following these two studies as a starting point, we extend the literature by examining the impact of four factors - oil supply shocks, aggregate demand shocks, oil-specific demand shocks, and policy uncertainty shocks - on the stock returns of clean energy companies listed in US exchanges. We employ a Structural Vector AutoRegression (SVAR) model to do this empirical research with monthly frequency data from January 2001 to December 2018.

Among four factors affecting the stock returns of clean energy companies, the first three - oil supply shocks, aggregate demand shocks, oil-specific demand shocks - are considered by Kilian (2009) to be the main factors affecting oil prices. They are also used by Kang, Ratti, et al. (2017) as the oil-related factors to examine their impacts on the stock returns of oil and gas companies. Since clean energy is substitutable with oil, these three factors are considered to affect the clean energy stock returns as well. For example, because some oil users who cannot afford high oil prices may increase the demand for clean energy and decrease the demand for oil.

A large number of studies investigated the impact of the last factor, policy uncertainty, on the stock market returns (Antonakakis et al. 2013, Kang and Ratti 2013a, Liu and Zhang 2015). Among them, Kang, Ratti, et al. (2017) showed that policy uncertainty significantly affects the stock returns of oil and gas companies. For the clean energy sector, policy supports the development of clean energy in its emerging stage through financial subsidies from the government, investment tax credits, accelerated depreciation, transfer payments, and preferential tax policies. As such, policy uncertainty can be considered as an important factor affecting the clean energy stock returns.

Our empirical study reveals the following results: (1) Oil supply shocks and aggregate demand shocks have a positive effect on the stock returns of clean energy companies, while policy uncertainty shocks and oil-specific demand shocks have a negative effect; (2) These shocks are shown to last relatively long; (3) The effects of oil shocks on the clean energy stock returns are amplified by adding policy uncertainty as an endogenous factor; (4) The impact of policy uncertainty is mainly transmitted by the uncertainty of inflation.

Our first result indicates that a decrease in oil supply leads to an increase in the clean energy stock returns, which implies that there exists a substitution effect between oil and clean energy. Clean energy companies can profit more when the oil supply decreases because oil users increase the demand for clean energy. Furthermore, an increase in oil-specific demand leads to a decrease in the clean energy stock return, which implies that there exists no substitution effect between oil and clean energy for oil-specific users. Clean energy companies lose more when the oil-specific demand increases because such oil-specific users do not increase the demand for clean energy. In addition, aggregate demand increases lead to increases in the clean energy stock returns, which implies that aggregate demand makes energy-related companies profit no matter what kinds of energy. Finally, an increase in policy uncertainty leads to a decrease in the clean energy stock returns, which implies that there is an uncertainty effect in the clean energy segment as well. Therefore, policy uncertainty can be viewed as an important factor affecting the clean energy stock returns.

Our second result shows that, from a long-term perspective, oil supply shocks explain 14% of the variation in the US real stock returns of clean energy companies, aggregate demand shocks explain 11%, oil-specific demand shocks explain 18%, and uncertainty shocks account for 15%. The four types of shocks explain 59% of the variation, revealing they are essential determinants of the clean energy stock returns.

Our third result reveals that policy uncertainty is negatively affected by an increase in aggregate demand and that it is significantly and negatively affected by a decrease in oil supply. Meanwhile, an increase in oil-specific demand has a positive effect on policy uncertainty. Through these three channels, the oil shocks are amplified to have a greater effect on the clean energy stock returns. Regarding the fourth result, our analysis shows that, among the four uncertainty components, the uncertainty in the inflation forecast has the most significantly-negative impact on the clean energy stock returns.

This chapter is the first study to analyze the joint effect of these four factors on clean energy stock returns using a structural VAR model. While the study by Kang, Ratti, et al. (2017) is similar to ours, our approach is different in that we analyze the clean energy stock returns instead of the oil and gas stock returns. Furthermore, several studies investigated the impact of oil-specific demand shocks on clean energy (Bondia et al. 2016, Dutta et al. 2018, Henriques and Sadorsky 2008, Inchauspe et al. 2015, Kumar et al. 2012, Managi and Okimoto 2013, Reboredo et al. 2017). However, no studies investigate the impact of oil supply and aggregate demand shocks on the clean energy stock market. This chapter contributes to the literature by using the structural VAR model to provide new evidence regarding the impact of oil supply and aggregate demand shocks on the clean energy stock returns.

Several studies also investigate the impact of uncertainty on oil prices (Aloui et al. 2016, Antonakakis et al. 2014, Degiannakis et al. 2018, Kang and Ratti 2013b). In addition, the impact of uncertainty on clean energy has also got some attention (Ferrer et al. 2018, Ji et al. 2018, Lundgren et al. 2018). For example, Lundgren et al. (2018) find spillover effects from American and European economic policy uncertainty on both returns and volatilities of several clean energy indices. Ji et al. (2018) use a time-varying copula-based conditional value at risk (CoVaR) model to estimate the impact of economic policy uncertainty on the global clean energy index. This chapter adds to the literature by specifically analyzing the impact over a two-year period and by separating the different sources of policy uncertainty to make the analysis more comprehensive using the structural VAR model.

The remainder of this chapter is structured as follows. Section 2.2 reviews the literature on the interaction between the stock returns of clean energy corporations, oil shocks, and policy uncertainty. Section 2.3 describes the dataset and the methodology used in this chapter. Section 2.4 presents the empirical analysis, in which we estimate the impact of both the structural oil price shocks and the policy uncertainty on the real stock returns of clean energy companies. Section 2.5 presents the conclusion of the chapter.

2.2 Literature review

The clean energy sector has been investigated from various perspectives. A growing body of literature has focused on the financial performance of clean energy companies in this decade. Many economic indicators related to the development of clean energy have been examined from a macroeconomic perspective, including oil prices, technology stocks, interest rates, stock market index, et cetera.

The first group of scholars focuses on the level and return of clean energy stocks.

Henriques and Sadorsky (2008) analyze the relationship between oil prices and clean energy stocks, noting that clean energy companies operate like high technology companies[7]. Using the Granger causality test and lag augmented-vector autoregressive (LA-VAR) model, they find that the technology stock prices affect the US clean energy stock prices more significantly than the oil prices. Kumar et al. (2012) employ the same method and extend this topic to the global clean energy stock market, confirming similar influential abilities of oil and technology. Managi and Okimoto (2013) further expand the study by Henriques and Sadorsky (2008) by considering the structural breaks. They find a positive impact of oil price on clean energy stock returns, which become more significant after 2008. Again, based on the study by Managi and Okimoto (2013), Bondia et al. (2016) employ the cointegration method with structural breaks to study the long-term relationship among stock prices of clean energy companies, oil prices, technology stocks, and interest rates. They report significant short-term causal relationships between macroeconomic variables and clean energy stock prices.

Aside from the VAR model, novel methods are increasingly being used in research on the clean energy stock markets. For example, Inchauspe et al. (2015) use a state-space approach to examine the time-varying impacts of the aggregate stock market, technology, and oil prices on stock returns of clean energy companies. They find that, in the sample period, the impacts of the aggregate stock market and technology are always significant, whereas the impact of oil prices is significantly lower before 2007 and gradually becomes more influential.

The second group of scholars focuses on the volatility of clean energy stocks and risk spillovers. Sadorsky (2012) analyzes the volatility dynamics of clean energy stocks and other

[7] We also add the same technology factor into our model, and the main findings are robust. To save space, results are not reported, but are available upon request.

financial variables. He confirms that the correlation level of oil prices is significant and emphasizes that technology stock prices have a higher correlation level with the US clean energy stock prices. Aware of the importance of oil on the variances of clean energy stocks, Dutta (2017) tests the impact of oil fluctuation on the realized volatility of clean energy stocks and find that oil uncertainty can provide some additional information that partially explains the volatility of clean energy stocks.

Reboredo (2015) investigates systemic risk and dependence between oil prices and clean energy stock returns. Focusing on the tail dependence, he finds that oil prices significantly contribute to about 30% of the tail risk of clean energy companies. A later study by Reboredo et al. (2017) extends the analysis of dependence and causality between oil prices and clean energy stock prices by considering different time scales. The authors document stronger dependence in the long run during 2008-2012 and mixed causality relationships for these two energy markets. This result is also supported by Paiva et al. (2018) within a detrended cross-correlation analysis framework. Using a multivariate vine-copula dependence method, Reboredo and Ugolini (2018a) extend the analysis of clean energy dependence even further. They highlight the impact of the prices of oil and electricity on the clean energy stock prices, comparing them to the prices of natural gas and coal.

The third group of scholars analyzes the uncertainty of clean energy stocks. Since Dutta (2017) scrutinizes the impact of oil uncertainty, scholars start to analyze other kinds of uncertainty. Lundgren et al. (2018) built a connectedness network among clean energy stocks and the uncertainty from the financial market and policy. They report the importance of uncertainty regarding the returns and volatility of clean energy stocks. Ferrer et al. (2018) go a step further to examine the connectedness of clean energy stocks using a dynamic time and frequency analysis method. They document a decoupling of two kinds of energy and find that clean energy is closer to a technology indicator when controlling for the impact of financial factors and the uncertainty of these financial factors. Ji et al. (2018) compare the impact of uncertainty from the financial market, oil market, and economic policy on the energy stock market. Using the CoVaR method to examine risk spillover and tail dependence, they conclude that policy uncertainty has a weaker effect than the other two factors. Compared to the conventional energy stocks, they also find that policy uncertainty is more important to the clean energy stocks.

2.3 Data, Methodology, and Hypotheses

2.3.1 Data description

We use monthly data series over the period from January 2001 to December 2018, as the data on the clean energy index is only available starting in January 2001. The stock returns of the clean energy industry (Δeco_t) is obtained using the first difference of the log index entitled WilderHill Clean Energy Index. This is a popular index displaying the fluctuations of clean energy in US stock markets. Like Kang, Perez de Gracia, et al. (2017), we also use the stock returns of the oil and gas industry (Δog_t) and of the overall stock market in the US (Δsp_t) to compare the difference of clean energy segments with conventional energy segments and the whole market. Data on the oil and gas industry are obtained from the Fama-French Data Library, and the S&P 500 index is from the Federal Reserve Economic Data website. All stock returns have subtracted the impact of the consumer price index (CPI) inflation rate in the US.

Following Kilian (2009), we use three series to display the underlying causes of oil price changes. Regarding supply, the supply shock is represented by the percent change in the global crude oil production ($\Delta prod_t$), calculated by the difference in log of world crude oil production in a month. Demand-side has two components: aggregate demand shock and oil-specific demand shock. Aggregate demand shock is measured by the global real economic activity index (rea_t). Kilian (2009) constructed this index using an equal-weighted index of the percent growth rates obtained from single voyage bulk dry cargo ocean shipping freight rates. The dry cargo ocean shipping freight rates show the demand for shipping services, which can indirectly represent the demand for global commodities and thus indicate the global economic activity. The oil-specific demand shock reflecting the oil consumers' precaution is represented by using the demeaned real price of oil (rpo_t). The real oil price is the US refiner acquisition cost of imported crude oil deflated by the US CPI. The crude oil price and production data are obtained from the US Department of Energy, and the global real economic activity index is obtained from Kilian's Data Library.

Baker et al. (2016) constructed the economic policy uncertainty index (pu_t) by using a weighted average method to incorporate the uncertainty information from four channels. Specifically, the news-based policy uncertainty quantified from the newspaper coverage of the policy-related economic uncertainty takes 1/2 of the weight. The tax legislation expiration uncertainty, represented by the number of federal tax code provisions set to expire in the future years, and the economic forecast interquartile ranges about US CPI and federal/state/local government expenditures occupy another half of the weight in the index (1/6 each).

Figure 2.1 displays the main variables we used in this chapter, showing the historical evolution of these time-series data between January 2001 and December 2018. We can see that oil production is always in an upward trend with diminishing changes (Figure 2.1 lower-right subplot). Also, real oil prices are relatively stable in the first half of the sample period while experiencing some dramatic ups and downs in the last ten years (Figure 2.1 upper subplot). The ups and downs of the economic activity index depict the global economic cycle in the past 18 years (Figure 2.1 lower-left subplot). And the economic policy uncertainty index reacts to the rise after the well-known events related to the oil market, such as the 2003 Iraq War, 2013 Arab Spring (Figure 2.1 upper subplot). The clean energy stock index is also relatively stable before the financial crisis. After the crisis, it once again falls into the lower stable zone (Figure 2.1 upper subplot).

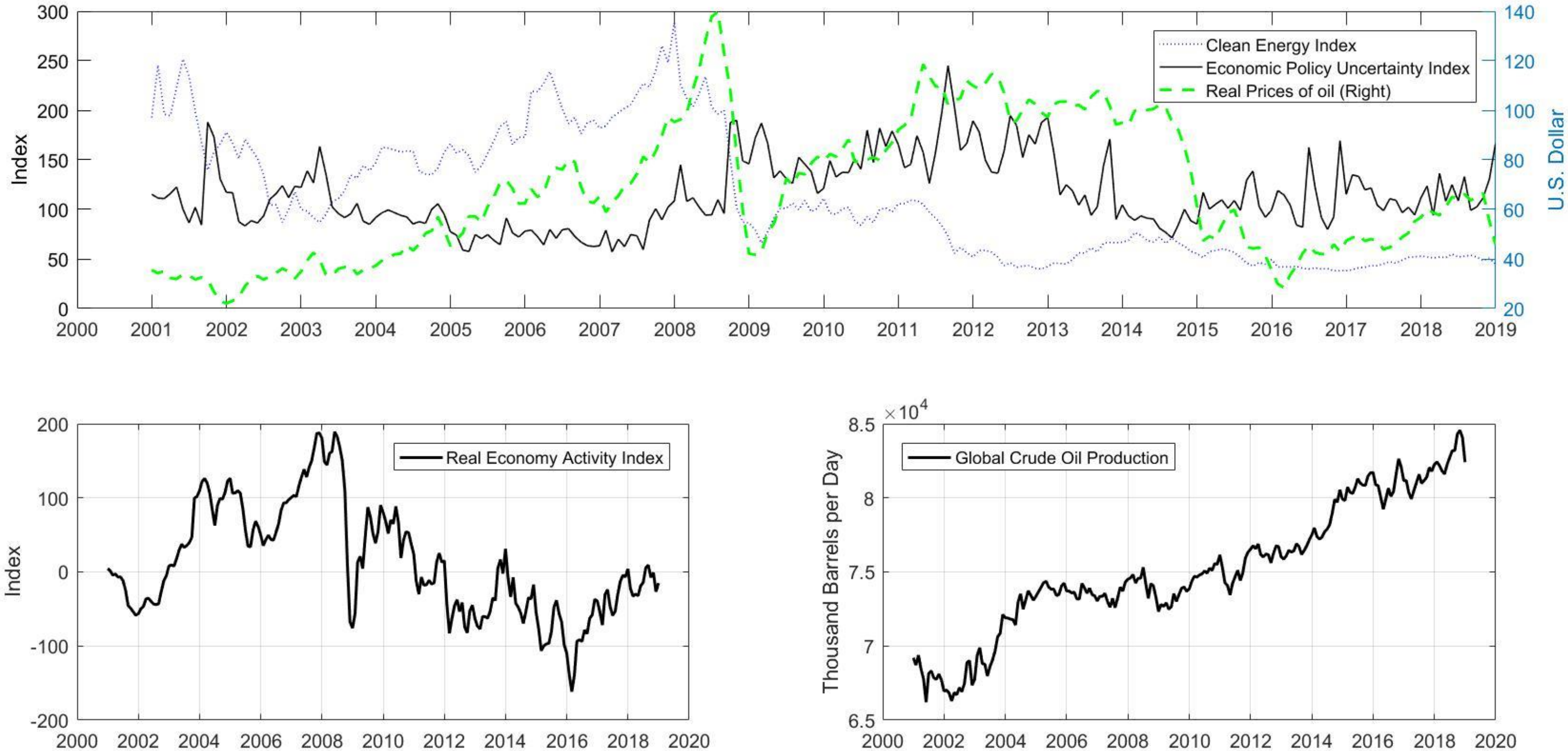

Figure 2.1 Time trends of main variables, 2001:01–2018:12.

Notes: Upper subplot shows monthly data of real oil prices, economic policy uncertainty index, and the real stock return of the oil and gas industry. The lower left subplot shows monthly data of the real economy activity index, constructed by Kilian using the bulk dry cargo ocean shipping freight rates. The lower right subplot shows monthly data of the world crude oil production.

2.3.2 Methodology

Using a structural VAR model, Kilian (2009) decomposed the real price of oil fluctuations into three structural shocks in the oil market and examined the endogenous relationships among these shocks. Other studies added more variables after three shocks to investigate the impacts of different oil shocks on GDP, CPI, stock returns, and policy uncertainty (Kang and Ratti 2013a, Kilian and Park 2009, Kim and Vera 2018).

In this chapter, we follow Kang, Perez de Gracia, et al. (2017) in estimating the impacts of the oil price shocks and US economic policy uncertainty on the stock returns of clean energy companies, using a structural VAR model with a 24 lag:

$$A_0 y_t = c_0 + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t \tag{2.1}$$

In this model, $y_t' = (\Delta prod_t, rea_t, rpo_t, pu_t, \Delta eco_t)$ is a 5 × 1 vector of endogenous variables, A_0 denotes a 5 × 5 contemporaneous coefficient matrix, c_0 represents a 5 × 1 vector of constant terms, A_i refers to 5 × 5 lagged coefficient matrices, and ε_t is a 5 × 1 vector of structural disturbances with no serial and mutual correlation. Following Kilian (2009), we used a two-year lag length of SVAR to acquire the potentially long-delayed effects of oil price shocks and uncertainty on the clean energy sector.

Kilian (2009) assumes that A_0^{-1} is a lower triangle coefficient matrix. This identifying restriction introduces a recursively identified structural VAR model as $e_t = A_0^{-1}\, \varepsilon_t$, where e_t represents errors from the reduced-form VAR model. This lower triangle assumption implies that oil production affects other variables within a given month, while the opposite impacts have a lag to wait for the adjustment of the production plan. It is a reasonable assumption because oil supply shocks are only affected by exogenous events. Similarly, due to the sluggishness of aggregate economic reaction, real economic activity does not respond to the fluctuation of the real prices of oil within a given month.

Kilian and Vega (2011) argue that oil prices are predetermined with respect to the US macroeconomic aggregates within the month. Therefore, economic policy uncertainty is affected by oil shocks within a given month, and the impact of policy uncertainty on oil shocks has a lag. The real stock return ordered at the final position implies that the direct effects of oil supply and demand shocks on the stock returns would be amplified by the endogenous policy uncertainty responses. This also reveals the amplification degree of the endogenous policy uncertainty in response to oil shocks. It also captures an important role of economic policy uncertainty in the transmission of the three structural oil price shocks in the US, the international stock markets, and the oil and gas stocks (Kang and Ratti 2013a, Kang, Perez de Gracia, et al. 2017).

2.3.3 Hypotheses

In this chapter, we focus on the impacts of four factors affecting the development of the clean energy sector. Based on the data available, we use the stock index of clean energy companies as a proxy for clean energy development. To scrutinize these impacts clearly, we propose four hypotheses that have not yet been tested in the clean energy sector.

Hypothesis 1. A decrease in oil supply increases the returns of clean energy stocks.

Unanticipated decreases in oil production affect almost any oil consumer's activities on the supply side. As clean energy is one alternative that can replace oil in some situations, the substitution effect can explain the relationship between clean energy and oil. Due to the substitution effect, some oil users cannot afford high oil prices transfer to clean energy. This energy transfer can increase the demand for clean energy, boost the clean energy sector, and increase the profits of clean energy companies. Therefore, we assume that an oil supply shock increases the returns of clean energy stocks. It is worth mentioning that Kilian (2009) reports that oil supply shocks are deemed weaker than other demand-side shocks. However, we believe that the substitution effect makes oil supply shocks just as crucial as other shocks.

Hypothesis 2. Aggregate economic activity increases the returns of clean energy stocks.

Unanticipated economic booms cause an increase in the energy demand of any energy consumption due to an optimistic forecast about future economic trends. Due to the substitution effect, some traditional energy consumers will make trade-offs between still using oil and turning to clean energy. We believe that this transition to environmentally-friendly energy is more easily achieved during periods of economic prosperity. Therefore, economic prosperity is good news for the clean energy sector and can increase the returns of clean energy stocks.

Hypothesis 3. The precautionary demand for crude oil decreases the returns of clean energy stocks.

The precautionary demand for crude oil is a factor that can provoke changes in oil prices after identifying the reasons mentioned above. Oil consumers increase their oil demand not because of increased oil demand in their production process but because of their anxiety about oil supply shortfalls in the future. It implies that these oil consumers rely on oil heavily and cannot transition to clean energy due to the increase in energy cost. Therefore, if there is no substitution effect in this kind of oil shock, the stocks of oil-related companies would benefit while clean energy stocks would experience decreased returns.

Hypothesis 4. Policy uncertainty decreases the returns of clean energy stocks and amplifies the impacts of oil shocks.

Unanticipated economic policy uncertainty is indicative of an unstable policy environment. Changes in or the elimination of supporting policies are disastrous for the clean energy sector. Therefore, in periods of high economic policy uncertainty, the sensitivities of clean energy companies make stock prices decrease. And oil price shocks, as predetermined economic factors, affect the changes in policy uncertainty.

2.4 Results

2.4.1 The effects of structural shocks on the clean energy stock returns

This subsection investigates the main results regarding the effects of structural shocks on the US real stock returns of clean energy companies. Figure 2.2 indicates the cumulative impulse responses of the real clean energy stock returns in a 24-month forecasting horizon to the four structural shocks. One and two standard error bands are constructed using a recursive-design wild bootstrap (Gonçalves and Kilian 2004). The estimates focus on structural shocks in oil supply, aggregate demand, oil-specific demand, and economic policy uncertainty. The real stock return of the clean energy industry is the fifth variable in the VAR model to represent other shocks from the clean energy sector (Figure 2.2). Following Kilian (2009), in the SVAR model, the oil supply shock has been normalized to represent a negative one standard deviation shock, whereas the aggregate demand shock and oil-specific demand shock are normalized as positive shocks. Thus, all three shocks tend to increase real oil prices. Like in the study by Kang, Perez de Gracia, et al. (2017), we do not adjust the policy uncertainty shock. An increase in the policy uncertainty index means more unpredicted policy changes, which would have a negative impact on the whole economy and almost all economic participants.

Figure 2.2 depicts the responses of real clean energy stock returns, which differ substantially depending on the four hypotheses of underlying causes in section 3.3. The first subfigure confirms hypothesis 1, showing that the effect of unanticipated oil supply disruption on the real stock returns of the clean energy companies is transient and has a marginal statistically significant negative effect in the second month. It then becomes positively sustained in the months 6 to 19 based on one-standard error bands. In the second subfigure, the responses of the stock returns to unpredicted oil-specific demand shocks, reflected hypothesis 3 about oil precautionary demand, are negative and statistically significant months 3 to 11. For hypothesis 4, An unanticipated economic policy uncertainty shock causes sustained and significant negative real stock returns with a lag over 8 to 24 months, in the third subfigure. In contrast, an unexpected aggregate demand shock causes episodical and significantly positive effects on the stock returns over months 3 to 6 and 10 to 20, in the fourth subfigure to supported hypothesis 2. These results show that return responses of clean energy companies are, on average, delayed in the first few months, and the considered factors show their impacts are consistent with the hypotheses.

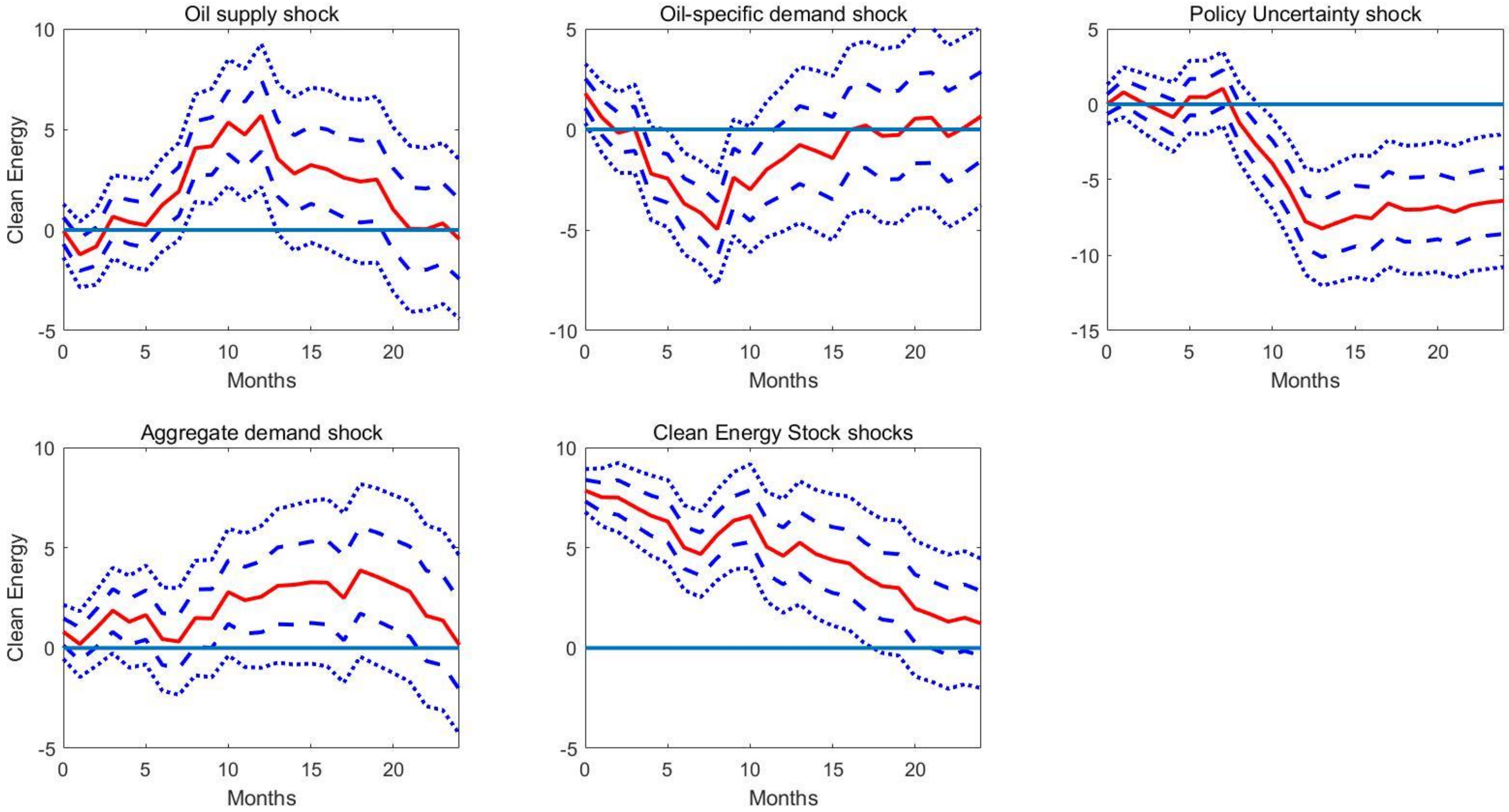

Figure 2.2 Responses of clean energy stock returns to one standard deviation structural shocks: 2001:01–2018:12.

Notes: The figure uses solid lines to show the impulse response functions to one standard deviation structural shock. The order of the SVAR model is oil supply shocks, aggregate demand shocks, oil-specific demand shocks, economic policy uncertainty index, and the real stock returns of the clean energy segment described in section 3.2. Point estimates are reported with one- and two-standard error bands (dashed lines and dotted lines) constructed using a recursive-design wild bootstrap.

The forecast error variance decomposition (FEVD) in Table 2.1 explains how important the driving factors are to US clean energy stock returns quantitatively in different forecast horizons. We mainly focus on short-run impacts at a 1-month forecast horizon (Row 1 in Panel A. of Table 1) and long-run impacts at a 60-month forecast horizon (Row 5 in Panel A. of Table 2.1). In the short-run, the oil-specific demand shocks account for 4.9% of the variation in the clean energy industry, whereas others are negligible (less than 1%). Their explanatory power, however, increases as the horizon is lengthened. In the long-run, 59% of the variation in clean energy stocks can be accounted for by oil and uncertainty shocks, more than three-fourths of which is associated with the shocks in the crude oil market. Specifically, oil supply shocks explain 14% of the variation in the US real clean energy stock returns. Having a powerful impact in the short-run, oil-specific market demand shocks are also the largest contributor to the clean energy returns in the long-run, accounting for 18% of the variability. The economic policy uncertainty shocks account for 15% and are the fundamental factor responsible for the variability of clean energy stock returns. The aggregate demand shocks can explain 11% of the variation, on average, after 60 months. The rest of the variation in the return of clean energy stocks (accounting for more than 41%) is attributed to other shocks affecting this market.

Table 2.1 Percent contribution of shocks in the crude oil market and uncertainty to the overall variability of Clean energy stock returns

Forecast Horizon	Oil supply shock	Oil-specific demand shock	Uncertainty shock	Aggregate demand shock	Clean energy shocks
Panel A. Policy Uncertainty					
1	0.0020	4.9049	0.0001	0.9884	94.1046
3	2.1684	7.3321	1.3698	2.3294	86.8004
12	9.4949	16.8234	12.4658	6.1415	55.0743
24	14.0741	16.8633	14.4559	8.0485	46.5581
60	14.5422	18.0255	15.0696	11.2935	41.0692

Notes: Each row indicates the percent contributions of demand and supply shocks in the crude oil market and policy uncertainty to the overall variability of real stock returns of clean energy stock index at different forecast horizons reported in the first column. The forecast error variance decomposition is based on the structural VAR model. The fourth variable of the SVAR model in each panel is each policy uncertainty component.

2.4.1.1. Comparison of clean energy returns with oil and gas stock returns

To compare the results between clean energy companies and fossil fuel companies, we also replaced the returns of the clean energy stock index with the oil and gas stock returns[8]. The impulse response functions of oil and gas stock returns to structural shocks are reported in Figure 2.3. The oil-specific market demand shock causes a significant and immediate increase in oil and gas returns in the first seven months and then has a negative impact between months 9 to 19. Compared with the results of clean energy stocks, this dissimilarity in effect is expected. An oil-specific market demand shock represents a positive innovation for the oil and gas companies due to the concern of oil users to increase oil demand. Conversely, the returns of oil and gas companies tend to decrease due to the sharp demand increases that raise their inventories and thus decrease the demand in the future. Policy uncertainty affects the oil and

[8] We replaced the fifth variable of y_t' in Eq. (2.1) with Δog_t.

gas companies through a sharp decrease and becomes positive in a 12-month period after the first 3 months. The positive impact of aggregate demand shocks on the oil and gas stock returns is more persistent than on clean energy stock returns, keeping an immediate and sustained increase from months 2 to 24. Unanticipated oil production shocks have a significant positive impact in the middle months for both oil and clean energy stock returns. Meanwhile, a significantly negative effect on the oil and gas stock returns is at the end of two years, and its effect on the clean energy stock returns is in the second month.

This comparison makes us understand the differences between two kinds of energy, as energy transition is an important trend in the energy industry. The main difference between oil and gas stock returns and clean energy stock returns is from oil-specific demand shocks and policy uncertainty shocks. The precautionary demand for oil cannot make an energy transition, which would increase the demand for oil while decreasing the demand for other kinds of energy. Therefore, the responses of oil and gas stock returns and clean energy stock returns change to different directions to the shocks of oil-specific demand. When policy uncertainty shocks occur, the stock returns of oil and gas companies have a negative impact immediately and turn positive soon. The whole significant response period is in the first 12 months. However, the clean energy stock returns respond to the policy uncertainty shocks significantly negatively with an 8-month lag. It shows that more policy supporting clean energy companies makes less sensitivity in the short-run, and delayed response means that clean energy companies hardly recover from the policy uncertainty in the long-run.

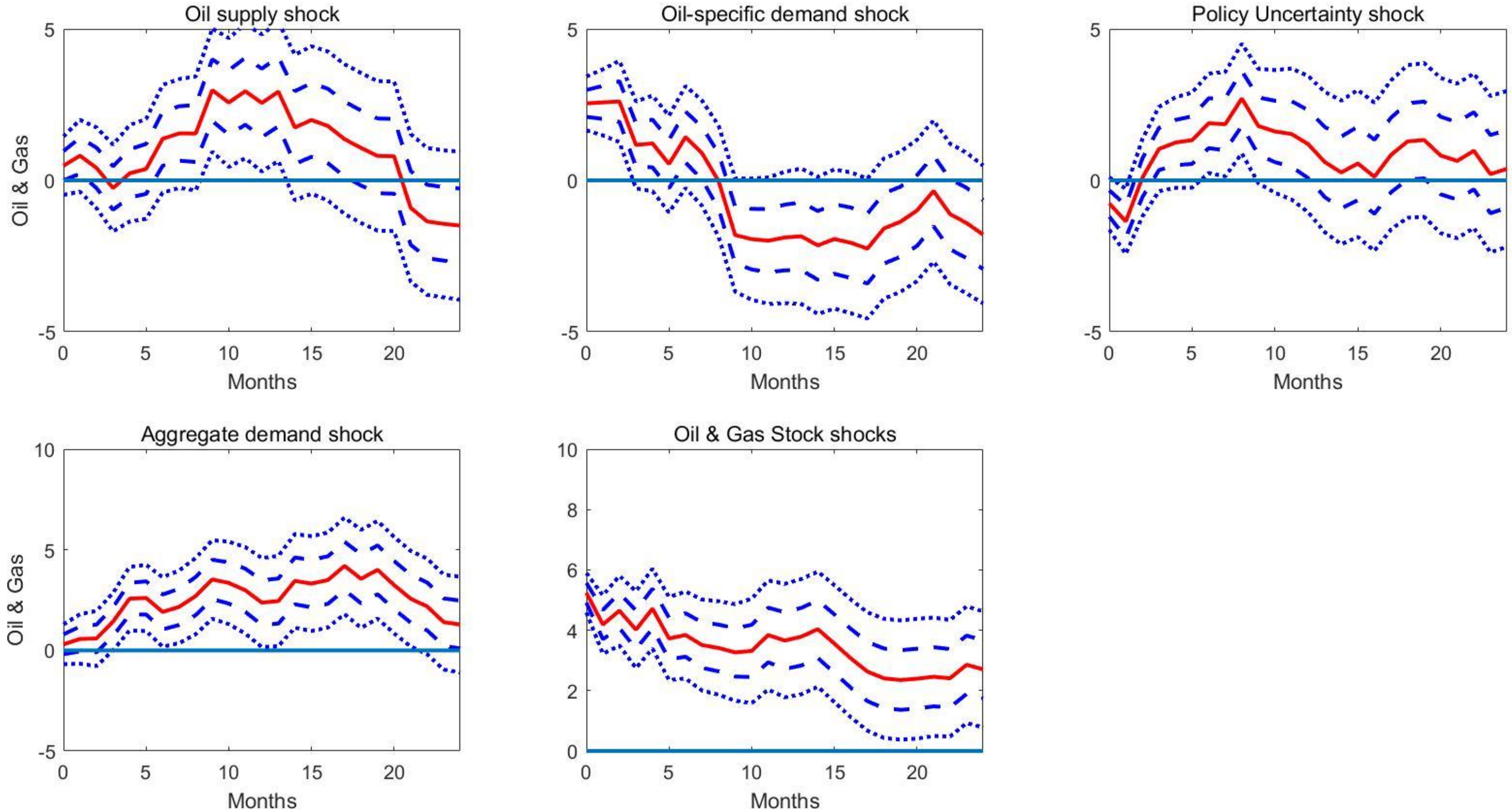

Figure 2.3 Responses of oil and gas stock returns to one standard deviation structural shocks: 2001:01–2018:12.

Notes: The figure uses solid lines to show the impulse response functions to one standard deviation structural shock. The order of the SVAR model is oil supply shocks, aggregate demand shocks, oil-specific demand shocks, economic policy uncertainty index, and the real stock returns of the oil and gas industry described in section 3.2. Point estimates are reported with one- and two-standard error bands (dashed lines and dotted lines) constructed using a recursive-design wild bootstrap.

2.4.1.2. Comparison of clean energy returns with stock market returns

In this subsection, we compare the energy-related companies with the whole stock market, and we also investigate the responses of the real stock return of the S & P 500 index to the structural shocks to represent the reactions of the overall stock market[9]. Figure 2.4 presents the real stock returns of the S & P 500 index responses to a structural shock for each driven factor. The response of the whole stock market is relatively weaker than the energy-related stocks. When there are oil supply and oil-specific demand shocks, the return responses of the stock market in Figure 2.4 have results similar to the return responses in Figures 2.2 and 2.3. However, the magnitude of the return responses to policy uncertainty is relatively smaller, which is significantly positive in months 3 to 5 and negative in months 13 to 17 and 19 to 23. For the aggregate demand shocks, unlike the positive impacts on the energy segments over most of the time horizon, they affect the overall stock return positively in the first four months and then have a negative impact in the second year.

[9] We replaced the fifth variable of y_t' in Eq. (2.1) with Δsp_t.

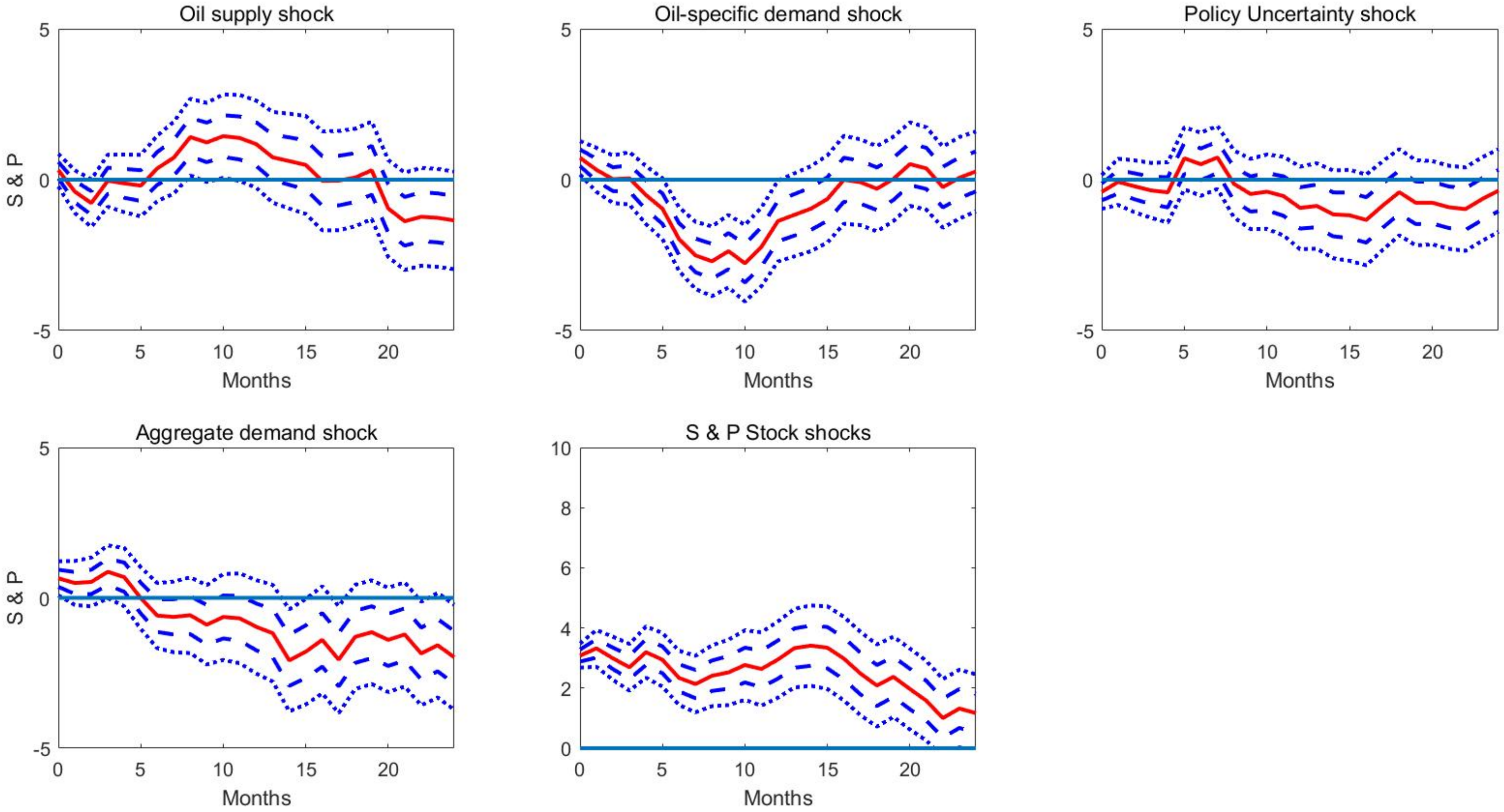

Figure 2.4 Responses of S&P 500 stock returns to one standard deviation structural shocks: 2001:01–2018:12.

Notes: The figure uses solid lines to show the impulse response functions to one standard deviation structural shock. The order of the SVAR model is oil supply shocks, aggregate demand shocks, oil-specific demand shocks, economic policy uncertainty index, and the real stock returns of the S&P 500 stock index described in section 3.2. Point estimates are reported with one- and two-standard error bands (dashed lines and dotted lines) constructed using a recursive-design wild bootstrap.

2.4.2 The role of economic policy uncertainty responses

Kilian and Vega (2011) argue that oil prices have a predetermined impact on US macroeconomic factors. Oil price shocks, manifested as oil prices increase, can affect inflation and then spread to consumption, investment, production, et cetera. It would draw policymakers' attention and cause some policy adjustments to consider the indirect channel of the oil shocks to affect the clean energy stock returns, though affecting the policy uncertainty. Therefore, it is necessary to include policy uncertainty in our model. This subsection elaborates on the role of the endogenous economic policy uncertainty in the transmission of the three structural changes in the oil prices to the US real clean energy stock returns. The impulse responses of economic policy uncertainty displayed in Figure 2.5 indicate the timing and magnitude of economic policy uncertainty affected by other shocks. More specifically, an unanticipated oil production disruption provokes a significantly negative effect on the economic policy uncertainty in months 9 through 12. The response of the economic policy uncertainty is significantly positive for unpredicted oil- specific demand shocks between 3 and 9 months. It indicates that, for the crude oil market, anticipations of oil shortages might draw more attention from policymakers and lead to an economic policy uncertainty increase. On average, aggregate demand shocks cause a negative effect on policy uncertainty, which is statistically significant over month 3 and 11 and significantly intermittent after month 19. It shows that an increase in the global aggregate demand for commodities might reduce the economic policy uncertainty due to a positive market environment.

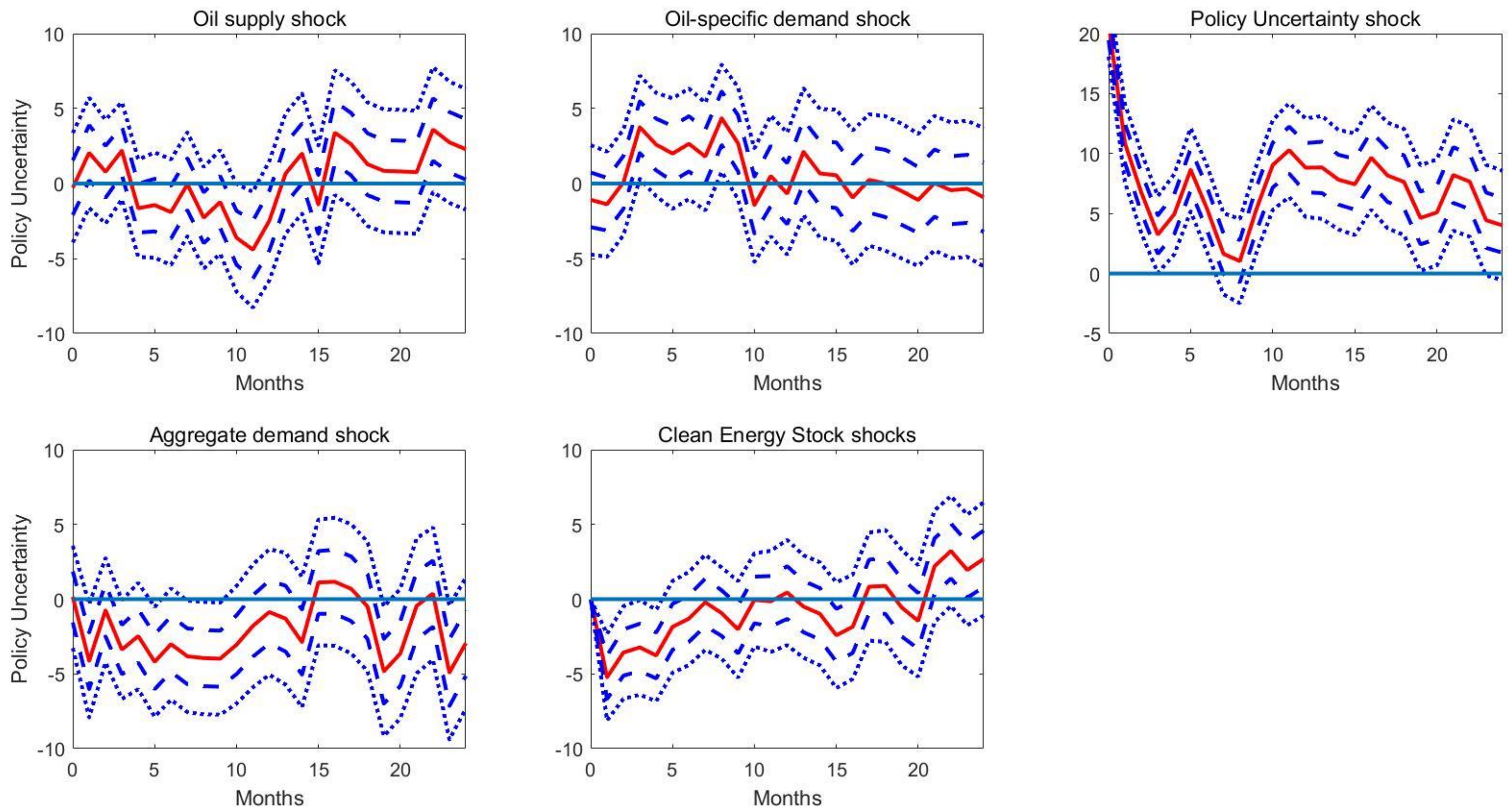

Figure 2.5 Responses of policy uncertainty to one standard deviation structural shocks: 2001:01–2018:12.

Notes: The figure uses solid lines to show the impulse response functions to one standard deviation structural shock. The order of the SVAR model is oil supply shocks, aggregate demand shocks, oil-specific demand shocks, economic policy uncertainty index, and the real stock returns of the clean energy segment described in section 3.2. Point estimates are reported with one- and two-standard error bands (dashed lines and dotted lines) constructed using a recursive-design wild bootstrap.

In Figure 2.6, the historical decomposition of the effect of the three structural oil price shocks on the economic policy uncertainty displays how the oil shocks have contributed to the economic policy uncertainty over time. The observed changes in the economic policy uncertainty can be explained from a historical perspective. The contribution of oil supply shocks to policy uncertainty is relatively weak, around zero. From the demand side, shocks from global aggregate demand and oil-specific demand have more influence on economic policy uncertainty with some short-period wings. It confirms that, historically, policy uncertainty has been affected by structural oil shocks (especially shocks from the demand side) in the crude oil market. Therefore, through these three channels, the oil shocks are amplified to have a greater effect on the clean energy stock returns by considering the policy uncertainty endogenously.

2.4.3 The transmission channel of policy uncertainty

The economic policy uncertainty index consists of four underlying components with a weighted average. The first uncertainty source is measured by the news coverage volume of some specific words representing the uncertainty from social media. The disagreement levels of government purchase forecast and the CPI forecast among economic forecasters are used as the proxies for government purchase and inflation uncertainty. The fourth uncertainty component is about the tax code expiration, reflecting the number of federal tax code provisions set to expire in future years (see Figure A 2.1).

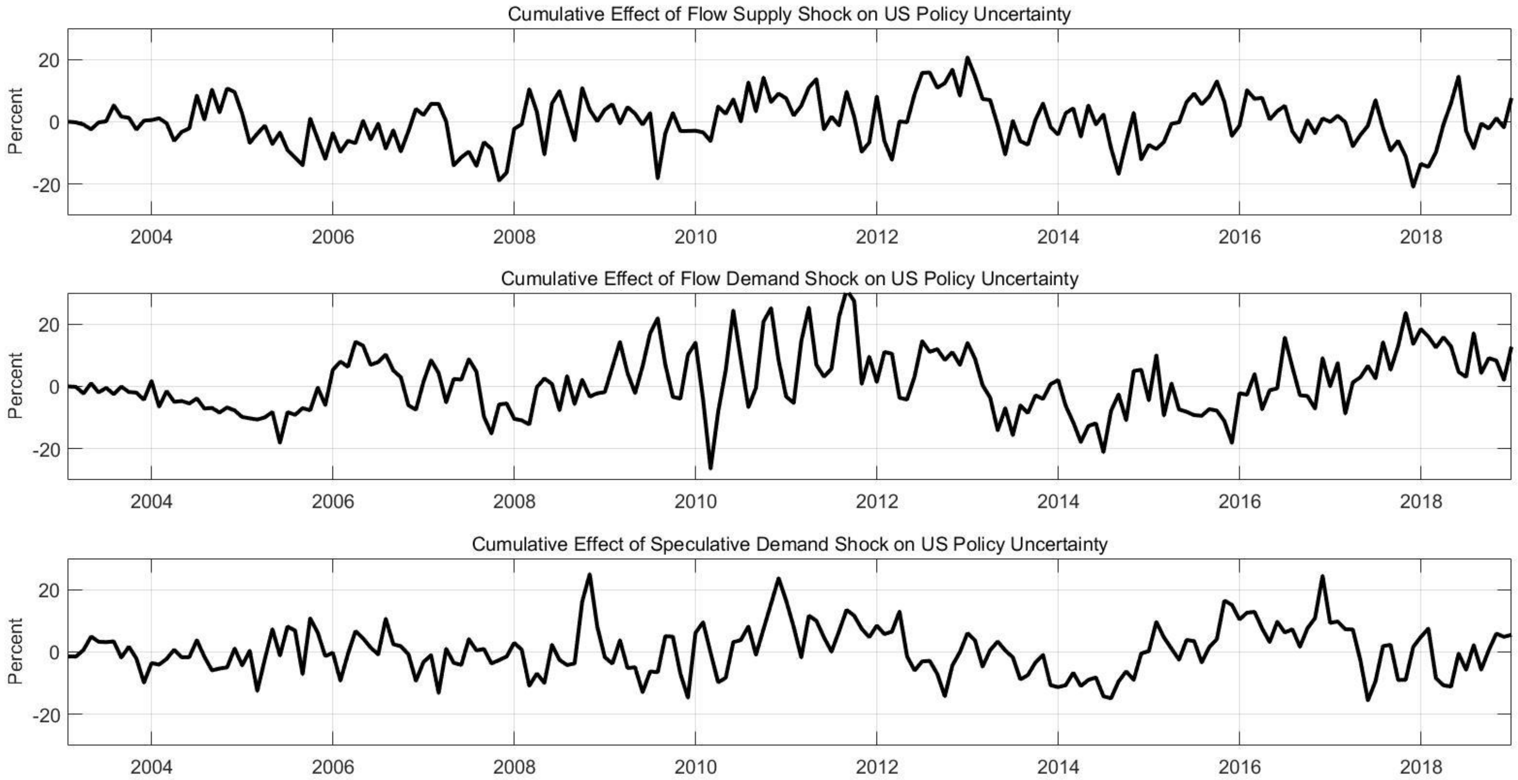

Figure 2.6 Historical decomposition of oil supply and demand shocks to economic policy uncertainty: 2003:01 to 2018:12.

Notes: The solid lines in this figure shows the cumulative effects of oil supply and demand shocks on the economic policy uncertainty, using the economic policy uncertainty index and the real stock returns of the clean energy segment in the VAR model.

Separating the four policy uncertainty components, we investigate the transmission channel through which policy uncertainty affects the stock returns of clean energy companies. Figure 2.7 shows that the magnitude of return responses is relatively larger when there are CPI forecaster disagreement and tax code expiration uncertainties. The negative return responses to news coverage shocks and government purchase forecast disagreement are also significant over most forecast horizons. It is worth mentioning that using these uncertainty components makes the impact of aggregate demand shocks weak and of oil supply shocks negative. We believe that it is caused by the difference in transmission channels. All these channels affect the views of investors and policy-makers about oil and clean energy. When analyzing the impact of oil shocks, the results are more precise with the overall uncertainty.

Table 2.2 has four panels that report the forecast error variance decomposition results with each policy uncertainty component in the fourth variable of the SVAR model. In the short run of the forecast horizon, oil-specific demand shock takes a steady share of the variation of clean energy stocks with different uncertainty components. However, oil supply shocks' proportion increases sharply with the uncertainty of CPI. The reason is that the oil supply is more vulnerable to inflation. With the uncertainty of CPI, oil suppliers would be more sensitive to adjust their production than other uncertainty sources. In the long run, historical decomposition shows that the shocks caused by news coverage and by the CPI forecaster disagreement account for 12.10% and 13.45% of the variation in the real clean energy stock returns, on average, after 60 months of the forecast horizon. These results imply that clean energy companies are more sensitive to information that reflects the uncertainty in inflation.

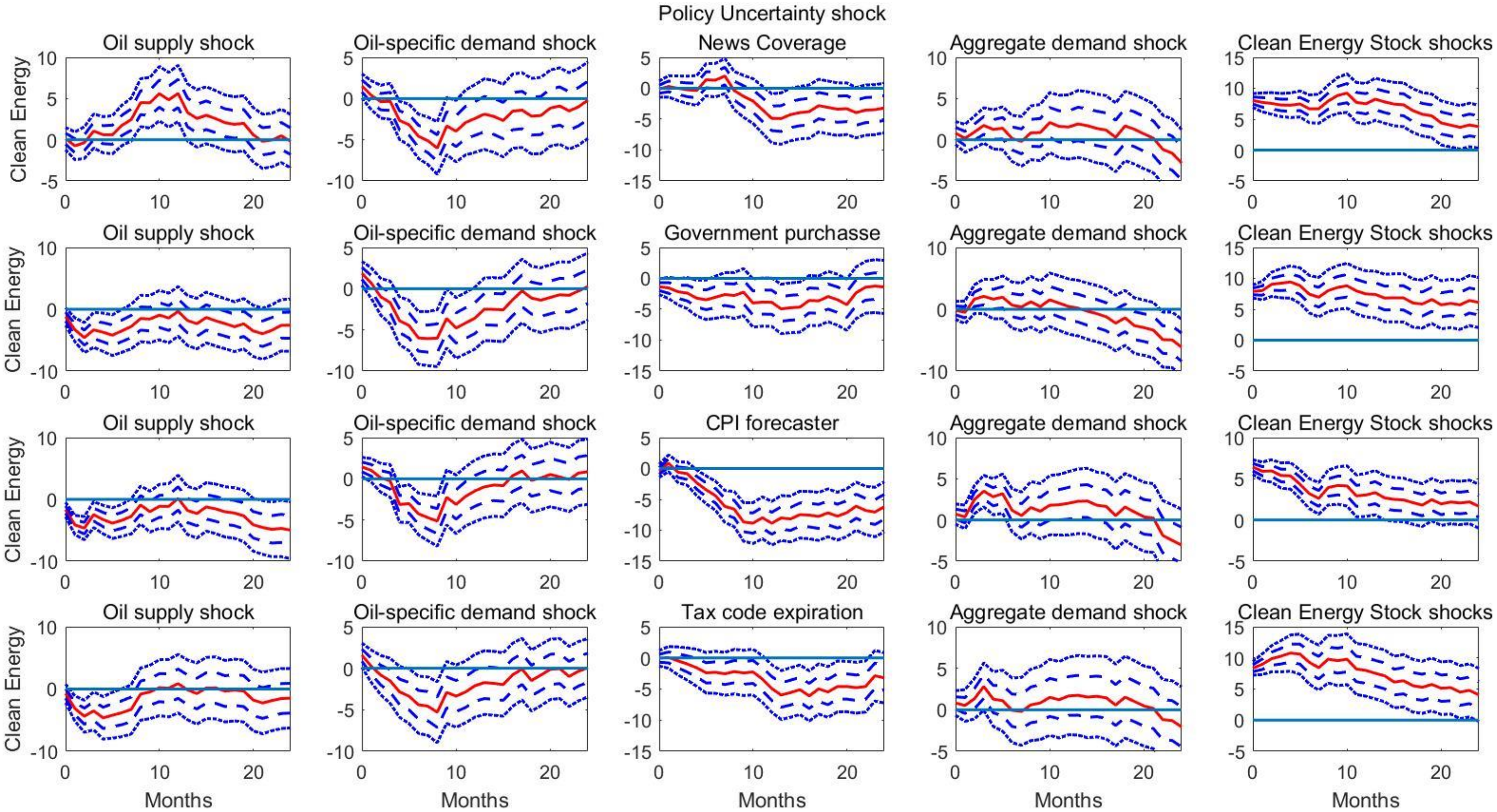

Figure 2.7 Responses of clean energy stock returns to one standard deviation structural shocks using policy uncertainty components as policy shocks: 2001:01–2018:12.

Notes: The figure uses solid lines to show the impulse response functions to one standard deviation structural shock. The order of the SVAR model is oil supply shocks, aggregate demand shocks, oil-specific demand shocks, one of the economic policy uncertainty components, and the real stock returns of the clean energy segment described in section 3.2. Point estimates are reported with one- and two-standard error bands (dashed lines and dotted lines) constructed using a recursive-design wild bootstrap.

Table 2.2 Percent contribution of shocks in the crude oil market and uncertainty components to the overall variability of Clean energy stock returns

Forecast Horizon	Oil supply shock	Oil-specific demand shock	Uncertainty shock	Aggregate demand shock	Clean energy shocks
Panel A. Policy Uncertainty—News coverage.					
1	0.0020	4.9049	0.0001	0.9884	94.1046
3	2.1684	7.3321	1.3698	2.3294	86.8004
12	9.4949	16.8234	12.4658	6.1415	55.0743
24	14.0741	16.8633	14.4559	8.0485	46.5581
60	14.5422	18.0255	15.0696	11.2935	41.0692
Panel B. Policy Uncertainty—the federal/state/local purchases disagreement measure.					
1	2.0578	5.0070	2.6246	0.0461	90.2645
3	8.8775	8.9108	2.6202	5.4471	74.1443
12	10.6530	19.1127	5.6464	8.1054	56.4825
24	13.6915	18.6774	9.9386	11.0289	46.6636
60	15.7700	18.9833	11.3337	13.7039	40.2091
Panel C. Policy Uncertainty—the CPI forecast disagreement measure.					
1	5.8820	4.4537	0.3148	1.0939	88.2556
3	14.7085	4.9218	5.9707	8.1116	66.2873
12	17.2047	19.2427	13.5727	10.6852	39.2948
24	20.3918	18.8068	14.0385	14.1066	32.6562
60	21.9406	19.6839	13.4504	16.5778	28.3473
Panel D. Policy Uncertainty—the federal tax code expirations					
1	0.6951	3.3805	0.0045	0.9095	95.0104
3	9.2458	6.2880	0.3777	1.6516	82.4369
12	14.0176	12.7905	2.5774	6.9051	63.7095
24	14.8854	14.662	8.6815	8.4580	53.3131
60	17.5761	15.0003	9.1604	10.7726	47.4904

Notes: Each row indicates the percent contributions of demand and supply shocks in the crude oil market and each component of policy uncertainty to the overall variability of real stock returns of clean energy stock index at different forecast horizons reported in the first column. The forecast error variance decomposition is based on the structural VAR model. The fourth variable of the SVAR model in each panel is each policy uncertainty component.

2.5 Conclusion

Previous studies have demonstrated that the impacts of different oil shocks and policy uncertainty on the US aggregate stock returns and oil and gas sector returns are qualitatively and quantitatively different (Kang and Ratti 2013a, Kang, Perez de Gracia, et al. 2017). In the context of the rapidly-developing clean energy sector, we followed Kilian (2009) to use the SVAR model to investigate the clean energy stock market fluctuations associated with three different oil price shocks and policy uncertainty endogenously. It shows that the clean energy stock returns significantly respond to oil shocks and policy uncertainty varying across different underlying sources of shocks. And these factors jointly accounted for more than half of the long-term variation in the US clean energy stock index. In doing so, we highlighted the importance of different oil shocks and policy uncertainty for the clean energy stock market. Our study also obtained useful information about the stock market behavior of clean energy companies and the portfolio choices of investors.

We find that the response of US real stock returns of clean energy segments to oil price changes varies substantially, depending on whether the substitution effect takes place among energy sectors. First, our results suggest that oil can affect the clean energy segment due to a substitution effect among energy alternatives through the oil supply channel. Oil supply shocks from an unpredicted decrease in oil production force oil consumers to adopt clean energy. This causes statistically significantly-positive effects on the stock returns of clean energy companies over forecasting periods of more than one year. In the long run, we find that oil supply shocks account for 14.54% of the variation in the stock returns of clean energy companies. In the context of economic prosperity, the aggregate demand shock also triggers a transition from oil to clean energy. Energy users are more willing to adopt new energy sources when there is a positive future economic outlook. Therefore, the aggregate demand shocks have a positive effect on the stock returns of clean energy companies. However, oil-specific demand shocks show that the substitution effect between oil and clean energy is a partial effect. The precautionary demand for oil is too sticky, for oil-specific consumers, to transition to clean energy even if the price of oil increases. Therefore, this kind of shock does not increase the demand for clean energy, as indicated by a negative impact of the oil-specific demand shocks on the clean energy stock returns.

While Kilian (2009) only analyzed political disturbances exogenously, we also considered the impact of economic policy uncertainty endogenously and exhaustively. The endogenous economic policy uncertainty in the transmission of the three structural oil prices is important to the US real stock returns of clean energy companies. This is because the direct effects of oil supply and demand shocks on the stock returns of clean energy companies are amplified by the endogenous policy uncertainty responses. Through a comprehensive analysis of the policy uncertainty transmission channels, we find that the news coverage shocks and the CPI forecaster disagreement shocks account for 12.10% and 13.45% of the variation in the real stock returns of the clean energy companies in the long run.

We find the oil price shocks with different underlying sources have different impacts on the clean energy stock returns, oil and gas stock returns, and stock market returns. Investors need to adjust their portfolios depending on the reasons that cause oil prices to change. Specifically, clean energy stock returns and oil and gas stock returns react differently to oil-specific demand shocks and economic policy uncertainty shocks. It implies some investment strategies to investors, such as decreasing the share of clean energy stocks when oil-specific demand shocks and policy uncertainty shocks occurred.

Based on the results of this chapter, there are still some further tasks worthy of doing some further investigations. This chapter reports that oil price shocks from the supply side have a positive impact on the clean energy stock returns with monthly data. There are still some investors with shorter horizons, such as hedge funds and day traders, concerning with the short-run performance of markets and paying more attention to ephemeral phenomena reflected in the daily or intraday stock returns. Therefore, it is meaningful to extend the research on the impact of oil price shocks from the supply side on the clean energy stock returns with daily data in the future.

This chapter also has some remained questions to be tackled. We employ five variables VAR models to analyze the response of clean energy stock returns to oil price shocks and policy uncertainty. Various important factors confirmed having clear impacts on the clean energy stocks are not included in our models, such as interest rate and other financial factors. Covering more important macroeconomic influences in the examination at the same time can convey more precise relationships between the macroeconomic influences and the clean energy stock returns. However, it relies on the emergence of advanced empirical methodologies to realize further examination in the future.

In this chapter, we mainly focus on the response of the clean energy stock returns with monthly data. As important as the return series, we also concern about the volatility of clean energy stocks. In the next chapter, we introduce an empirical study about the impacts of macroeconomic influences on the long-run variance of the clean energy stock returns.

Appendix 2

A 2.1. Real Economic Activity Index (REA)

Kilian (2009) constructs a monthly index of global real economic activity to reflect the shifts of the demand for industrial commodities in global business markets, using the dry cargo single voyage ocean freight rates. Because the demand for transport services heavily depends on world economic activity. Due to a relative vertical supply curve of this sector. The freight rates may be viewed as an indicator of global demand pressures. This index fully indicates the timing of important fluctuations in global real economic activity and has been used in various empirical research. The raw data of shipment is from Drewry Shipping Consultants Ltd. This company publishes a “Shipping Statistics and Economics” that introduces a monthly report about the information of single-voyage freight rates, which include various bulk dry cargoes such as coal, fertilizer, grain, iron ore, oilseeds, and scrap metal. Kilian confirms that changes in crude oil prices do not affect this index in the same month, with a zero contemporaneous correlation between these two series. Please read Kilian (2009) to know more about the specific construction method of this index.

A 2.2. Economic Policy Uncertainty Index (EPU)

Baker et al. (2016) construct a monthly index of economic policy uncertainty aggregate four different policy uncertainty sources. The first component to measure economic policy uncertainty is from search results from 10 large newspapers. This social media-related information is captured through performing a monthly frequency search for articles containing the term 'uncertainty,' 'economic,' 'congress,' 'deficit,' 'federal reserve,' 'legislation,' 'regulation,' and 'white house.' The second component reflects the information about scheduled expirations of federal tax code reported by the Congressional Budget Office (CBO). The third and fourth components use the information from the Survey of Professional Forecasters collected by the Federal Reserve Bank of Philadelphia. The forecast of CPI, purchases of goods and services by state and local governments, and purchases of goods and services by the federal government are used to construct dispersion in the individual-level data of economic forecasters.

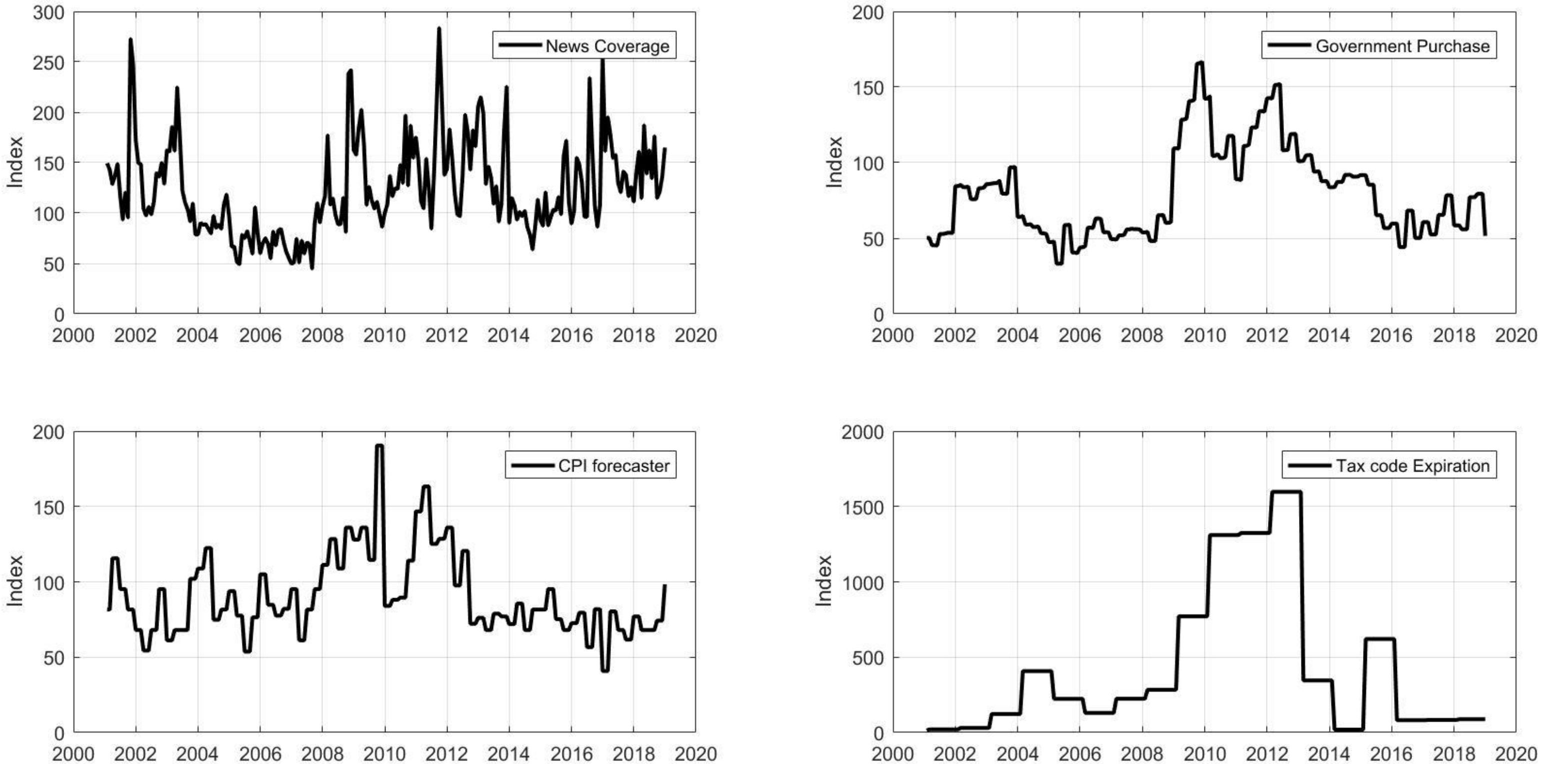

Figure A2.1 Time trends of economic policy uncertainty components, 2001:01–2018:12.

Notes: The upper left subplot shows monthly data of news coverage about EPU. The upper right subplot shows quarterly data of economic forecaster disagreement about government purchases. The lower left subplot shows quarterly data of economic forecaster disagreement about CPI. The lower right subplot shows yearly data of the US federal tax code expirations.

A 2.3. Descriptive statistics of data

Table A2.1 Descriptive statistics

	RE	OG	SP	REA	PROD	OIL	EPU
Obs.	216	216	216	216	216	216	216
Mean	-0.707	0.642	0.316	12.658	1.075	0.000	115.465
Median	-0.007	0.830	0.877	-3.532	1.421	2.061	108.379
Maximum	23.659	19.130	10.231	189.220	34.642	82.254	245.127
Minimum	-38.657	-16.870	-18.564	-161.643	-29.105	-102.537	57.203
Std. Dev.	9.263	5.846	4.233	74.878	9.287	43.302	35.624
Skewness	-0.645	-0.180	-0.845	0.407	0.040	-0.195	0.734
Kurtosis	4.194	3.448	4.741	2.427	3.966	2.000	3.063
JB test	***		***	**	***	***	***

Note: Asterisks denote statistical significance at 10% by *, 5% by **and 1% by ***. JB test is the Jarque–Bera test. Std. Dev. is the standard deviation. OIL represents the changes in the real WTI spot price. RE, OG, and SP are the returns of the US clean energy index, oil & gas index, and S&P 500 index, respectively. PROD is the changes in global oil production. REA is the real economic activity index. EPU is the economic policy uncertainty index. These abbreviations are only used in Chapter 2.

3 Does Energy Insecurity Affect Global Energy Stock Volatilities in the Long-run?

In chapter 2, we explain the effects of some critical factors on clean energy stock returns. In this chapter, an empirical study is introduced to investigate the volatility of the clean energy stock returns in the long-run.

3.1 Introduction

Energy security issues[10] concerning uneven energy supply and demand have been widely discussed and researched since the oil crisis in the 1970s and subsequent related events (Costantini et al. 2007, Filipović et al. 2018). Energy companies regard the energy security issues as a top-level emergency, and policymakers and investors also monitor these issues. Currently, regarding the security issues of conventional fuels that are primarily concentrated in oil markets, diversification and localization of energy sources become breakthroughs as renewable alternatives increase their importance (Escribano Francés et al. 2013, Li 2005, Hamed and Bressler 2019, Hache 2018). Clean energy has attracted attention to deal with the energy shortage issues by replacing conventional fuels in some fields. Previous research on energy security usually focuses on oil markets. As a counterpart of traditional energy sources, examining the impact of energy insecurity on clean energy reveals the resistance or the vulnerability of clean energy to energy insecurity.

[10] The IEA defines energy security as "the uninterrupted availability of energy sources at an affordable price". Energy security has many dimensions: long-term energy security mainly deals with timely investments to supply energy in alignment with economic developments and sustainable environmental needs. Short-term energy security focuses on the ability of the energy system to react promptly to sudden changes within the supply-demand balance. Source is from https://www.iea.org/topics/energysecurity/whatisenergysecurity/

Many macroeconomic factors have been investigated concerning their impacts on stock prices of energy companies (Kang, Perez de Gracia, et al. 2017, Ji et al. 2018, Boyer and Filion 2007, Gupta 2016, Sadorsky 2001). Some of them affect energy stock prices by conveying negative news on energy insecurity. This chapter examines the impact of the following five energy insecurity-related but ignored factors, including macroeconomic uncertainty, geopolitical uncertainty, economic growth, oil supply, and oil demand, to enrich the existing literature. Basic and straightforward factors are three factors regarding oil shocks from economic growth, oil supply, and oil demand. These three factors are identified by Kilian (2009) to represent the oil price changes caused by different underlying sources. Specifically, Kilian (2009) uses oil production, oil prices, and an economic growth index to separately represent the oil price changes caused by oil supply, oil-specific demand, and aggregate demand for energy, respectively.

The fourth factor is macroeconomic uncertainty, for example, the uncertainty of economic growth and inflation, which also disturbs the energy demand and the expected profits of the energy companies (Van Robays 2016, Joëts et al. 2017). The fifth inevitable factor for energy insecurity is the geopolitical risk, mainly from the physical distribution of conventional energy concentrated in some oil-abundant regions. Energy supply is vulnerable to geopolitical events, particularly in the regions where oil production are extracted (Gupta 2008, Correljé and van der Linde 2006). Together with globalization, economic crisis and political instability spread rapidly around the world. The stock markets also respond to the energy insecurity factors soon, especially showing more fluctuations in energy-related stocks.

The main purpose of this chapter is to investigate the impact of energy security issues on the stock volatility of clean energy companies and oil and gas companies. We regard the oil and gas stock index as a benchmark and compare the volatility of the clean energy stock index with that of the benchmark. We have two research objectives. For the first objective, we examine the impact of energy insecurity related macroeconomic variables on the long-run clean energy stock volatility and on the long-run oil and gas stock volatility, using a modified mixed data sampling (MIDAS) methodology in the generalized autoregressive conditional heteroskedasticity (GARCH) process (Engle et al. 2013). For the second objective, an Auto-Regressive Distributed Lag (ARDL) model is employed to examine the impact of volatility of the selected macroeconomic variables on the long-run volatility of two energy-related indices. The sample period examined runs from January 2001 to December 2018 for almost all variables.

The main findings in this chapter are the following results. First, based on the GARCH-MIDAS model, energy insecurity factors significantly affect long-run variances of the two energy stock indices: oil and gas index and clean energy index. Second, oil demand, aggregate demand for energy, and geopolitical risk have a positive impact on the long-run variance of the oil and gas stock returns. In contrast, they have a negative impact on the long-run variance of the clean energy stock returns. Third, macroeconomic uncertainty affects the long-run variances of both energy stock returns positively. Last, according to the ARDL model results, only the volatility of aggregate demand for energy has a significant long-run impact on the long-run variances of both energy stock returns.

This chapter enriches the research on the energy-related stock index through three main contributions. First, in the literature analyzing energy security, financial uncertainty and policy uncertainty have been examined that their impacts are significant on the volatility of clean energy stock returns (Lundgren et al. 2018, Ferrer et al. 2018, Ji et al. 2018). This chapter extends the research to examine two novel uncertainty measures, namely macroeconomic uncertainty and geopolitical risk. There is no literature that focuses on these two variables or estimates their impacts on the long-run variances of two energy stock return series. Ozturk and Sheng (2018) construct a global economic uncertainty measure that can capture the perceived uncertainty of the macroeconomy. We first examine whether this global macroeconomic uncertainty measure affects the volatilities of two energy-related indices. About the research on the geopolitical risk, the existing literature examines its impact on the overall stock market index (Bouras et al. 2019, Gkillas et al. 2018) or the oil prices (Liu et al. 2019). We extend the research to examine how geopolitical risk can affect the energy-related indices specifically.

Second, this chapter is the first study to empirically analyze the impact of oil prices on the long-run variance of clean energy stocks after distinguishing the different sources that drive oil price movements. Considering the oil's impact separately on the stock market started from Kilian and Park (2009) on the US stock market return. Kang, Perez de Gracia, et al. (2017) extend the investigation by focusing on three oil shocks on the oil and gas stock returns. Zhang et al. (2020) further examine the three oil shocks on clean energy stock returns. However, so far, no research considers the impacts of different kinds of oil shocks on the variance of clean energy stock returns and oil and gas stock returns.

Finally, we use a mixed data sampling (MIDAS) model to link the data with different frequencies. Because of the GARCH-MIDAS model, we can estimate the determinates of the fluctuations of energy indices more accurately. This model separately estimates the impact of daily market information and the lower-frequency monthly macroeconomic variables on the daily stock variances simultaneously. Using the GARCH–MIDAS model extends the general univariate GARCH model by incorporating relatively more realistic estimates of monthly macroeconomic variables. Therefore, the econometric framework in the GARCH–MIDAS model can provide a more precise description of the volatility of the clean energy stock markets due to less information loss. Among the existing literature, Pan et al. (2017) use the GARCH-MIDAS model to examine the relationship between the daily oil price volatility and the monthly changes in oil supply and demand. Fang et al. (2018) examine the effect of monthly economic policy uncertainty on the daily S&P 500 index. To the best of our knowledge, no research on the energy stock markets uses this GARCH-MIDAS model to examine the impact of the low-frequency macroeconomic factors.

The outline of the chapter is as follows. Section 3.2 introduces the existing literature about the relationship between macroeconomic variables and energy stock markets. Section 3.3 explains the GARCH-MIDAS methodology. Section 3.4 describes the data used in this chapter. Section 3.5 discusses the empirical results of two energy-related indices. Section 3.6 concludes the chapter.

3.2 Literature review

Oil price is in the predominant position for researchers to examine the situation of the oil industry. Many studies have expounded on the bilateral relationship between oil prices and other factors. In contrast, the investigation of the financial performance of oil and gas stocks is incomprehensive. The oil and gas sector is usually viewed as one sector representing the energy industry in sector-level research. For example, Nandha and Faff (2008), Reboredo and Rivera-

Castro (2014), and Caporale et al. (2015) investigate how oil prices affect various stock sectors in the global stock markets, the European stock markets, the US stock markets, and the China stock market, respectively. The consistent results show a significantly positive impact of oil prices on the returns of the oil and gas sector.

Sadorsky (2001) first focuses on the Canadian oil and gas index and finds positive reactions of the returns of the oil and gas index to the changes in the stock market index and oil prices, whereas negative reactions to the interest rates and exchange rates. Boyer and Filion (2007) also assess the Canadian oil and gas stocks by adding gas prices and specific firm-level indicators using a panel regression. El-Sharif et al. (2005) find a positive relationship between oil price and oil and gas stocks in the UK, the largest oil producer in the European Union. However, Mohanty et al. (2010) find no significant impact of the oil prices on the stock returns of oil and gas companies in Central and Eastern European countries. After controlling the firm-level variables, Dayanandan and Donker (2011) show a positive impact of oil prices on the firm performance variables of US oil and gas companies from 1990 to 2008. In addition to using oil prices, Ramos and Veiga (2011) analyze the impact of risk factors, including world and local market return, currency variations, the returns and volatility of oil prices and interest rates gap, on the financial performance of the oil and gas industry in 34 countries. Moreover, they indicate that the oil and gas sector in developed countries responds more strongly to oil price changes than this sector in emerging markets.

The research mentioned above on the oil and gas sector investigate this sector surrounding the stock returns. Limited research pays attention to the volatility of the oil and gas stocks. Arouri et al. (2012) investigate the volatility spillover between oil and stock markets in Europe and show significant volatility spillover between oil prices and some sector stock returns. However, this research does not include the oil sector. Antonakakis et al. (2018) examine the volatility spillover and co-movements among oil prices and the stock prices of major oil and gas corporations. The significant volatility spillover effect is found between oil prices and the stock volatility of the oil and gas companies.

Kilian and Park (2009) examine the oil shocks proposed by Kilian (2009) in the stock market, explaining a valuable message that separated oil shocks impact US real stock returns differently, much depending on the driving factors of the oil shocks. Using the same decomposition method, Degiannakis et al. (2014) focus on the European stock market volatility. Their results indicate no significant impacts of supply-side shocks and oil-specific demand shocks, whereas aggregate demand shocks lead to a reduction in stock market volatility. Bastianin and Manera (2018) extend the examination to the impact of three shocks on the US stock market volatility. The results indicate that volatility responds significantly to the oil price shocks caused by unexpected changes in aggregate and oil-specific demand. However, the response is negligible to the impact of supply-side shocks. For the oil and gas industry, Kang, Perez de Gracia, et al. (2017) document the effects of three kinds of oil price shocks and economic policy uncertainty on the oil and gas stock returns. They confirm a positive oil demand-side shock and negative policy uncertainty impact on the oil and gas stock returns. For clean energy stocks, research rarely considers the impact of oil prices caused by different shocks separately.

The second strand of the research is on the clean energy stock market. Limited by no general price for the clean energy products, the research focusing on this sector concentrates more on the financial market. Henriques and Sadorsky (2008) is the pioneer study to examine the relationship between oil prices and alternative clean energy stocks using the Granger causality test and LA-VAR model. They report that clean energy stock returns are closely correlated with the technology stock returns, implying that investors view the clean energy companies are similar to the high technology companies. Kumar et al. (2012) extend and confirm this topic to the global clean energy stock market. Since Sadorsky (2012) shows that the nexus between oil and clean energy increases in 2008, many time-varying methods and models with structural breaks are employed to verify this evidence (Managi and Okimoto 2013, Inchauspe et al. 2015, Bondia et al. 2016, Reboredo et al. 2017).

Regarding the volatility research on clean energy stocks, Sadorsky (2012) first examines the volatility spillover between oil prices and stock prices of technology and clean energy companies using several GARCH models. The results indicate that the oil prices and the technology index have significant correlations with clean energy indices, and the technology index has a more substantial spillover effect than the oil prices. Ahmad (2017) reports consistent results about the returns and volatility spillover among the oil prices, the US clean energy index, and the technology stock index. In terms of uncertainty in oil markets, Dutta (2017) examines volatility relationships between the CBOE crude oil volatility index (OVX) and several realized volatilities of the US clean energy stock index and finds the positive impact of the OVX on the realized volatility of the clean energy index, especially in crisis periods. After 2018, research concerning the clean energy stock market focuses more on financial and policy uncertainty. Specifically, Lundgren et al. (2018) examine the spillover effects from American and European economic policy uncertainty, the CBOE volatility index (VIX), and the financial stress index to the returns and volatilities of several clean energy indices. They show that clean energy indices are more closely related to two financial uncertainty proxies than two policy uncertainty indices. Ji et al. (2018) elaborate upon the impacts of economic policy uncertainty, VIX, and OVX with a time-varying copula-based CoVaR model, showing that the global clean energy index is more sensitive to the financial and oil uncertainties than the policy uncertainty. Ahmad et al. (2018) argue that the VIX is the best asset for hedging clean energy equities, followed by crude oil prices and the OVX. Ferrer et al. (2018) find evidence supporting that the VIX is a key transmitter persistently affecting US clean energy indices.

In the above introduced clean energy research, some important macroeconomic variables are also taken into consideration. Interest rates have a significant impact on any participant of a financial market, and clean energy stocks are not an exception (Henriques and Sadorsky 2008, Kumar et al. 2012, Managi and Okimoto 2013, Bondia et al. 2016, Lundgren et al. 2018, Ferrer et al. 2018). Due to environmental reasons, Kumar et al. (2012) include European Emission Allowances (EUA) prices but fail to find a significant impact on the US and global clean energy stock indices. However, Dutta et al. (2018) prove that the impact of EUA prices on clean energy stock returns is significant in the European market while insignificant in other markets. Shocks from the overall stock market index have a strong influence (Inchauspe et al. 2015, Lundgren et al. 2018). About investor sentiment. Reboredo and Ugolini (2018b) find no significant impact of the Twitter sentiment on clean energy stocks. As for other financial factors, Lundgren et al. (2018) test that the USD/EUR exchange rate has a weak impact. And Ferrer et al. (2018) report that the default spread is only significant during the financial crisis period.

Wen et al. (2014) analyze a comparative study of the return and volatility spillover effects between the stock prices of the clean energy companies and the fossil fuel companies in China. Their results suggest to regard two indices as competing assets and that the news from one kind of energy affects the stock investment of two energy indices differently.

3.3 Methodology

MIDAS models proposed by Ghysels et al. (2007) are a series of models that jointly incorporate the data of different frequencies to obtain complete information while avoiding the information bias caused by misspecifications simultaneously. GARCH-MIDAS model proposed by Engle et al. (2013) combines a mean-reverting high-frequency GARCH process introduced by Engle and Rangel (2008) and a MIDAS polynomial allowing for including the low-frequency variables into the model. By identifying information on long-run elements, fluctuations in long-run volatility are more precisely measured.

We specifically employ the GARCH-MIDAS model using monthly and daily data as the low-frequency and high-frequency data series, respectively. This model also can be applied to estimate variables having other different frequencies. The unexpected returns of the daily financial series are defined as follows:

$$r_{i.t} - E_{i-1,t}(r_{i,t}) = \sqrt{\tau_t \cdot g_{i,t}}\varepsilon_{i,t} \tag{3.1}$$

where $r_{i.t}$ is the log return of day i of month t, and $E_{i-1,t}(r_{i,t})$ is the conditional expectation of $r_{i.t}$ based on the information up to day i-1, $\varepsilon_{i,t}|\Phi_{i-1,t}$ is a random variable following a standard normal distribution with conditional information Φ at day i-1, τ_t is the long-run component of the conditional variance of returns, and $g_{i,t}$ is the short-run component. In other words, the conditional variance of the daily financial series is divided into two components:

short-run daily fluctuation $g_{i,t}$ identified by a GARCH process and long-run volatility τ_t represented by a MIDAS term.

Daily fluctuation $g_{i,t}$ is assumed to follow a GARCH (1, 1) process:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t} + \beta g_{i-1,t} \tag{3.2}$$

where α represents the ARCH effect showing how volatility reacts to new short-run information[11], and α indicates the GARCH effect about the persistence of the volatility in the long-run. We set a condition $\alpha+\beta<0$. Higher $\alpha+\beta$ means lower decays of volatility over time. We assume μ is a constant term to represent $E_{i-1,t}\left(r_{i,t}\right)$.

We assume that the long-term component τ_t can be represented by the realized volatility RV_t of the returns with a weighting scheme of MIDAS filters. Alternatively, the long-run component comes from a macroeconomic variable. When the long-run component reflecting the information of the macroeconomic variable, the logarithmic form of the long-term component is used to render lower-frequency variables feasible with any sign. Therefore, the long-term component τ_t has two forms as follows:

$$log(\tau_t) = m^1 + \theta\sum_{k=1}^{K}\varphi_k^1 MV_{t-k} \tag{3.3}$$

$$\tau_t = m^2 + \gamma\sum_{k=1}^{K}\varphi_k^2 RV_{t-k} \tag{3.4}$$

, respectively. The coefficients θ and γ are the slopes of the sum of the weighted lags of MV_t and RV_t, respectively. MV_t represents the macroeconomic variable. RV_t is a realized volatility of return series at time *t* calculated as $RV_t = \sum_{h=1}^{N} r_{h,t}^2$, where *N* is the number of

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[11] $\frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t}$ is to obtain $g_{i,t}\varepsilon_{i,t}{}^2$, so only the new short run information is invited in the GARCH process.

trading days in month t. The optimal lag K is derived from the Bayesian information criterion (BIC). We choose the one-parameter Beta polynomial weighting function φ_k proposed by Ghysels et al. (2007) and Engle et al. (2013) as a weighting scheme for the long-run variables in Eq. (3.3) and Eq. (3.4). The weighting function is displayed in Eq. (3.5).

$$\varphi_k^s(\omega^s) = \frac{(1-k/K)^{\omega^s-1}}{\sum_{j=1}^{K}(j/K)^{\omega^s-1}}, k = 1, \ldots, K, s = 1,2 \tag{3.5}$$

For all $\varphi_k^s(\omega^s)$, we assume $1 > \varphi_k^i(\omega) > 0$ and $\sum_{k=1}^{K}\varphi_k^s(\omega^s) = 1$. This weighting scheme shows a decaying pattern where large (small) values of ω^s denote rapid (slow) decay.

3.4 Data

We choose two representative indices to describe the trends of the energy-related industry in the global stock market. The conventional energy index is the MSCI world oil gas & consumable fuels index (OG), comprising the leading companies in the oil, natural gas, and consumable energy industry worldwide. The other novel energy index is the WilderHill New Energy Global Innovation Index (RE), composed of worldwide companies relevant to clean energy generation, low carbon technology, and energy efficiency improvement. We choose daily data samples of these two stock indices from January 2nd, 2001 to December 30th, 2018 (Figure 3.1). These indices show more similarities in the trend. Before the 2008 global economic crisis, two indices had stable rises to the peak, and then steep falls of them inevitably occurred. After the crisis, these two indices remain relatively steady with some moderate fluctuations, while RE's fluctuations are relatively sharper.

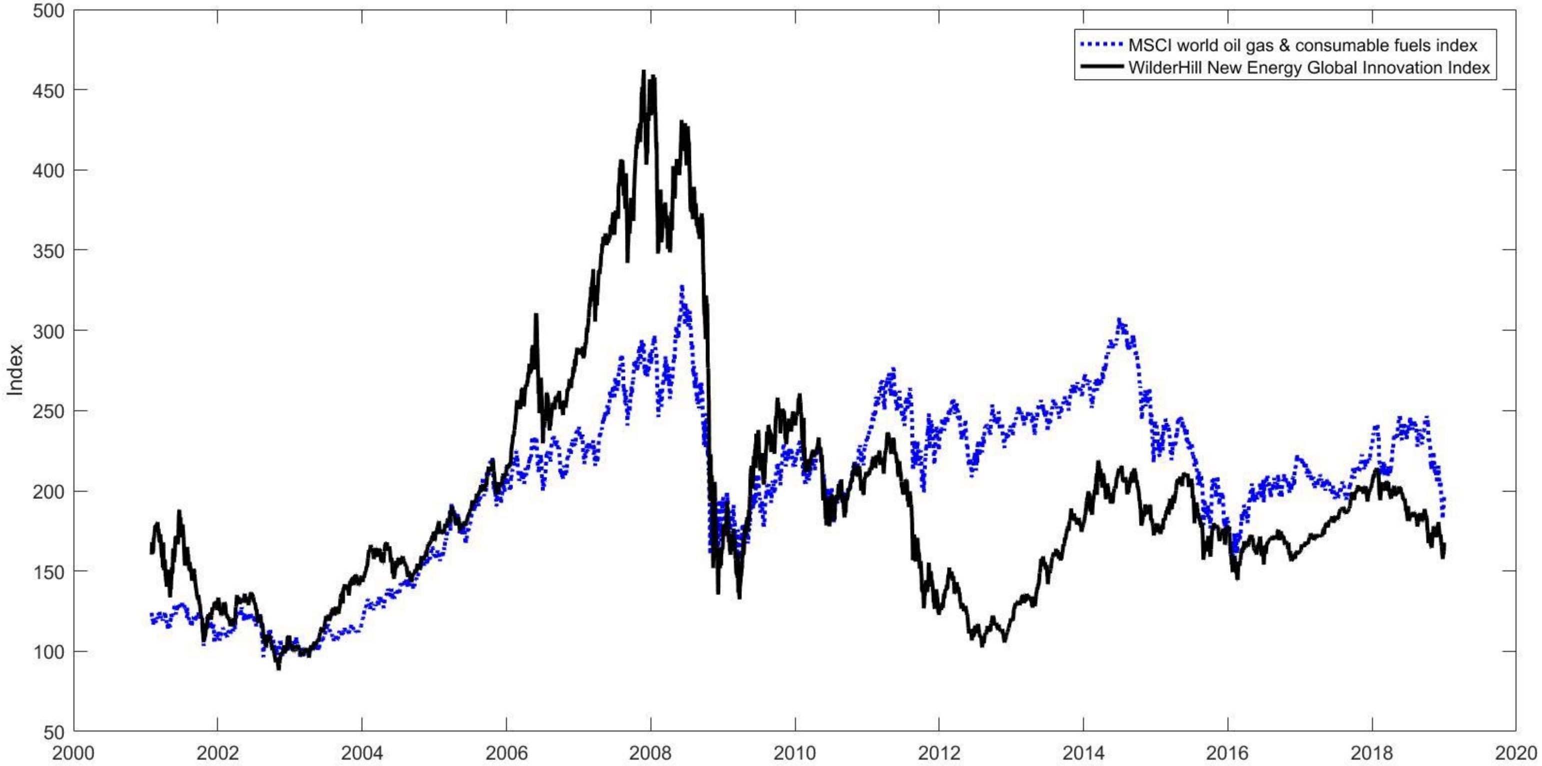

Figure 3.1 Time trends of global energy-related indices, 2001:01–2018:12.

Notes: Blue dotted line is the MSCI world oil gas & consumable fuels index (OG), and the solid black line is the WilderHill New Energy Global Innovation Index (RE).

Five monthly macroeconomic variables are selected to show the energy security issues, plotted in Figure 3.2. Oil-related variables represent the impact of oil supply, oil-specific demand, and aggregate energy demand. We follow the decomposition of Kilian (2009) to classify oil impacts by using percentage changes in the global oil production and the real spot price of West Texas Intermediate crude oil (WTI) to indicate oil supply (PROD) and oil-specific demand (OIL). These two raw data are downloaded from the US Energy Information Administration. We also follow Kilian (2009) to use the real economic activity index (REA)[12] to grab the aggregate energy demand changes from economic growth. This index extracted the news of economic growth from the global dry cargo single voyage ocean freight rates of primary industrial commodities.

The economic uncertainty measure (EU)[13], constructed by Ozturk and Sheng (2018), uses survey data from subjective forecasts of market participants to create 45 country-specific monthly uncertainty measures and averagely weights country-specific measures to obtain the global measure used in this chapter. Based on the specific news collected from the newspapers, Caldara and Iacoviello (2018) constructed a geopolitical risk index (GPR)[14] to represents the information concerning the instability brought by geopolitics issues. This index can depict the tension level of the global geopolitical situations and highlight the broadcasting events, such as the gulf war, the 2003 Iraq invasion, 2014 Ukraine crisis, implying that is a good proxy of the geopolitics uncertainty.

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[12] The REA index can be found on Kilian's website and the REA index is the latest version revising the double logged problem in 2018.08. The other two data are drawn from the EIA website.

[13] Economic uncertainty data can be found at https://www.american.edu/cas/faculty/sheng.cfm.

[14] The GPR index can be found at http://www.policyuncertainty.com/gpr.html.

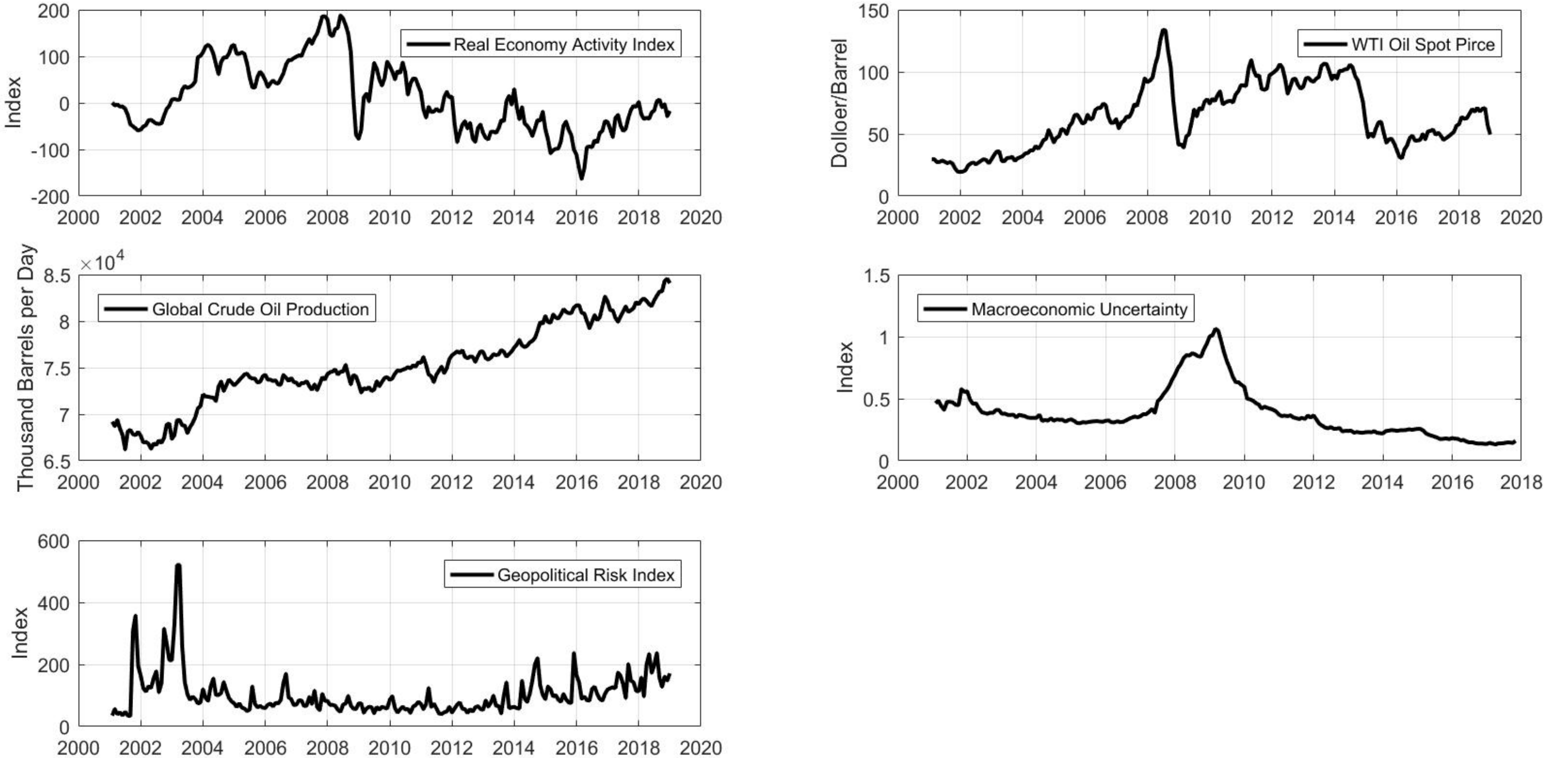

Figure 3.2 Time trends of macroeconomic variables, 2001:01–2018:12.

Notes: the first row introduces the real economic activity index and the spot prices of WTI oil; the second row displays the global production of crude oil and the macroeconomic uncertainty measure; the last row shows the geopolitical risk index.

In Figure 3.2, we find that the REA index is more active before 2009, and after the financial crisis, it remains in a relatively stable and weak zone. Before peaking in 2008, oil prices surge is similar to the stock index, while it recovered soon after the crisis. However, the world oil price went into a low-level stage from 2015 onwards. The total amount of oil production steadily rises. EU displays an apparent peak in the global financial crisis period while shows a relatively stable tendency in other periods. However, the GPR index shows more temporary surges, representing many unpredicted events related to the geopolitical shocks.

Table 3.1 reports the statistical summary of the daily return series of the oil and gas index, the clean energy index, and five monthly-frequency series of the macroeconomic variables in the final form used in the estimation. $r_{i,t}^{og}$, $r_{i,t}^{re}$, OIL, and PROD are taken into the first difference of the logarithm form to convert data into returns or changes forms. And REA, EU, and GPR keep their original forms in the estimation. Due to the data availability, the published EU data released as of October 2017, and the other six series are available until December 2018. So the examination of the impact of the EU is ended in October 2017, and the other four macroeconomic influences are ended in December 2018

The average mean of RE and EU are negative, while others are positive. The mean REA value is 11.197, with an interval of over 350. The GPR shows a larger gap and interval. EU changes between 0 to 2. Among the series with a near-zero mean, REA has the highest standard deviation, while PROD presents the lowest standard deviation. About skewness, OIL and two stock indices exhibit a more negative skewness while EU, REA, and PROD exhibit a positive skewness. Regarding kurtosis, only REA is platykurtic, while others are leptokurtic. The Jarque-Bera test confirms that the distributions of each series are not normal.

Table 3.1 Descriptive statistics

	$r_{i,t}^{og}$	$r_{i,t}^{re}$	OIL	REA	PROD	GPR	EU
Obs.	4752	4752	216	216	216	216	202
Mean	0.009	-0.001	0.327	11.197	0.097	103.72	0.380
Median	0.039	0.037	1.428	-4.545	0.118	82.769	0.337
Maximum	13.321	12.071	21.387	187.898	2.887	520.124	1.064
Minimum	-12.962	-10.485	-33.198	-163.431	-2.425	33.328	0.131
Std. Dev.	1.382	1.378	8.744	75.019	0.788	69.086	0.202
Skewness	-0.472	-0.391	-0.858	0.407	0.118	2.935	1.458
Kurtosis	12.491	10.768	4.612	2.424	4.005	15.269	4.860
JB test	***	***	***	**	***	***	***

Note: Asterisks denote statistical significance at 10% by *, 5% by **, and 1% by ***. JB test is the Jarque–Bera test. Std. Dev. is the standard deviation. $r_{i,t}^{og}$ and $r_{i,t}^{re}$ are returns of the global oil & gas index (OG) and the clean energy index (RE), respectively. OIL represents the changes in the real WTI spot price. REA is the real economic activity index. PROD is the changes in global oil production. GPR is the geopolitical risk index. EU is the uncertainty measure of the economy.

This chapter also investigates the impact of the volatility of five energy insecurity factors on the energy stock indices. Following the method of Schwert (1989) and Engle et al. (2013), we use squared residuals of an AR (12) model of the macroeconomic variables with seasonality to proxy the monthly volatilities of macroeconomic variables (VMV), as follows:

$$MV_t = \sum_{k=1}^{12} a_k D_{k,t} + \sum_{k=1}^{12} b_k MV_{t-k} + \eta_t \tag{3.6}$$

where $D_{k,t}$ is seasonal dummy, $D_{k,t} = 1$ at the *k*th period, otherwise $D_{k,t} = 0, k = 1, \dots, 12$. MV_t represents one of the five considered macroeconomic variables in this chapter. We define $VMV_t = \hat{\eta}_t^2$, where $\hat{\eta}_t^2$ is the sum of the squared residuals in Eq. (3.6). Table 3.2 provides a statistical summary of five VMV variables.

Table 3.2 Descriptive statistics: Volatility of macroeconomic variables

	VPROD	VREA	VWTI	VGPR	VEU
Obs.	216	216	216	216	202
Mean	0.4394	289.6374	61.1007	1730.977	0.0004
Median	0.2141	85.2759	25.2244	403.7108	9.47E-05
Maximum	6.0660	7214.408	670.6978	57642.53	0.0077
Minimum	9.77E-06	0.0135	0.0018	0.0032	3.54E-08
Std. Dev.	0.7335	629.9641	91.0016	5558.132	0.0011
Skewness	4.0804	6.8904	2.9055	7.2305	4.7668
Kurtosis	25.1200	70.0780	14.4684	63.4657	28.2423
JB test	***	***	***	***	***

Note: Asterisks denote statistical significance at 10% by *, 5% by **, and 1% by ***. JB test is the Jarque–Bera test. Std. Dev. is the standard deviation. The volatility of each macroeconomic variable is calculated as Eq.(3.6), where. VOIL represents the volatility of the changes in the real WTI spot price. VPROD is the volatility of the changes in global oil production. VREA is the volatility of the real economic activity index. VGPR is the volatility of the geopolitical risk index. VEU is the volatility of the uncertainty measures of the macroeconomy.

3.5 Results

3.5.1 GARCH-MIDAS model results

This chapter uses the GARCH-MIDAS model to examine the impacts of energy insecurity-related macroeconomic variables on the long-run volatilities of two energy-related stock indices. We modify the model by adding extra variables to make the estimation more appropriate for the stock returns. Considering the impact directly from the stock market, we include the Fama-French three factors[15] into the mean equation (Eq.(3.7)) to filter out the impact of the stock market and then use the residuals to represent the remaining volatility of the stock returns. We

[15] The Fama-French factors are from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

assume that the long-tun component involves the realized volatility and monthly macroeconomic determinants simultaneously in the long-run variance equation. This approach helps assess the impacts of macroeconomic variables more precisely. According to the BIC, optimal two-year lag is selected to weight the long-run impact of macroeconomic variables and realized volatilities using the one-parameter polynomial weighting function in Eq. (3.5). Therefore, Eq. (3.1) and Eq. (3.3) are replaced by Eq. (3.7) and Eq. (3.8) as follows.

$$r_{i,t}^{re/og} + \psi_1 r_{i,t}^{mkt} + \psi_2 smb_{i.t} + \psi_3 hml_{i.t} = \sqrt{\tau_t \cdot g_{i,t}}\varepsilon_{i,t} \tag{3.7}$$

$$\log(\tau_t) = m + \theta \sum_{k=1}^{24} \varphi_k^1 MV_{t-k} + \gamma \sum_{k=1}^{24} \varphi_k^2 RV_{t-k} \tag{3.8}$$

where $r_{i.t}$ is the returns of the index at day *i* of month *t*, where $r_{i,t}^{mkt}$, $smb_{i.t}$ and $hml_{i.t}$ are the Fama-French three factors about total market portfolio return, size premium and value premium and ψ_i are the coefficients of each factor. Other parameters have the same meaning as the original model in section 3.3.

To investigate the long-run volatility of the oil and gas index, we report the parameter estimation results from the GARCH-MIDAS model are reported in Table 3. Each column in Table 3 corresponds to one macroeconomic variable (MV). Most of the coefficients included in the variance equation are significant (in Eq. (3.2) and (3.8)). In all columns, significant α and β imply that these stock indices can be used in the GARCH model to depict a short-run clustering pattern. Additionally, the boundary condition of GARCH parameters $\alpha + \beta < 1$ denotes that the short-run volatility component is mean-reverting.

Table 3.3 GARCH-MIDAS model results: Dependent variables Oil and Gas Index

Parameter	Macroeconomic variables				
Estimates	OIL	REA	PROD	GPR	EU
	(i)	(ii)	(iii)	(iv)	(v)
α	0.051***	0.046***	0.053***	0.054***	0.051***
	(10.808)	(11.844)	(10.884)	(10.435)	(11.775)
β	0.944***	0.953***	0.945***	0.939***	0.949***
	(166.150)	(242.000)	(189.870)	(163.690)	(218.010)
θ	0.110**	0.014***	0.156	0.007***	4.543***
	(2.114)	(4.185)	(0.780)	(3.687)	(3.053)
γ	0.016	-0.047**	-0.005	-0.003	-0.073**
	(1.039)	(-2.116)	(-0.672)	(-0.626)	(-2.242)
ω^1	1.483***	1.001***	12.401	1.028***	5.414
	(2.603)	(14.148)	(0.677)	(8.446)	(1.276)
ω^2	2.657	1.001**	18.462	28.072	1.334***
	(1.169)	(25.207)	(0.420)	(0.346)	(3.891)
m	-0.733*	1.757**	0.053	-1.241***	0.169
	(-1.837)	(2.561)	(0.165)	(-4.394)	(0.267)
LogL	-4361.88	-4356.27	-4361.87	-4359.5	-3987.9
AIC	8737.76	8726.53	8737.74	8733	7989.81
BIC	8783.03	8771.8	8783.01	8778.27	8034.6

Note: The number in parentheses is t-statistic; Asterisks denote statistical significance at 10% by *, 5% by **, and 1% by ***. Parameters are estimated by Eq. (3.2), (3.5), (3.7), and (3.8). LogL is log-likelihood; AIC and BIC mean the information criterion from Akaike and Bayesian. OIL represents the changes in the real WTI spot price. PROD is the changes in global oil production. REA is the real economic activity index. GPR is the geopolitical risk index. EU is the uncertainty measure of the economy. RV represents the realized volatility of the oil and gas index.

For the long-run variance, the impact of each considered macroeconomic variable represented by coefficient θ is of interest in each column (in Eq. (3.8)). In column (i), the impact of oil demand (OIL) shows a significantly positive impact on the long-run variance of the oil and gas index, implying that the long-run volatility of oil and gas companies increases in the background of the oil price surge. In column (ii), economic growth (REA) increases the long-run variance of the oil and gas index, indicating that the aggregate demand for energy increases causes a rise in the variance of the oil and gas companies' stocks. In column (iii), oil supply (PROD) reports an insignificant impact on the long-run variance of the oil and gas index. This weak impact of the oil supply side is consistent with Kilian (2009), reflecting that the oil supply has no long-run impact. In column (iv), a positive impact of geopolitical risk (GPR) reflects the critical sensitivity of the oil and gas companies to unpredicted geopolitical events. In the last column (v), macroeconomic uncertainty (EU) also shows a significantly positive impact on the long-run variance of the oil and gas index, exhibiting an essential impact of uncertainty in the macroeconomy.

Moreover, coefficient γ means the impact of realized volatility of the oil and gas index in the long-run. When investigating the impact of realized volatility with economic growth (REA) and macroeconomic uncertainty (EU), it exhibits a significantly negative impact on the long-run variance, in columns (ii) and (v), respectively. However, realized volatility shows an insignificant impact on the long-run variance of the oil and gas index when we use WTI, PROD, and GPR in columns (i), (iii), and (iv), respectively.

Table 3.4 shows the parameter estimation results of the GARCH-MIDAS model with the clean energy index as the dependent variable. For the clean energy sector, the coefficient α is relatively larger than its counterpart in the oil and gas sector, displaying a larger ARCH effect. In contrast, the coefficient β of the clean energy index reflects a smaller GARCH effect than its counterpart.

As for the long-run variance, the coefficient θ demonstrates the impacts of considered macroeconomic variables. In column (i), the impact of oil demand (OIL) shows a significantly negative impact on the long-run variance of the clean energy index, reflecting that oil price increases lead to the long-run volatility of the clean energy companies decreases. In column (ii), economic growth (REA) decreases the long-run variance of the clean energy companies, showing that the surge of aggregate demand of energy reduces the volatility of the clean energy sector. In column (iii), oil supply (PROD) keeps its insignificant impact on the long-run variances of the clean energy index. In column (iv), unpredicted geopolitical events have a negative impact on the variance of the clean energy index, showing less volatility when facing unpredicted geopolitical events. In the last column (v), as same as the oil and gas index, macroeconomic uncertainty (EU) also shows a significantly positive impact on the long-run variance of the clean energy index, emphasizing the critical impact of the macroeconomy uncertainty in both energy sectors. Furthermore, the realized volatility coefficient γ in each column displays a negative impact with different extents of significance.

Table 3.4 GARCH-MIDAS model results: Dependent variables Clean Energy Index

Parameter	Macroeconomic variables				
Estimates	OIL	REA	PROD	GPR	EU
	(i)	(ii)	(iii)	(iv)	(v)
α	0.082***	0.080***	0.081***	0.085***	0.069***
	(15.856)	(16.247)	(16.070)	(22.650)	(16.652)
β	0.909***	0.912***	0.911***	0.915***	0.918***
	(133.120)	(144.500)	(141.600)	(271.430)	(152.440)
θ	-0.078**	-0.002*	0.363	-0.017***	3.050***
	(-2.062)	(-1.656)	(0.868)	(-3.251)	(6.003)
γ	-0.032*	-0.035*	-0.031*	-0.179***	-0.052***
	(-1.791)	(-1.895)	(-1.781)	(-6.980)	(-2.580)
ω^1	1.154***	49.953	7.120	4.768**	49.990
	(3.181)	(0.293)	(0.854)	(2.558)	(0.496)
ω^2	8.598*	8.457*	8.743*	5.707***	5.089**
	(1.673)	(1.760)	(1.668)	(7.730)	(2.547)
m	-0.099	-0.043	-0.136	-1.104	-1.250***
	(-0.291)	(-0.117)	(-0.371)	(-0.861)	(-5.960)
LogL	-4077.73	-4078.25	-4077.45	-4227.44	-3688.4
AIC	8169.45	8170.51	8168.89	8468.89	7390.81
BIC	8214.72	8215.77	8214.16	8514.15	7435.6

Note: The number in parentheses is t-statistic; Asterisks denote statistical significance at 10% by *, 5% by **, and 1% by ***. Parameters are estimated by Eq. (3.2), (3.5), (3.7), and (3.8). LogL is log-likelihood; AIC and BIC mean the information criterion from Akaike and Bayesian. OIL represents the changes in the real WTI spot price. PROD is the changes in global oil production. REA is the real economic activity index. GPR is the geopolitical risk index. EU is the uncertainty measure of the economy. RV represents the realized volatility of the clean energy index.

This chapter focuses on the impacts of each considered macroeconomic variable represented by the coefficient θ. Comparing the results in Table 3.3 and Table 3.4 indicates the different reactions between two energy segments to some insecurity causes. First, two demand-side factors of oil (OIL and REA) are significant for both segment indices. However, the impact is contradictory that the demand for oil increases the oil stock volatilities while decreasing the clean energy stocks in the long-run, no matter what reasons causing the increase of oil demand (economic growth and precaution). Oil companies are more flurried when facing an indistinct future oil demand situation that increases the oil and gas stock volatility. The raised demand for oil also indicates the uncertainty in this market and implies the relative stability in the oil alternative market. Therefore, facing the shock caused by oil demand, clean energy stocks show fewer fluctuations in the long-run variance.

Second, the oil supply factor (PROD) is statistically insignificant for both stock indices. It does not contradict other research that also observes insignificant oil supply influence in the financial market (Degiannakis et al. 2014, Kang, Perez de Gracia, et al. 2017). For some oil companies, such as mining, production reduction is controlled by themselves. For the other companies, such as refining, a sudden announcement about oil production reduction can trigger a ready stock of oil, then storage adjustment implementation. Thus, in the long-run, oil supply has a weak influence. A plausible explanation for the reaction of clean energy stocks is that the clean energy listed companies are more closely correlated with technology companies. Therefore, oil production cannot affect them.

Third, about the uncertainty factors, geopolitical risk (GPR) typically has a positive impact on oil volatility in the long-run because geopolitical risk affects the oil supply from an angle that companies cannot control and tackle. The long-run variance of the clean energy stocks responds to the geopolitical risk shocks to decrease its volatility. The geographical isolation of the clean energy segment to the geopolitical uncertainty makes the clean energy stock volatility decrease during the high geopolitical tension period. Fourth, only the macroeconomic uncertainty has the same positive impact on the long-run variance of both energy indices. Due to the rapid spread of information, any energy sector cannot avoid the impact of economic crisis, and unprecedented economic uncertainty makes energy companies run in an unstable situation. It also makes the stock market investors feel uncertain about the stock forecast and thus makes the energy stock volatility increase.

3.5.2 ARDL model results

In the previous section, we explain the impact of energy insecurity related to five macroeconomic variables. Almost variables indicate significant impacts on the long-run variance of the energy stocks, with one exception of the oil supply. However, besides these macroeconomic variables, the volatilities of these variables also need to be examined to indicate the impact of the fluctuations of these energy insecurity variables on the energy stock volatility.

To indicate the impact of the volatility of the energy insecurity factors, we estimate the following ARDL model for two energy indices:

$$\log(\hat{\tau}_t) = \lambda + \sum_{j=1}^{\max(6)} \delta_j \log(\hat{\tau}_{t-j}) + \sum_{h=0}^{\max(6)} \kappa_h VMV_{t-h} + \upsilon_t \tag{3.9}$$

In Eq. (3.9), the dependent variable is the monthly long-run variance of the energy indices $\log\left(\hat{\tau}_t^{og/re}\right)$ obtained from the estimation of Eq. (3.3). Moreover, the monthly volatility series of macroeconomic variables (VMV) are calculated as the squared residuals in Eq. (3.6) with different MVs.

Table 3.5 ARDL model results: Dependent variables long-run variance of OG and RE

Dependent variable / ARDL Lags / Regressor VMV	$\log(\hat{\tau}_t^{og})$	$\log(\hat{\tau}_t^{re})$
	ARDL(4,2,2,2,0,0)	ARDL(6,0,3,1,0,0)
PROD	4.185	-0.243
	(0.640)	(-0.065)
VREA	0.038***	0.032***
	(5.098)	(3.995)
VOIL	0.055	0.089**
	(1.223)	(2.067)
VGPR	0.000	0.000
	(-0.123)	(-0.666)
VEU	2152.803	4455.818
	(0.803)	(1.443)
C	-2.695	-1.124
	(-0.740)	(-0.287)

Note: The number in parentheses is t-statistic; Asterisks denote statistical significance at 10% by *, 5% by **, and 1% by ***. According to Pesaran et al. (2001), The long-run coefficients representing the response of the dependent variable to a unit change in regressors are estimated by $\vartheta_j = \frac{\sum_{i=1}^{q_j} \hat{\kappa}_{j,i}}{1-\sum_{i=1}^{p} \hat{\delta}_i}$.

The results of Table 3.5 reveal that volatility of the aggregate demand (VREA), represented by the economic activity fluctuations, is the only significant determinant of the long-run variance of the oil and gas stock index. Moreover, for the long-run clean energy stock variance, volatilities of the aggregate demand (VREA) and the oil-specific demand (VOIL) represented by oil price volatility have significantly positive impacts. In contrast, neither the long-run variance of oil and gas index nor of clean energy index obtains significant long-run impact affected by volatilities of the oil supply (VPROD), the geopolitical risk (VGPR), and the macroeconomic uncertainty (VEU). These results show that the positive long-run impact of economic activity fluctuations on the variances of two energy indices is as expected that the volatility of the aggregate demand increases the variance of the energy stocks. The impact of the oil price volatility mainly affects in the short-run, whereas a long-run impact on the clean energy variance implies the long-run volatility relationship between these two energy sectors.

3.6 Conclusion

This chapter aims to examine the impacts of energy security issues on the long-run variances of the stock indices consisted of energy-related companies. In particular, we investigate the long-run volatilities of the oil and gas index and clean energy index by examining the impact of several factors and their volatilities as the proxies of energy insecurity. We find that energy security plays an essential role in the long run variances of two indices. The impacts of economic growth, oil prices, and geopolitical risk on the long-run clean energy index volatility are opposite to their impacts on the oil and gas index volatility. Specifically, these three factors increase the long-run volatility of the oil and gas index while they decrease the long-run volatility of the clean energy index. Macroeconomic uncertainty brings more bursts of the volatilities of two energy segments significantly. However, oil production has no significant impact on both indices. Considering the volatility impact of these macroeconomic variables, we find that the volatility of real economic growth (aggregate energy demand) has a significantly positive impact on the long-run variances of two energy-related indices. Moreover, the long-run variance of the clean energy index is also affected by long-run oil price volatility.

These results imply that, for energy consumers, the oil and gas segment and the clean energy segment have a rival relationship. The insecurity news in the oil market increases the fluctuations in stock prices of oil-related listed companies. It makes the stocks of clean energy companies with lower risk unless the insecurity source is from the whole macroeconomy. Furthermore, the influence of these factors lasts in the long-run. Therefore, when investors face shocks specific to the oil market, it is wise to replace the oil stocks in their portfolio with clean energy stocks. Due to the vulnerability of both energy segments in the high general uncertainty period, it is necessary to include risk aversion assets in the portfolio at the pre-crisis stage. For the energy security factors, their volatility impacts are weak in the long-run variances of the energy stocks. Nevertheless, the impact of volatility of the aggregate energy demand is still worthy of attention, implying the impact of the uncertainty from economic growth disturbs the energy demand and fluctuates the stock prices of the oil and gas companies and the clean energy companies.

Appendix 3

Table A3.1 Definition of variable

Variables	Definition
$r_{i,t}^{og}$	Return of the MSCI world oil gas & consumable fuels index (OG).
$r_{i,t}^{re}$	Return of the WilderHill New Energy Global Innovation Index (RE).
OIL	Changes in the real WTI spot prices (WTI_P).
REA	Real economy activity index.
PROD	Changes in global oil production (OIL_P).
GPR	Geopolitical risk index.
EU	Uncertainty measures of the macroeconomy.
r^{mkt}	Total market portfolio returns from Fama-French Data Library.
Smb	Size premium from Fama-French Data Library.
Hml	Value premium from Fama-French Data Library.
RV	Realized volatilities in the GARCH-MIDAS model.
$\log(\tau_{t,og})$	The monthly long-run variance of the oil and gas index: calculated by summing the daily long-run components in month *t* from a GARCH-MIDAS model with a fixed rolling window(=22) estimation with realized volatilities of oil and gas index in the long run component.
$\log(\tau_{t,re})$	The monthly long-run variance of the clean energy index: calculated by summing the daily long-run components in month *t* from a GARCH-MIDAS model with a fixed rolling window(=22) estimation with realized volatilities of clean energy index in the long run component.
VOIL	The volatility of OIL: the squared residuals of an AR (12) model of the OIL with seasonality dummy.
VREA	The volatility of REA: the squared residuals of an AR (12) model of the REA with seasonality dummy.
VPROD	The volatility of PROD: the squared residuals of an AR (12) model of the PROD with seasonality dummy.
VGPR	The volatility of GPR: the squared residuals of an AR (12) model of the GPR with seasonality dummy.
VEU	The volatility of EU: the squared residuals of an AR (12) model of the EU with seasonality dummy.

Notes: these abbreviations are only used in Chapter 3.

4 Conclusion

4.1 Conclusion

This study aims to investigate the clean energy stock market from a macroeconomic perspective focusing on the impact of macroeconomic factors on the clean energy stock returns. To enrich the research on the impact of macroeconomic influences, we include oil price changes and uncertainty related factors to examine the impact of them on the clean energy stock returns and the variance of clean energy stock returns.

As a key factor, oil price changes affect clean energy stocks through various channels. It makes the impact of oil prices ambiguous. Therefore, this study following an oil price decomposition method that separates the oil price changes into three kinds based on different underlying sources: oil supply shocks, aggregate demand shocks, and oil-specific demand shocks. Chapter 2 and Chapter 3 examine how different oil price changes affect the clean energy stock returns and the variance of clean energy stock returns, respectively. The results show that the impacts of different oil shocks have a clear heterogeneity. Specifically, oil supply shocks and aggregate demand shocks have a positive effect on the returns of clean energy companies. In contrast, oil-specific demand shocks have a negative effect on the returns of clean energy companies. In term of variance, the oil supply shocks and the oil-specific demand shocks have a negative impact on the long-run variance of the clean energy stock returns. In comparison, the aggregate demand shocks have a positive effect on the variance of clean energy stock returns.

For examining the impact of uncertainty, this study investigates the uncertainty indicators measuring the uncertainty from economic policy, macroeconomy, and geopolitical events. These factors are related to the development of the clean energy sectors but have less examination. The main findings of the policy uncertainty are that it has a negative effect on the clean energy stock returns, and the effects of oil shocks on the clean energy stock returns are amplified by adding the policy uncertainty as an endogenously driven factor. Macroeconomic uncertainty affects the long-run variances of the clean energy stock returns positively. In contrast, geopolitical risk has a negative impact on the long-run variance of the clean energy stock returns.

4.2 Remaining questions

In this study, the clean energy stocks market has been investigated in how they would be affected by some macroeconomic influences. However, there are still some remaining tasks that are of interest to analyze in the future about the clean energy stock market.

First, in chapter 2, the SVAR model is used to analyze the impact of macroeconomic variables on the clean energy stock returns. However, this methodology shows the results based on the whole sample period. It ignores the possibility that the impact of macroeconomic variables on clean energy stock returns is time-varying (Kang et al. 2015). Therefore, a further analysis considering the structure break or dynamic impact of the driven factors on the clean energy stock returns remains necessary.

Second, in chapter 3, the GARCH-MIDAS model is employed, which uses one exogenous macroeconomic variable and realized volatility in the regression. The GARCH-MIDAS model, with more than two variables in the long-run component, is difficult to estimate due to a relatively insensitive likelihood to changes in the weighting parameters (Conrad and Kleen 2020). However, the financial market's real situation is that all macroeconomic factors affect the clean energy stock volatility simultaneously. In order to capture the information contained in various economic variables and investigate the combined effect of these variables, using some techniques to reduce the dimensionality, such as principal component analysis, is the future investigation of this topic (Asgharian et al. 2013).

Third, in chapter 3, we combine a MIDAS model with a general GARCH model. It concludes based on the conditional mean relationship that uncertainty has a significant impact on the long-run volatility of the clean energy stock returns. However, we do not consider the difference between high uncertainty periods and low uncertainty periods. The tail relationships between the clean energy stock volatility and uncertainty indicators may have different results during the high uncertainty periods. Therefore, in the next step, using a quantile regression estimation of GARCH models (Xiao and Koenker 2009) is essential to reveal the nonlinear clean energy stock volatility under different risk circumstances.

4.3 Future tasks

Besides the remaining questions derived from this study, there are many directions worthy of paying attention to the clean energy stock investment or green investments with various instruments. The following part introduces some further research directions in this field.

In this study, to examine the oil price shocks with different underlying sources and report different impacts on the clean energy stock returns, two clean energy stock indices are used to represent the clean energy stocks listed in the US exchange and worldwide. The clean energy sector has also achieved remarkable development in developing countries. Therefore, it is necessary to analyze the clean energy stock market in developing countries and compare them with developed countries.

This study selects two uncertainty series, namely macroeconomic uncertainty and geopolitical risk, to examine their impacts on the long-run variances of clean energy stock returns. There are also several macroeconomic influences having a lower frequency that can affect the clean energy stock market, such as industrial production, the export amount of energy, et cetera. The limit of mismatching of these lower frequency series can be fixed by the MIDAS model. Including these factors in the examination can supplement some deficiencies and improve relevant research on the clean energy sector.

This study uses a MIDAS model combined with a univariate GARCH model to analyze the impact of some macroeconomic influences on the long-run variances of the clean energy stock returns. The MIDAS model can also combine with multivariate GARCH models to analyze how realized volatility of the targeted daily series or other macroeconomic influences can simultaneously affect the dynamic correlation between clean energy stock index and other daily frequency series. Therefore, after we examined the clean energy stock returns and their variance in this thesis, we can investigate the dependence between clean energy stock returns and other variables of interest, under consideration of the impact of macroeconomic influences.

References

Ahmad, Wasim. 2017. "On the dynamic dependence and investment performance of crude oil and clean energy stocks." *Research in International Business and Finance* 42:376-389.

Ahmad, Wasim, Perry Sadorsky, and Amit Sharma. 2018. "Optimal hedge ratios for clean energy equities." *Economic Modelling* 72:278-295.

Aloui, Riadh, Rangan Gupta, and Stephen M. Miller. 2016. "Uncertainty and crude oil returns." *Energy Economics* 55:92-100.

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and George Filis. 2013. "Dynamic co-movements of stock market returns, implied volatility and policy uncertainty." *Economics Letters* 120 (1):87-92.

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and George Filis. 2014. "Dynamic spillovers of oil price shocks and economic policy uncertainty." *Energy Economics* 44:433-447.

Antonakakis, Nikolaos, Juncal Cunado, George Filis, David Gabauer, and Fernando Perez de Gracia. 2018. "Oil volatility, oil and gas firms and portfolio diversification." *Energy Economics* 70:499-515.

Arouri, Mohamed El Hedi, Jamel Jouini, and Duc Khuong Nguyen. 2012. "On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness." *Energy Economics* 34 (2):611-617.

Asgharian, Hossein, Ai Jun Hou, and Farrukh Javed. 2013. "The Importance of the Macroeconomic Variables in Forecasting Stock Return Variance: A GARCH-MIDAS Approach." *Journal of Forecasting* 32 (7):600-612.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016. "Measuring economic policy uncertainty*." *The Quarterly Journal of Economics* 131 (4):1593-1636.

Baldi, Lucia, Massimo Peri, and Daniela Vandone. 2014. "Clean energy industries and rare earth materials: Economic and financial issues." *Energy Policy* 66:53-61.

Bastianin, Andrea, and Matteo Manera. 2018. "How does stock market volatility react to oil price shocks?" *Macroeconomic Dynamics* 22 (3):666-682.

Bohl, Martin T., Philipp Kaufmann, and Pierre L. Siklos. 2015. "What drove the mid-2000s explosiveness in alternative energy stock prices? Evidence from U.S., European and global indices." *International Review of Financial Analysis* 40:194-206.

Bondia, Ripsy, Sajal Ghosh, and Kakali Kanjilal. 2016. "International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks." *Energy* 101:558-565.

Bouras, Christos, Christina Christou, Rangan Gupta, and Tahir Suleman. 2019. "Geopolitical Risks, Returns, and Volatility in Emerging Stock Markets: Evidence from a Panel GARCH Model." *Emerging Markets Finance and Trade* 55 (8):1841-1856.

Bouri, Elie, Riza Demirer, Rangan Gupta, and Hardik A. Marfatia. 2019. "Geopolitical Risks and Movements in Islamic Bond and Equity Markets: A Note." *Defence and Peace Economics* 30 (3):367-379.

Boyer, M. Martin, and Didier Filion. 2007. "Common and fundamental factors in stock returns of Canadian oil and gas companies." *Energy Economics* 29 (3):428-453.

Broadstock, David C., and Louis T. W. Cheng. 2019. "Time-varying relation between black and green bond price benchmarks: Macroeconomic determinants for the first decade." *Finance Research Letters* 29:17-22.

Caldara, Dario, and Matteo Iacoviello. 2018. "Measuring Geopolitical Risk." *FRB International Finance Discussion Paper No. 1222*.

Caporale, Guglielmo Maria, Faek Menla Ali, and Nicola Spagnolo. 2015. "Oil price uncertainty and sectoral stock returns in China: A time-varying approach." *China Economic Review* 34:311-321.

Conrad, Christian, and Onno Kleen. 2020. "Two are better than one: Volatility forecasting using multiplicative component GARCH-MIDAS models." *Journal of Applied Econometrics* 35 (1):19-45.

Correljé, Aad, and Coby van der Linde. 2006. "Energy supply security and geopolitics: A European perspective." *Energy Policy* 34 (5):532-543.

Costantini, Valeria, Francesco Gracceva, Anil Markandya, and Giorgio Vicini. 2007. "Security of energy supply: Comparing scenarios from a European perspective." *Energy Policy* 35 (1):210-226.

Dayanandan, Ajit, and Han Donker. 2011. "Oil prices and accounting profits of oil and gas companies." *International Review of Financial Analysis* 20 (5):252-257.

Degiannakis, Stavros, George Filis, and Renatas Kizys. 2014. "The Effects of Oil Price Shocks on Stock Market Volatility: Evidence from European Data." *The Energy Journal* 35 (1):35-56.

Degiannakis, Stavros, George Filis, and Sofia Panagiotakopoulou. 2018. "Oil price shocks and uncertainty: How stable is their relationship over time?" *Economic Modelling*.

Dutta, Anupam. 2017. "Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index." *Journal of Cleaner Production* 164:1157-1166.

Dutta, Anupam, Elie Bouri, Debojyoti Das, and David Roubaud. 2020. "Assessment and optimization of clean energy equity risks and commodity price volatility indexes: Implications for sustainability." *Journal of Cleaner Production* 243:118669.

Dutta, Anupam, Elie Bouri, and Md Hasib Noor. 2018. "Return and volatility linkages between CO2 emission and clean energy stock prices." *Energy* 164:803-810.

El-Sharif, Idris, Dick Brown, Bruce Burton, Bill Nixon, and Alex Russell. 2005. "Evidence on the nature and extent of the relationship between oil prices and equity values in the UK." *Energy Economics* 27 (6):819-830.

Elie, Bouri, Jalkh Naji, Anupam Dutta, and Gazi Salah Uddin. 2019. "Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach." *Energy* 178:544-553.

Engle, Robert F., Eric Ghysels, and Bumjean Sohn. 2013. "Stock market volatility and macroeconomic fundamentals." *The Review of Economics and Statistics* 95 (3):776-797.

Engle, Robert F., and Jose Gonzalo Rangel. 2008. "The Spline-GARCH model for low-frequency volatility and its global macroeconomic causes." *The Review of Financial Studies* 21 (3):1187-1222.

Escribano Francés, Gonzalo, José María Marín-Quemada, and Enrique San Martín González. 2013. "RES and risk: Renewable energy's contribution to energy security. A portfolio-based approach." *Renewable and Sustainable Energy Reviews* 26:549-559.

Fama, Eugene F., and Kenneth R. French. 1989. "Business conditions and expected returns on stocks and bonds." *Journal of Financial Economics* 25 (1):23-49.

Fang, Libing, Baizhu Chen, Honghai Yu, and Cheng Xiong. 2018. "The effect of economic policy uncertainty on the long-run correlation between crude oil and the U.S. stock markets." *Finance Research Letters* 24:56-63.

Ferrer, Román, Syed Jawad Hussain Shahzad, Raquel López, and Francisco Jareño. 2018. "Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices." *Energy Economics* 76:1-20.

Filipović, Sanja, Mirjana Radovanović, and Vladimir Golušin. 2018. "Macroeconomic and political aspects of energy security – Exploratory data analysis." *Renewable and Sustainable Energy Reviews* 97:428-435.

Flammer, Caroline. 2020. "Corporate Green Bonds." *Journal of Financial Economics (JFE), Forthcoming*.

Ghysels, Eric, Arthur Sinko, and Rossen Valkanov. 2007. "MIDAS regressions: further results and new directions." *Econometric Reviews* 26 (1):53-90.

Gkillas, Konstantinos, Rangan Gupta, and Mark E. Wohar. 2018. "Volatility jumps: The role of geopolitical risks." *Finance Research Letters* 27:247-258.

Gonçalves, Sílvia, and Lutz Kilian. 2004. "Bootstrapping autoregressions with conditional heteroskedasticity of unknown form." *Journal of Econometrics* 123 (1):89-120.

Gupta, Eshita. 2008. "Oil vulnerability index of oil-importing countries." *Energy Policy* 36 (3):1195-1211.

Gupta, Kartick. 2016. "Oil price shocks, competition, and oil & gas stock returns — Global evidence." *Energy Economics* 57:140-153.

Gupta, Kartick. 2017. "Do economic and societal factors influence the financial performance of alternative energy firms?" *Energy Economics* 65:172-182.

Hache, Emmanuel. 2018. "Do renewable energies improve energy security in the long run?" *International Economics* 156:127-135.

Hachenberg, Britta, and Dirk Schiereck. 2018. "Are green bonds priced differently from conventional bonds?" *Journal of Asset Management* 19 (6):371-383.

Hamed, Tareq Abu, and Lindsey Bressler. 2019. "Energy security in Israel and Jordan: The role of renewable energy sources." *Renewable Energy* 135:378-389.

Henriques, Irene, and Perry Sadorsky. 2008. "Oil prices and the stock prices of alternative energy companies." *Energy Economics* 30 (3):998-1010.

Hyun, Suk, Donghyun Park, and Shu Tian. 2020. "The price of going green: the role of greenness in green bond markets." *Accounting & Finance* 60 (1):73-95.

Inchauspe, Julian, Ronald D. Ripple, and Stefan Trück. 2015. "The dynamics of returns on renewable energy companies: A state-space approach." *Energy Economics* 48:325-335.

Ji, Qiang, Bing-Yue Liu, Henrik Nehler, and Gazi Salah Uddin. 2018. "Uncertainties and extreme risk spillover in the energy markets: A time-varying copula-based CoVaR approach." *Energy Economics* 76:115-126.

Joëts, Marc, Valérie Mignon, and Tovonony Razafindrabe. 2017. "Does the volatility of commodity prices reflect macroeconomic uncertainty?" *Energy Economics* 68:313-326.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring uncertainty." *American Economic Review* 105 (3):1177-1216.

Kahlenborn, Walter, Annica Cochu, Ivo Georgiev, Frederik Eisinger, and Dominic Hogg. 2017. *Defining "green" in the context of green finance. Final Report*.

Kaminker, Christopher, and Fiona Stewart. 2012. "The Role of Institutional Investors in Financing Clean Energy."

Kanamura, Takashi. 2020. "A model of price correlations between clean energy indices and energy commodities." *Journal of Sustainable Finance & Investment*:1-41.

Kang, Wensheng, Fernando Perez de Gracia, and Ronald A. Ratti. 2017. "Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations." *Journal of International Money and Finance* 70:344-359.

Kang, Wensheng, and Ronald A. Ratti. 2013a. "Oil shocks, policy uncertainty and stock market return." *Journal of International Financial Markets, Institutions and Money* 26:305-318.

Kang, Wensheng, and Ronald A. Ratti. 2013b. "Structural oil price shocks and policy uncertainty." *Economic Modelling* 35:314-319.

Kang, Wensheng, Ronald A. Ratti, and Joaquin L. Vespignani. 2017. "Oil price shocks and policy uncertainty: New evidence on the effects of US and non-US oil production." *Energy Economics* 66:536-546.

Kang, Wensheng, Ronald A. Ratti, and Kyung Hwan Yoon. 2015. "Time-varying effect of oil market shocks on the stock market." *Journal of Banking & Finance* 61:S150-S163.

Karpf, Andreas, and Antoine Mandel. 2018. "The changing value of the 'green' label on the US municipal bond market." *Nature Climate Change* 8 (2):161-165.

Kilian, Lutz. 2009. "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market." *American Economic Review* 99 (3):1053-69.

Kilian, Lutz, and Cheolbeom Park. 2009. "The impact of oil price shocks on the U.S. stock market*." *International Economic Review* 50 (4):1267-1287.

Kilian, Lutz, and Clara Vega. 2011. "Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices." *The Review of Economics and Statistics* 93 (2):660-671.

Kim, Gil, and David Vera. 2018. "Recent drivers of the real oil price: Revisiting and extending Kilian's (2009) findings." *Energy Economics*.

Kocaarslan, Baris, and Ugur Soytas. 2019a. "Asymmetric pass-through between oil prices and the stock prices of clean energy firms: New evidence from a nonlinear analysis." *Energy Reports* 5:117-125.

Kocaarslan, Baris, and Ugur Soytas. 2019b. "Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (US dollar)." *Energy Economics* 84:104502.

Kumar, Surender, Shunsuke Managi, and Akimi Matsuda. 2012. "Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis." *Energy Economics* 34 (1):215-226.

Kyritsis, Evangelos, and Apostolos Serletis. 2019. "Oil Prices and the Renewable Energy Sector." *The Energy Journal* 40.

Lee, Donggyu, and Jungho Baek. 2018. "Stock Prices of Renewable Energy Firms: Are There Asymmetric Responses to Oil Price Changes?" *Economies* 6 (4):59.

Li, Xianguo. 2005. "Diversification and localization of energy systems for sustainable development and energy security." *Energy Policy* 33 (17):2237-2243.

Liu, Jing, Feng Ma, Yingkai Tang, and Yaojie Zhang. 2019. "Geopolitical risk and oil volatility: A new insight." *Energy Economics* 84:104548.

Liu, Li, and Tao Zhang. 2015. "Economic policy uncertainty and stock market volatility." *Finance Research Letters* 15:99-105.

Ludvigson, Sydney C., Sai Ma, and Serena Ng. 2015. "Uncertainty and business cycles: Exogenous impulse or endogenous response?" *National Bureau of Economic Research*

Working Paper Series No. 21803.

Lundgren, Amanda Ivarsson, Adriana Milicevic, Gazi Salah Uddin, and Sang Hoon Kang. 2018. "Connectedness network and dependence structure mechanism in green investments." *Energy Economics* 72:145-153.

Lv, Xin, Xinyang Dong, and Weijia Dong. 2019. "Oil Prices and Stock Prices of Clean Energy: New Evidence from Chinese Subsectoral Data." *Emerging Markets Finance and Trade*:1-15.

Maghyereh, Aktham I., Basel Awartani, and Hussein Abdoh. 2019. "The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations." *Energy* 169:895-913.

Managi, Shunsuke, and Tatsuyoshi Okimoto. 2013. "Does the price of oil interact with clean energy prices in the stock market?" *Japan and the World Economy* 27:1-9.

Mohanty, Sunil, Mohan Nandha, and Gabor Bota. 2010. "Oil shocks and stock returns: The case of the Central and Eastern European (CEE) oil and gas sectors." *Emerging Markets Review* 11 (4):358-372.

Mork, Knut Anton, Øystein Olsen, and Hans Terje Mysen. 1994. "Macroeconomic Responses to Oil Price Increases and Decreases in Seven OECD Countries." *The Energy Journal* 15 (4):19-35.

Nanayakkara, Madurika, and Sisira Colombage. 2019. "Do investors in Green Bond market pay a premium? Global evidence." *Applied Economics* 51 (40):4425-4437.

Nandha, Mohan, and Robert Faff. 2008. "Does oil move equity prices? A global view." *Energy Economics* 30 (3):986-997.

Nasreen, Samia, Aviral Kumar Tiwari, Juncal Cuñado Eizaguirre, and Mark E. Wohar. 2020. "Dynamic connectedness between oil prices and stock returns of clean energy and technology companies." *Journal of Cleaner Production* 260:121015.

Ozturk, Ezgi O., and Xuguang Simon Sheng. 2018. "Measuring global and country-specific uncertainty." *Journal of International Money and Finance* 88:276-295.

Paiva, Aureliano Sancho Souza, Miguel Angel Rivera-Castro, and Roberto Fernandes Silva Andrade. 2018. "DCCA analysis of renewable and conventional energy prices." *Physica A: Statistical Mechanics and its Applications* 490:1408-1414.

Pan, Zhiyuan, Yudong Wang, Chongfeng Wu, and Libo Yin. 2017. "Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model." *Journal of Empirical Finance* 43:130-142.

Pham, Linh. 2016. "Is it risky to go green? A volatility analysis of the green bond market." *Journal of Sustainable Finance & Investment* 6 (4):263-291.

Pham, Linh. 2019. "Do all clean energy stocks respond homogeneously to oil price?" *Energy Economics* 81:355-379.

Ramos, Sofia B., and Helena Veiga. 2011. "Risk factors in oil and gas industry returns: International evidence." *Energy Economics* 33 (3):525-542.

Reboredo, Juan C. 2015. "Is there dependence and systemic risk between oil and renewable energy stock prices?" *Energy Economics* 48:32-45.

Reboredo, Juan C. 2018. "Green bond and financial markets: Co-movement, diversification and price spillover effects." *Energy Economics* 74:38-50.

Reboredo, Juan C., and Miguel A. Rivera-Castro. 2014. "Wavelet-based evidence of the impact of oil prices on stock returns." *International Review of Economics & Finance* 29:145-176.

Reboredo, Juan C., Miguel A. Rivera-Castro, and Andrea Ugolini. 2017. "Wavelet-based test of co-movement and causality between oil and renewable energy stock prices." *Energy Economics* 61:241-252.

Reboredo, Juan C., and Andrea Ugolini. 2018a. "The impact of energy prices on clean energy stock prices. A multivariate quantile dependence approach." *Energy Economics* 76:136-152.

Reboredo, Juan C., and Andrea Ugolini. 2018b. "The impact of Twitter sentiment on renewable energy stocks." *Energy Economics* 76:153-169.

Sadorsky, Perry. 2001. "Risk factors in stock returns of Canadian oil and gas companies." *Energy Economics* 23 (1):17-28.

Sadorsky, Perry. 2012. "Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies." *Energy Economics* 34 (1):248-255.

Schwert, G. William. 1989. "Why does stock market volatility change over time?" *The Journal of Finance* 44 (5):1115-1153.

Song, Yingjie, Qiang Ji, Ya-Juan Du, and Jiang-Bo Geng. 2019. “The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets.” *Energy Economics* 84:104564.

Sun, Chuanwang, Dan Ding, Xingming Fang, Huiming Zhang, and Jianglong Li. 2019. “How do fossil energy prices affect the stock prices of new energy companies? Evidence from Divisia energy price index in China's market.” *Energy* 169:637-645.

Symitsi, Efthymia, and Konstantinos J. Chalvatzis. 2018. “Return, volatility and shock spillovers of Bitcoin with energy and technology companies.” *Economics Letters* 170:127-130.

Uddin, Gazi Salah, Md Lutfur Rahman, Axel Hedström, and Ali Ahmed. 2019. “Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes.” *Energy Economics* 80:743-759.

Van Robays, Ine. 2016. “Macroeconomic uncertainty and oil price volatility.” *Oxford Bulletin of Economics and Statistics* 78 (5):671-693.

Wen, Xiaoqian, Yanfeng Guo, Yu Wei, and Dengshi Huang. 2014. “How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China.” *Energy Economics* 41:63-75.

Xia, Tongshui, Qiang Ji, Dayong Zhang, and Jinhong Han. 2019. “Asymmetric and extreme influence of energy price changes on renewable energy stock performance.” *Journal of Cleaner Production* 241:118338.

Xiao, Zhijie, and Roger Koenker. 2009. “Conditional Quantile Estimation for Generalized Autoregressive Conditional Heteroscedasticity Models.” *Journal of the American Statistical Association* 104 (488):1696-1712.

Zerbib, Olivier David. 2019. “The effect of pro-environmental preferences on bond prices: Evidence from green bonds.” *Journal of Banking & Finance* 98:39-60.

Zhang, Hao, Guixin Cai, and Dongxiao Yang. 2020. “The impact of oil price shocks on clean energy stocks: Fresh evidence from multi-scale perspective.” *Energy* 196:117099.