The Impact of Energy Structure Transition on the Electric Utility Industry

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Declaration of Originality

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Related Publications

The following list indicates the related publications derived from the author's PhD research.

Journal Articles

Xiong, C., Luo, D. and Han, L. (2023) 'The cost efficiency of the electricity retailers with the integration of the Cloud Energy Storage', *International Journal of Energy Research*, 2023, pp. 1–23. doi:10.1155/2023/2425608.

Working Papers

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Abstract

Being the largest emitter of greenhouse gas, the electric utility industry plays a key role in the energy structure transition. However, the substantial investment required for the transition poses a huge financial challenge for them. This thesis aims to investigate the specific impact of energy structure transition on the electric utility industry and seeks to provide valuable implications.

The first study examines the impact of energy structure transition on the electric utilities' capital structure. It reveals that the inclusion of energy variables improves the average leverage prediction accuracy by 12%. Notably, wind (solar) energy negatively (positively) contributes to firms' gearing. Next, firms' leverage adjustment speed is in line with the dynamic trade-off theory and adjusts quickly, with a half-life of 0.67 years for book leverage. Therefore, electric utilities can use more loans for solar projects and internal accruals or alternative financing for wind projects. Effective policies should be implemented to encourage the development of green credit and bonds.

The second study investigates whether energy structure transition affects electric utilities' risk exposure. The results manifest that including the energy variables significantly improves the classification accuracy of systematic, idiosyncratic, and total risks. Both wind and solar energy show negative correlation with systematic risk. Meanwhile, wind (solar) energy is negatively (positively) correlated with idiosyncratic and total risks. Given the different impacts of wind and solar energy on systematic and idiosyncratic risks, a sophisticated allocation between them should be designed to minimise total risk. Further, electric utilities should diversify financing sources beyond equity for higher-risk solar projects.

The third study proposes a new business model for electric supply utilities for utilising energy storage. The findings confirm that renting cloud energy storage can significantly

reduce costs and maximise profits for electricity supply utilities. The biggest saving reaches 24.5%. With the rapid fall in battery prices, the proposed strategy will be more advantageous.

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List of Abbreviations

ADASYN	Adaptive Synthetic
ANN	Artificial Neural Network
CAPM	Capital Asset Pricing Model
CBPS	Corporate Bond Purchase Scheme
CER	Corporate Environmental Responsibility
CES	Cloud Energy Storage
CSR	Corporate Social Responsibility
EIA	Energy Information Administration
ER-CES	Electricity Retailers with the CES
ESG	Environmental, Social, and Corporate Governance
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GHG	Greenhouse Gas
KLD	Kinder Lydenburg Domini
KMO	Kaiser-Meyer-Olkin
LCOE	Levelised Cost of Electricity
NRBV	Natural Resource-Based View
NSW	New South Wales
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PV	Photovoltaic
RF	Random Forest
RMSE	Root Mean Squared Error
SVM	Support Vector Machine
SVR	Support Vector Regression
TOU	Time-of-Use

Chapter 1: Introduction

1.1. Research Background

Climate change is currently one of the most extensively discussed global issues. In contrast to the pre-industrial times, the earth's average temperature has risen by 1.1°C, and the most recent decade from 2011 to 2020 is notably one of the warmest periods on record. Along with rising temperatures, extreme climatic events, food security crises, infectious disease outbreaks, and several other events have happened, all of which are jeopardising the economy, and threatening the physical and mental health of billions of people (Hernández-Delgado, 2015; Nordhaus, 2019; United Nations, 2023a). To deal with these challenges, major economies have reached consensus to address climate change. Signed by 196 parties in December 2015, the Paris Agreement sets a long-term aim of limiting global temperature rise to well below 2 °C above pre-industrial levels, and preferably to 1.5 °C.

Energy demand has been one of the foremost drivers of climate change (United Nations, 2022). The combustion of fossil fuels, including coal, oil, and gas, for the generation of electricity and heat contributes to more than 75% to global greenhouse gas (GHG) emissions and nearly 90% of all carbon dioxide emissions (United Nations, 2023b). To keep global warming below 1.5 °C, global emissions must be cut by half by 2030 and reach net-zero by 2050 (Climate Analytics, 2022). To achieve this target, the energy system must transition from fossil fuels to renewable energy[1]. Being the single largest emitter of GHG emissions, the electricity industry plays a key role in the energy structure transition among all sectors (IEA, 2021a). Currently, burning fossil fuels for power generation is responsible for over 40% of all energy-related emissions (World

[1] A wide range of renewable energy sources mainly includes wind energy, solar energy, hydropower, geothermal energy, biomass energy, and others. This study primarily focuses on the two most widely used renewable energy sources: wind and solar energy.

Nuclear Association, 2022). Moreover, the electric industry accounted for 46% of the global increase in emissions in 2021 (IEA, 2022a).

In order to meet the net-zero objective, renewable energy sources should make up almost 90% of worldwide electricity production by 2050, a significant increase from the 23% recorded in 2015, with solar photovoltaic (PV) and wind contributing to nearly 70% (IEA, 2021a, 2016). However, such large penetration will amplify instability within the power grid due to the inherent fluctuation in output of renewable energy sources. Energy storage can play a crucial role in supporting the high penetration of renewable energy (Gallo et al., 2016; IEA, 2023a). It can help avoid a significant amount of curtailment in renewables, leading to higher energy efficiency, and a more flexible and stable power grid (Arbabzadeh et al., 2019). Yet, large-scale energy storage is still in the early stages of rapid development, and must grow at an exponential pace to achieve the clean energy target (IEA, 2020a).

As the two primary forces to realise the energy structure transition, both renewable energy and energy storage require substantial investment. Indeed, over 80% of total power sector investment is currently allocated to renewables, grids, and storage (IEA, 2022b). However, the investment gap is still large. To reach net-zero targe by 2050, more than triple the annual clean energy investment will be needed until 2030 at $4 trillion per year (IEA, 2021a). Given the high capital requirements, the energy structure transition poses significant challenges and risks to the electric utility sector (Bird et al., 2013; Sinsel et al., 2020). This is mainly because the electric utilities of major economies are now market driven after the electricity market reform in the 1990s, empowering them to make independent decisions rather than being subject to direct state intervention (Sioshansi and Pfaffenberger, 2006). Under fierce market competition, they may weigh these environmental investments against their impact on firm performance. Therefore, the energy structure transition is more of an economic challenge rather than a technical obstacle as substantial funding is needed for clean projects (Donovan, 2015).

Such significant financial requirements are likely to change electric utility firms' original financing channels, thereby adjusting their capital structure. Currently, governments in major economics have implemented various subsidies and tax policies to support renewable energy investments (Murray et al., 2014; Nicolini and Tavoni, 2017; Shen and Luo, 2015). Both debt and equity market have made commitments to adjust their lending portfolios and returns to boost the deployment of clean projects (Bank of America, 2021; Bank of England, 2021; Bolton and Kacperczyk, 2021; Wen et al., 2020). However, fossil fuel subsidies are rebounding (IEA, 2023b), and the practices of both lenders and investors are not fully in line with their commitments (Larcker and Watts, 2020; Li and Pan, 2022; Monasterolo and De Angelis, 2020). In this situation, it remains uncertain whether utilities are effectively progressing the energy structure transition by actually adjusting their capital structure. Few empirical studies examine whether the energy structure transition influences capital structure. Clarifying this issue is meaningful in assessing whether market mechanisms can help in achieving the energy structure transition and determining the extent of macro-level support needed. In market mechanism do have an effect, we need to understand how the capital structure dynamically evolves as the energy structure transition progresses. Do firms actively adjust financing channels to pursue funding or inertly wait for suitable funds? Understanding this question can help in creating appropriate incentive policies.

In addition, substantial environment-related investments are often closely linked to firms' risk exposure. Studies have yielded heterogeneous results based on different markets, samples, and measurements (Albuquerque et al., 2019; Bouslah et al., 2013; Oikonomou et al., 2012; Salama et al., 2011; Sassen et al., 2016). Effectively managing risk exposure is crucial for electric utility firms, as it ensures a stable electricity price. In the face of significant risk, firms may need to decrease or even temporarily halt investments in renewable energy to control risk. Indeed, despite their rapid growth, global renewable energy investments have witnessed declines in some years in the past

(IEA, 2018). Therefore, given the importance and distinctiveness of the electric utility sector, gaining a comprehensive understanding of how the energy structure transition impacts risk exposure, along with assessing the degree of influence, becomes essential for timely adjustment of financing approaches, and facilitating a smooth and efficient energy transition process.

Finally, we need to understand how energy storage can work with the growing penetration of renewable energy to effectively mitigate the challenges posed by its inherent fluctuations. Energy storage technologies are undergoing rapid development, and equipment costs are continuously decreasing (IEA, 2023a). However, different kinds of energy storage technologies possess distinct characteristics which require specific application environments (Aneke and Wang, 2016; Gallo et al., 2016). No single energy storage technology can cater to all scenarios. Furthermore, despite the reduction in equipment costs, higher application costs and lower operational efficiency have hindered the widespread adoption of energy storage (Liu et al., 2017). Therefore, a suitable business model is needed which can overcome these disadvantages and fully capitalise on the potential benefits of energy storage technology.

In summary, this thesis investigates the effects of the energy structure transition on the capital structure and risk exposure of electric utility industry. Furthermore, it explores an innovative energy storage business model that strives to promote higher energy utilisation efficiency to accelerate the energy structure transition. It endeavours to offer insights and suggestions regarding the energy structure transition for the electricity utility industry and governments.

1.2. Development of Research Questions

With the electricity market reforms, the traditional vertically integrated electric utilities have been split into generation, transmission, distribution, and supply sectors through privatisation, restructuring, and deregulation (Sioshansi and Pfaffenberger, 2006). Utilities can be categorised into the four sectors based on their functions. Further, the business scope of large utilities often encompasses more than one sectors. The production and consumption of electricity energy are the responsibility of generation and supply sectors, respectively, which are the most market-oriented and fiercely competitive sectors. The other two sectors of transmission and distribution are responsible for power delivery. As natural monopolies, several transmission and distribution utilities are still public-owned enterprises in many countries. Therefore, when it comes to research on electric utilities, most studies tend to focus on the two sectors: generation and supply.

As the two pillars of energy structure transition, renewable energy is the primary means to achieve the transition, and energy storage is the essential supporting measure to address fluctuations during this transition. According to the function, the generation sector is responsible for making investments in renewable energies. Therefore, in this thesis, we tried to investigate the impact of the energy structure transition on utility firms' capital structure and risk exposure in the generation sector (reported in Chapters 3 and 4, respectively). Then after that, given the high penetration of renewable energy in electric utilities, we then conduced an empirical analysis to explore effective ways to utilise energy storage in dealing with fluctuations in renewables. In fact, energy storage devices can be installed in any sector of the power grid according to their different types (Ding et al., 2019; Locatelli et al., 2015). However, as the ultimate purpose of electricity production is consumption, electric supply utilities need an effective business model which optimises energy storage device utilisation. Through this, it can effectively address the fluctuations in renewable energy sources, thereby improving energy efficiency and enhancing grid flexibility. Chapter 5 explores the construction of this business model for incorporating energy storage in the supply sector. Through conducting these three studies on both sectors, a thorough understanding of the impact of energy structure transition on the electric utility sector can be obtained.

In terms of renewable energy investment, different financing channels for energy structure transition have distinct costs (IEA, 2021b). According to trade-off theory, to maximise value, a firm must find an optimised mix of debt and equity finance, referred to the optimal capital structure, which can minimise its cost of capital (Kraus and Litzenberger, 1973). As the costs of different types of capital for renewable energy investments vary with environmental conditions and policies, one must also examine whether the capital structure of electric utility firms adjusts accordingly.

Alongside the increase in renewable energy, fossil fuel use is slowing down and even decreasing, particularly coal. Consequently, the potential decrease in investments in fossil fuels might also impact the capital structure. Hence, one must further examine whether the effects on the capital structure stem from changes in renewable energy, fossil fuels, or a combination of both. Therefore, in Chapter 3, the first research question is: Do changes of the renewable energy and fossil fuels in the energy structure affect the capital structure of electric utility firms? Moreover, considering different renewable energy types possess their own distinct characteristics, it should be explored: Are the impacts of different renewable energy types on firm's capital structure consistent?

Another issue is whether electric utility firms' capital structure actively responds to the changes in the energy structure. In other word, how and at what speed does firms' capital structure adjust to reflect these changes? Estimating this speed can help in answering the last research question: Can existing capital structure theories explain the capital structure of the electric utility industry? Chapter 3 investigates these questions based on a sample of US listed electric utility companies over the period from 2010 to 2020. Understanding how electric utility firms dynamically adjust their capital structure in response to changes in their energy structure is crucial for further acceleration of the transition and formulating appropriate policies. Crucially, it can provide the useful suggestions for electric utility firms to select the most suitable financing methods for different kinds of renewable energy sources, thus achieving the optimal capital structure and maximising firm value.

Furthermore, the significant investments in energy structure transition can be viewed as a part of a company's corporate social responsibility (CSR) or corporate environmental responsibility (CER) investments. Research indicates that engaging in CSR or CER investments brings many benefits to firms, including increasing product diversity, enhancing corporate reputation, and adopting more flexible strategies (Albuquerque et al., 2019; Aragón-Correa and Sharma, 2003; Miles and Covin, 2000; Miller et al., 2020). Such advantages can lead to cost reductions, enhanced short- and long-term profits, and mitigation of firm risk (Hart and Ahuja, 1996; Liu and Lu, 2021; Oikonomou et al., 2012; Salama et al., 2011). Nevertheless, some studies indicate that CSR or CER investments can impose additional financial burdens on firms, leading to negative financial performance and increased exposure to higher risks (Barnett and Salomon, 2006; Bouslah et al., 2013; Palmer et al., 1995; Preston and O'Bannon, 1997; Sassen et al., 2016). These inconsistencies in findings might arise from two reasons. First, CSR encompasses multiple dimensions, and the selection of different proxies may result in varying estimation outcomes (Bouslah et al., 2013; Johnson and Greening, 1999; Rehbein et al., 2004; Ruggiero and Lehkonen, 2017). Different risk indicators also lead to diverse results (Albuquerque et al., 2019; Bouslah et al., 2013; Oikonomou et al., 2012; Salama et al., 2011; Sassen et al., 2016). Therefore, as a more specific environmental dimension, this thesis examines the impact of the energy structure transition on different kinds of risk exposure. The following research questions are investigated in Chapter 4: Whether and how the development of renewables affects all different types of risks faced by firms? And do different kinds of renewable energy have consistent impacts on these risks? Employing a US sample of listed electric utility firms from 2010 to 2020, Chapter 4 aims to clarify the relationship between the energy structure transition and risk exposure of electric utility firms. Separately analysing the impact of energy structure transition on each type of risk is essential as it can provide more precise information for risk management. Smaller fluctuations in risk can stabilise the market, facilitating a smoother and more efficient energy structure transition process.

Lastly, to encourage the integration of energy storage, electric supply utilities need a business model that ensures profitability for them. Electric supply utilities are often called as electricity retailers in practice. Owing to the randomness of the electricity load, electricity retailers find it impossible to formulate a completely accurate electricity procurement plan in advance to meet customer demand. Therefore, this electricity deviation needs to be traded from the spot market at a higher cost (Nazari and Akbari Foroud, 2013). The penetration of renewable energy intensifies this imbalance. Their inherent fluctuations could potentially magnify the volume of electricity procured from the spot market, thereby leading to additional cost increases. To address this situation, energy storage is undergoing rapid development and deployment. By deploying appropriate and enough storage at scale, utilities can pre-purchase electricity during periods of abundant renewable energy at more cost-effective contract rates, and subsequently, release and use it when needed. However, energy storage technologies exhibit distinct characteristics and potential application scenarios (Aneke and Wang, 2016; Gallo et al., 2016). No single technology outperforms in all aspects. This indicates that catering to different application scenarios requires investments in multiple energy storage technologies, thereby increasing investment costs. Indeed, the economic feasibility of energy storage business models has become one of the obstacles to the large-scale deployment of storage (Arbabzadeh et al., 2019; Gallo et al., 2016). In response to this challenge, this thesis adopts a rental approach to avoid direct investments in energy storage equipment and enhance economic benefits. Given the unpredictable nature of load demand, establishing an optimised model for determining the optimal amount of energy storage to be rented to maximise electricity retailers' profits is a key focus of this thesis. Chapter 5 explores this business model.

1.3. Contributions

First, as climate change accelerates, there is an increasing demand to shift from fossil fuels to cleaner energy sources. An increasing number of economic and financial studies have primarily focused on investigating the effects of diverse subjects, including environmental policies, climate risk, and carbon emissions, among others, on various samples. However, being the foremost provider of energy and largest emitter of GHG, the electric utility industry has received relatively less scholarly attention. Furthermore, many research samples exclude this industry due to its distinctive corporate characteristics. To fill this gap, this thesis thoroughly investigates the impact of the energy structure transition on the electric utility industry. The findings can provide useful references for policymakers, aid the financial sector in refining investment strategies, and empower electric utility firms to adjust their financing plans.

Second, CSR investments and their impact on firms have been a long-standing research issue. However, using a comprehensive measure of CSR can lead to biased results because it encompasses various dimensions. These dimensions may have diverse or even contrary impact on the firm; thus, the integrated measurement of CSR may lead to confounding effects (Bouslah et al., 2013; Johnson and Greening, 1999; Rehbein et al., 2004). In response to the increasing demand for separate testing of specific subthemes (Bouslah et al., 2013; Busch and Lewandowski, 2018), this research focuses on a unique issue, the energy structure transition, which belongs to the environmental dimension of CSR, and tests its impact on electric utility firms' capital structure and risk exposure. The findings show that the energy structure transition can affect both the capital structure and risk exposure of electric utility firms. This is mainly caused by the development of the renewable energy.

Third, this thesis examines the individual impact of wind and solar energy, as they exhibit different characteristics. The results show that wind and solar energy has opposite impacts on electric utility firms' capital structure and risk exposure. Thus, from the perspective of the debt and equity markets, wind and solar energy have different level of risks for lenders and investors. In particular, solar (wind) has a positive (negative) impact on leverage, suggesting that lenders would like to invest in solar energy rather than wind energy. In contrast, solar (wind) has (higher) lower risk in the equity market, indicating that investors prefer wind energy to solar energy. Such distinct impacts of wind and solar energy can provide valuable insights for financing across different capital types, as well as informing government's policy formulation.

Fourth, this thesis explores the utilisation of energy storage to improve the profits of electricity retailers. Differing from previous business models for investing in energy storage devices by the electricity retailers (Ju et al., 2020; Sun et al., 2022; Yang et al., 2020), this thesis' model considers a renting strategy to acquire energy storage capacity, thereby avoiding significant fixed costs. The rented energy storage capacities come from a centralised cloud energy storage (CES) provider, which centrally invests in and manages a range of diverse energy storage devices. The range of energy storage options helps overcome the issue of no single energy storage device being capable of adapting to all application scenarios. Moreover, an optimisation model is developed to determine precise charging and discharging rental capacities for electricity retailers. This novel business collaboration between electricity retailers and CES suppliers maximises the utilisation of each party's information and technological strengths, thus promoting large-scale energy storage utilisation and generating greater profits via economies of scale. This can further mitigate the fluctuations caused by renewable energy sources and enhances grid flexibility.

Fifth, this thesis extends the application of machine learning in the field of finance. Although some finance scholars have used machine learning methods, studies have mainly focused on specific areas, such as bankruptcy and credit risk (Härdle et al., 2009; Harris, 2013; Kim and Sohn, 2010; Shin et al., 2005; Zhou et al., 2014). Most other studies still rely on traditional econometric regression methods. However, regression methods may not effectively identify nonlinear relationships, which could lead to biased results (Amini et al., 2021). For instance, linear regression techniques may find it challenging to accurately identify relevant features while examining the impact of the energy structure transition on electric utility firms. This difficulty arises from the relatively short period of energy structure transition and the non-linear characteristics associated with the development of renewable energy. In contrast, machine learning exhibits a notable advantage in handling non-linear relationships. By utilising machine learning methods to dynamically capture the multifaceted effects of energy structure transition on electric utilities, this thesis expands its application to examining capital structure and firm risk.

1.4. Structure of the Thesis

This thesis has six chapters. Chapter 1 presents an overview research background. Chapter 2 discusses the theoretical framework and reviews the literature. Chapter 3 investigates the impact of energy structure transition on electric utility firms' capital structure. Chapter 4 examines the effect of energy structure transition on their risk exposure. Chapter 5 discusses the cost optimisation of electricity retailers with the integration of energy storage. Finally, Chapter 6 summarises the primary findings of the three studies, along with drawing conclusions and policy implications.

Chapter 2: Literature Review

2.1. Theoretical Background

"Does it pay to be green?" is a long-debated question that has not reached an agreement. According to neoclassical economic theory, the primary objective of any company is to maximise its profits and shareholders' return (Friedman, 1970; King and Lenox, 2002). However, environmental investments can consume a company's financial resources and generate additional costs (Haveman and Christainsen, 1981; Walley and Whitehead, 1994). This, in turn, can diminish a company's marginal returns (van Soest and Bulte, 2001), and thus, its competitiveness (Hull and Rothenberg, 2008). Such outcomes deviate from the objectives of neoclassical economic theory.

The natural resource-based view (NRBV) presents an alternative perspective (Hart, 1995; Majumdar and Marcus, 2001; Porter and van der Linde, 1995). It argues that pollution is economically wasteful, signifying inefficient resource utilisation, especially given the limited nature of resources. Therefore, it encourages companies to proactively adopt environmental strategies, such as seeking alternative resources, driving green technological innovation, and restructuring supply chains to reduce resource wastage. The implementation of these strategies can increase production efficiency (Sharma and Vredenburg, 1998), improve employee skills and qualities (Hart and Ahuja, 1996; Reinhardt, 1999), and enhance corporate reputation (Miles and Covin, 2000). These advantages can bolster a company's competitive advantage and promote financial performance (Chan, 2005; Hart, 1995; Hart and Dowell, 2010).

Stakeholder theory offers another viewpoint on the positive impact of environmental investments on corporate performance (Clarkson, 1995; Donaldson and Preston, 1995; Freeman, 1984). It asserts that firms should consider the needs of all stakeholders, not just shareholders. These stakeholders encompass creditors, employees, customers, suppliers, public interest groups, and government agencies, among others. Meeting their demands can create value for shareholders (Freeman, 2010). Welford et al (2008) found that the environment is a primary concern for stakeholders. Therefore, investments in environmental initiatives can yield several benefits, including building a strong reputation, and fostering long-term relationships with suppliers and consumers, which can enhance the competitiveness and financial performance of firms (Hillman and Keim, 2001; Lankoski, 2008). Moreover, aligning with stakeholders' environmental preferences can provide companies with diversification advantages, leading to customer loyalty, and thus, increasing profits and reducing risks (Berman et al., 1999; Galdeano-Gómez et al., 2008; Rivera, 2002).

However, some scholars have pointed out that the benefits of environmental protection activities may not fully compensate for the incurred costs (Preston and O'Bannon, 1997; Waddock et al., 1997). Therefore, rational managers should make a trade-off between environmental investments and achieving good firm performance (McWilliams and Siegel, 2001).

2.2. Relationship between Energy Structure Transition and Capital Structure

Firm value is often related to the capital structure due to the different costs of debt and equity. A rational optimal arrangement of debt and equity can reduce costs and enhance firm value. Different capital structure theories provide diverse rationales for allocating capital. Modigliani and Miller (1958) argue that in a perfect market, the capital structure is irrelevant to firm value due to the absence of any advantages derived from shifting between equity and debt. However, the capital structure matters in reality. Different capital structure theorems have been developed based on diverse relaxations of the assumptions. Trade-off theory demonstrates that firms can achieve an optimal capital structure while maximising firm value by finding the right balance between debt and equity financing (Fischer et al., 1989; Kraus and Litzenberger, 1973; Strebulaev, 2007).

Static version of trade-off theory suggests that firms can take advantage of the benefit of tax shield while simultaneously considering the cost of financial distress to adjust the debt level to the optimal point (Kraus and Litzenberger, 1973). Meanwhile, the dynamic version further considers the adjustment costs and claims that a debt ratio range is a better target for firms to make adjustments (Fischer et al., 1989; Strebulaev, 2007). According to their difference, the static trade-off theory argues that firms adjust their leverage instantly when a deviation happens, resulting in an adjustment speed close to one. In contrast, the dynamic trade-off theory contends that the adjustment speed is between zero and one (Amini et al., 2021).

The other two popular capital structure theories are pecking order and market timing theories. Both claim no optimal capital structure (Baker and Wurgler, 2002; Myers, 2001; Myers and Majluf, 1984). Pecking order theory emphasises that firms prioritise using internal accruals, followed by debt and finally equity because of their increasing costs. It also suggests that seeking external financing is viewed negatively by the market due to information asymmetry, leading firms to avoid it. Market timing theory asserts that the decision about capital structure is simply the cumulative result of efforts to time the equity market. All three theories have been demonstrated as valid in certain cases, but have also faced criticism (Amini et al., 2021; Flannery and Rangan, 2006; Frank and Goyal, 2003; Huang and Ritter, 2009; Myers, 2001).

Scholars argue that no single universal capital structure theory can be applied to all scenarios. Therefore, one must individually investigate the capital structure of each research sample (Akhtar, 2005; Chang et al., 2014; Frank and Goyal, 2009; Öztekin, 2015). Clearly, the core difference between these theories lies in the assumption of a target leverage. Therefore, except for the static and dynamic trade-off theories, the adjustment speed for both pecking order and market timing theories are zero, as they claim no optimal capital structure (Amini et al., 2021). However, since the target leverage cannot be directly observed, it must be deduced from predictions. Hence, confirming the key determinants becomes essential.

Lots of studies have focused on the firm-level accounting and financial variables as well as macroeconomic ones, confirming a group of widely accepted determinants of capital structure (Akhtar, 2005; Amini et al., 2021; Frank and Goyal, 2009; Öztekin, 2015; Rajan and Zingales, 1995). As environmental issues have attracted more public attention in recent years, scholars find that firms with environmental problems, such as the climate risks, tend to have lower debt levels (Ginglinger and Moreau, 2019; Nguyen and Phan, 2020). The increasing importance of environmental factors makes them unignorable in explaining capital structure; otherwise, results on the target leverage estimation can be biased (Amini et al., 2021).

As the energy producer, energy structure of the electric utility sector is closely related to the amount of carbon emissions (Li et al., 2021; Matsumoto, 2015; Yu et al., 2018). Firms with lower emissions often attract financial institutions with lower interest, which enables them to achieve higher leverage (Chava, 2014; Sharfman and Fernando, 2008). However, the costs associated with emission reduction are often high and volatile, which conveys a risk signal to the market, ultimately leading to decreased borrowing capacity (Nguyen and Phan, 2020; Ni et al., 2022; Shu et al., 2023; Yang et al., 2022). Hence, carbon emissions and capital structure may have a dynamic relationship, which is closely linked to the emissions reduction costs at different stages. These expenses often include investments in renewable energy and carbon compliance costs related to fossil fuels, which can be effectively represented by changes in energy structure.

In addition, financing for renewable energy and fossil fuels exhibits different characteristics. Despite gaining government financing support, renewable energy still faces a significant funding gap (Curtin et al., 2017; Ng and Tao, 2016). Banks play a crucial role in supporting renewable energy projects. Besides providing substantial loans, state investment banks also implement educational programs within the financing sector, thereby facilitating future loans by reducing information gaps (Geddes et al., 2018; Moody's Investor Service, 2019). Moreover, other debt financing sources, like green bonds, have gradually assumed a more significant role (Ng and Tao, 2016). With this continuous financial support, the risks (costs) in investing renewable energy have declined (Egli, 2020; In et al., 2022; Shrimali, 2021). By contrast, fossil fuels have faced steady or even rising costs due to increased mining and transportation expenses, higher pollution management costs, and additional taxes and compliance fees (In et al., 2022; Shrimali, 2021). Consequently, their investment risk now surpasses that of renewables (Shrimali, 2021). Therefore, risk-averse capital may instinctively move away from firms heavily depending on fossil fuels.

Notably, different types of renewables possess their own distinct traits. Although the global weighted average levelised cost of electricity (LCOE) of solar photovoltaic (PV) is still higher than that of onshore wind in 2020, it experienced a much larger decline in cost between 2010 and 2021 (IRENA, 2021). Moreover, compared with solar energy, wind energy usually comes with a higher risk of resource fluctuations (Shrimali, 2021). Consequently, the impact of different renewable energy sources on capital structure may also be diverse.

As an important industry for fighting against climate change, whether electric utility firms have a target capital structure to maximise their value and adjust towards it during the energy structure transition is uncertain. To fill in this research gap, Chapter 3 first investigates whether changes of the renewable energy and fossil fuels in the energy structure affects electric utility firms' capital structure. Then, given that wind and solar energy have distinct characteristics, this thesis further analyses whether they have different influences on the capital structure. Finally, the leverage adjustment speed is calculated to evaluate the presence of an optimal capital structure, which helps in examining whether existing capital structure theories can account for these changes.

2.3. Relationship between Energy Structure Transition and Risk Exposure

Firms' risk exposure is an important aspect of firm performance. This thesis estimates firm risk based on three different risk measures: total, systematic, and idiosyncratic risks. Total risk is a firm's stock volatility and measured by the variance or standard deviation of stock returns from the past year (Bouslah et al., 2013; Jo and Na, 2012; Sassen et al., 2016). It consists of systematic and idiosyncratic risks (Jo and Na, 2012; Sassen et al., 2016). Systematic risk is a firm's reaction to market volatilities that impact all stocks, whereas idiosyncratic risk refers to firm-specific uncertainties that cannot be explained by total market fluctuations (Bouslah et al., 2013; Luo and Bhattacharya, 2009; Sassen et al., 2016; Sharpe, 1964). Based on modern portfolio theory, only systematic risk matters to asset pricing because idiosyncratic risk can be fully diversified away in a well-constructed market (Markowitz, 1952). Therefore, some corporate social responsibility (CSR) or corporate environmental responsibility (CER) studies exclusively concentrate on systematic risk. Nevertheless, recent research highlights that idiosyncratic risk is also influenced by CSR (CER), given the near impossibility of complete diversification in the actual market (Bouslah et al., 2013; Goyal and Santa-Clara, 2003; Lee and Faff, 2009; Sassen et al., 2016).

A negative correlation is often observed between systematic risk and CSR (CER) (Albuquerque et al., 2019; Oikonomou et al., 2012; Salama et al., 2011). According to stakeholder theory, one important potential reason is the diversification of CSR (CER) products, which is attractive to stakeholders with similar preferences (Dmytriyev et al., 2021; Donaldson and Preston, 1995; Ruf et al., 2001). Research on energy structure transition suggests that investments by electric utility firms in renewable energy align with customers who prefer green products, which encourages them to switch to greener energy providers (Richter, 2013). Such loyalty promotion can lead to increased profits and reduced systematic risk for firms (Albuquerque et al., 2019). However, the relationships of idiosyncratic and total risks with CSR (CER) have yielded inconsistent outcomes (Bouslah et al., 2013; Cai et al., 2016; Lee and Faff, 2009; Sassen et al., 2016). One potential explanation suggests that environmental concerns, such as climate change, could send mixed signals to the market (Bouslah et al., 2013). Specifically, the substantial initial investment required for green projects might impede shareholders' enthusiasm for further investment (Fernando et al., 2010). In addition, wind and solar energy exhibit different cost characteristics (GOV.UK, 2020; IRENA, 2021), which may lead to different effects on these risks.

As comprehensive CSR or CER proxies can confound the impacts of different dimensions (Bouslah et al., 2013; Rehbein et al., 2004), some scholars have pointed out the need to divide this issue into subthemes (Busch and Lewandowski, 2018; Correia et al., 2021). As energy structure transition is an important subtheme in the CER dimension, investigating its influence on electric utility firms' different risk types separately can perhaps shed light on and resolve controversies related to CSR or CER's influence on different kinds of risks. Hence, Chapter 4 first assesses whether and how the development of renewables affects all different types of risks faced by firms. Furthermore, due to the distinct cost characteristics of wind and solar energy, the thesis separately examines their effects on each risk.

2.4. Energy Storage and Electricity Retailers

Due to the nature of electricity, it should be produced and consumed at the same time to maintain equilibrium. Otherwise, it may lead to additional maintenance costs, insufficient energy efficiency, and even market failure, like the California crisis (Griffin and Puller, 2005; Joskow, 2001; Müsgens et al., 2014). As the intermediary between the power producers and consumers, the key role of electricity retailers is to balance supply and demand. However, both consumer demand and retail electricity price are volatile. The larger the unbalance, the higher the cost for retailers. Therefore, retailers need to work carefully with both the consumer and wholesale market sides to survive under tough competition. They use various techniques to improve the prediction accuracy of consumer load (Cecati et al., 2015; Hong et al., 2014; Xie et al., 2015). Furthermore, many procurement strategies are undertaken to address the electricity price volatility (Ciarreta et al., 2020; Hatami et al., 2009; Yang et al., 2018). They also use some financial tools to hedge the related risks (Boroumand et al., 2015; Deng and Oren, 2006; Stevenson et al., 2006).

With the increasing penetration of the renewable energy, its fluctuating nature will bring extra maintenance cost for electricity retailers, which will be reflected in an even higher electricity price. Energy storage can play a crucial role in addressing this problem of fluctuating output of renewable energy (Gallo et al., 2016). Energy storage can help in avoiding a significant amount of renewables curtailment, leading to higher energy efficiency and a more flexible and stable power grid (Arbabzadeh et al., 2019). Based on the NRBV, reducing waste and improving resource utilisation can enhance a company's competitive advantage and promote outstanding financial performance (Chan, 2005; Hart, 1995; Hart and Dowell, 2010).

However, different kinds of energy storage technologies possess distinct characteristics which require specific application environments (Aneke and Wang, 2016; Gallo et al., 2016). No single energy storage technology can cater to all scenarios. Therefore, the efficient use of energy storage is closely linked to a useful business model (Arbabzadeh et al., 2019; Gallo et al., 2016). Many optimisation models have been constructed to maximise the profit of the electricity retailers by using the energy storage system in different scenarios (Liu et al., 2021; Sun et al., 2022; Yang et al., 2020). All models verify the viability of employing energy storage to reduce costs and maximise profits for electricity retailers. However, all optimisation models assume that energy storage devices are purchased by electricity retailers. Practical obstacles, including high maintenance expenditure, policy constrains, and low control efficiency, may deter small retailers from investing in energy storage devices. To avoid the direct investment, cloud energy storage (CES), a virtual energy storage service system which invests in and manages centralised energy storage devices, has been proposed (Liu et al., 2017).

The emergence of CES provides a new option for electricity retailers to use energy storage. By renting energy storage capacity from CES, electricity retailers can utilise different kinds of energy storage devices without having to invest in all types. This flexible rental approach also helps avoid unnecessary fixed investments. However, customer demand is volatile. Therefore, retailers must figure out how they can set an optimal rental amount of energy storage to achieve equilibrium and simultaneously maximise their profits. Chapter 5 develops a business model for electricity retailers to determine the optimal rental amount of energy storage to maximise their profits.

Chapter 3: Can Energy Structure Transition Explain Capital Structure? Evidence from the Electric Utility Industry Based on Machine Learning

3.1. Introduction

Climate change is one of the most intensely discussed global issues nowadays. It refers to global warming and the long-term shift in weather patterns. Compared with preindustrial times, the average temperature of the earth is 1.1 °C higher, with the most recent decade of 2011–2020 being one of the warmest ones in recorded history. Human activities have been recognised as the primary cause of climate change, primarily owing to the burning of fossil fuels, such as coal, oil, and gas, which produce the majority of greenhouse gas (GHG) (United Nations, 2022). In response, major economies have undertaken several efforts to tackle climate change, including the creation of the Paris Agreement in 2015 to undertake joint actions. According to the consensus, to slow down further temperature rise, the global emission level must be cut in half by 2030 and reach net-zero by 2050 (Climate Analytics, 2022). This requires an extensive reform of the energy system, and switching from fossil fuels to renewables in the near future. For instance, fossil fuel consumption must be reduced by 6% annually between 2020 and 2030 to achieve the aforementioned target (United Nations, 2020).

Among various industries, the electric utility industry plays a critical role in the energy structure transition. Cumulatively, more than 40% of all energy-related CO_2 emissions are caused by burning fossil fuels for electricity generation (World Nuclear Association, 2022); it also accounted for 46% of the global increase in emissions in 2021 (IEA, 2022a). Over the past decades, the electricity generation sector has undergone significant structural changes. Figure 3.1 shows that the global growth of traditional fossil fuels, particularly coal, has significantly slowed down in recent years. Renewable energy sources (e.g. wind and solar energy), while not yet dominant in terms of overall electricity generation, are experiencing rapid development. Along with technological advancement, the electric utility industry may transform into a cleaner sector with more renewables in the near future.

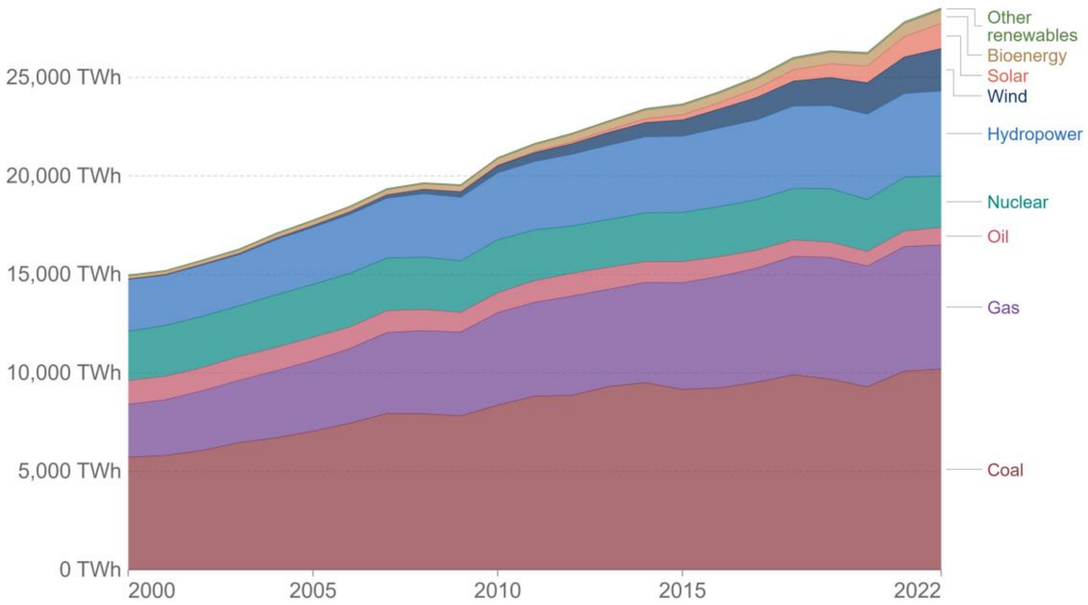

Figure 3.1. World electricity production by source (2000–2022)
Data source: https://ourworldindata.org/grapher/electricity-prod-source-stacked?time=2000..2022&facet=none

However, this energy structure transition may also bring new challenges and even shocks to electric utility firms (Bird et al., 2013; Sinsel et al., 2020). From the 1990s, all major economies across the world including the US and the UK have gradually unbundled the traditional vertically integrated electricity utilities and introduced competition via privatisation, restructuring, and deregulation (Sioshansi and Pfaffenberger, 2006). Thus, energy structure transition is no longer being completely and directly influenced by the government's direct intervention. Instead, firms are empowered to make their own decisions and strategies according to the external and internal factors, including government policies and regulations, the market environment, financing choices, operational situation, and management capabilities (Bird et al., 2013; Carley, 2009; Donovan, 2015; Richter, 2013; Yi and Feiock, 2014). Meanwhile, unlike some industries which rely heavily on fossil fuels, with the support of advanced technologies, the electric utility industry can replace fossil fuels with cleaner renewables. This can substantially reduce GHG emissions of the electricity system.

Yet, the extensive adoption of renewables remains uncertain due to the large amount of investments needed, and the subsequent balance costs caused by the fluctuating nature of renewable energy (Geddes et al., 2018). Thus, effectively and smoothly achieving the energy structure transition is not only a technical problem but more of an economic issue (Donovan, 2015). In the financial market, large landers like the Bank of America and the Bank of England have both committed to take actions on reducing GHG emissions through adjusting their lending policies and portfolios. In April 2021, the Bank of America (2021) announced to increase its 2019 commitment of $300 billion target by 2030 to $1 trillion to accelerate the transition to a low-carbon, sustainable economy as part of its Environmental Business Initiative. Meanwhile, the Bank of England (2021) is targeting a 25% reduction in the carbon intensity of its Corporate Bond Purchase Scheme (CBPS) portfolio by 2025, and net zero by 2050; further, the CBPS will tilt towards firms with stronger climate performance within their sectors. Investors have also expressed concerns over firms' exposure to higher carbon emission risk by demanding a higher return (Bolton and Kacperczyk, 2021; Wen et al., 2020).

However, in practice, the evidence is mixed as neither banks nor investors have been found to fully incorporate climate issues into their decision-makings (Larcker and Watts, 2020; Li and Pan, 2022; Monasterolo and De Angelis, 2020). Hence, this has made funding one of the major obstacles that constrains the electric utility sector's transition from fossil fuels to renewables. Consequently, firms may need to continually adjust their funding models to possible financing channels, which can directly affect their capital structures. According to Kraus and Litzenberger (1973), the trade-off theory suggests that if a firm wants to maximise its value, it needs to find the right mix of debt and equity finance to minimise the cost of capital. As both the choice of different types of finance and firms' transition to cleaner energy are heavily affected by management's decisions, exploring the relationship between the two can yield interesting and valuable insights.

This study investigates the following questions: First, do changes of the renewable energy and fossil fuels in the energy structure affect the capital structure of electric utility firms? Second, are the impacts of different types of renewable energy on firm's capital structure consistent? Third, as firms' operation may be affected by both external (e.g. government regulations towards emission reduction, loan requirements of financial institutions, and public pressure) and internal factors (e.g. changes in corporate strategy), how and at what speed does firms' capital structure adjust to reflect these changes? Lastly, can existing capital structure theories explain the capital structure of the electric utility sector?

To answer these questions, this study employs data of 42 listed US electric utility companies from 2010 to 2020. We use the machine learning approach to model the relationship between the energy structure transition and capital structure. Compared with the linear models employed by most studies, the machine learning method is more suitable for capturing the nonlinear relationships between independent and dependent variables of capital structure (Amini et al., 2021; Graham and Leary, 2011). It can also generate more reliable estimations for relatively small samples (Mountrakis et al., 2011). As the capital structure can be affected by various country, industrial, and macroeconomic factors (Akhtar, 2005; Chang et al., 2014; Frank and Goyal, 2009; Öztekin, 2015; Rajan and Zingales, 1995), focusing on the capital structure of a particular industry is more appropriate for greater precision and accuracy. With 42 publicly listed firms in the electricity sector, to our knowledge, only the US has the most comprehensive disclosures on energy data. That is one of the main reasons why we focus on US firms.

We construct two datasets of independent variables (often called as input variables in machine learning). The first dataset (hereafter, Dataset 1) consists of several firm-level accounting and financial variables (such as firm size, growth opportunities, and profitability) which are widely recognised as determinants of capital structure, while the second dataset (hereafter, Dataset 2) includes energy structure variables in addition to variables in Dataset 1. The out-of-sample R-squared (hereafter, R_{os}^2) and root mean squared error (RMSE) are compared to assess whether the inclusion of the energy structure transition can improve the prediction accuracy of the capital structure. For robustness, three machine learning methods, Support Vector Regression (SVR), Artificial Neural Network (ANN), and Random Forest (RF), are used to verify the tested results. The results of all three methods consistently indicate that R_{os}^2 of Dataset 2 are significantly higher than that of Dataset 1. This shows a sign that the energy structure transition may affect the capital structure of firms in the electric utility sector. Then Taylor expansion method is conducted to confirm the influential variables in the energy structure.

This study's contributions are five-fold. First, this study contributes to the broader literature examining the determinants of the capital structure (Akhtar, 2005; Chang et al., 2014; Frank and Goyal, 2009; Öztekin, 2015; Rajan and Zingales, 1995). We show that besides traditional accounting and financial variables, energy variables, such as renewable energy, can also affect the capital structure. This is consistent with prior findings that the environmental performance of firms does impact their capital structure (Ginglinger and Moreau, 2019; Nguyen and Phan, 2020; Sharfman and Fernando, 2008).

Second, this study uses energy structure, rather than the conventional carbon emission data or published environmental performance index to reflect the cleanness of firms' operation (Nguyen and Phan, 2020; Sharfman and Fernando, 2008). To the best of our knowledge, this is the very first study to do so; this is considered to be a more precise measurement of firms' environmental performance. The newly constructed energy structure data are hand collected from the power generation data and include all different types of energy sources used by electric utilities. It captures the dynamic variation of fossil fuels and renewable energy in firms' energy structure. A higher percentage of renewable energy tends to be associated with less carbon emission, and hence, better environment performance. Although the energy structure and carbon emission data can be seen as two sides of a coin in measuring firms' environmental performance, the former is considered to be more accurate and objective as some emissions data are hard to capture and are not reported by all companies (Bolton and Kacperczyk, 2021).

Third, by measuring the importance of each variable, this study reveals that renewable variables are playing a more significant role than traditional fossil fuels in determining the capital structure of electric utility firms. Moreover, by testing the influencing directions of solar and wind energy, this study reveals that they have opposing impacts on leverage. Solar energy positively affects leverage, whereas increased wind energy lowers firms' debt level. Thus, from the perspective of the debt market, solar investment tends to be less risky than wind investments. Therefore, this study contributes to the literature examining the investment risks and costs of renewable energy (Egli et al., 2018; Feldman and Margolis, 2019; Shrimali, 2021).

Fourth, this study confirms that the leverage adjustment speed of electric utility firms is in line with the dynamic trade-off theory (Fischer et al., 1989; Strebulaev, 2007); and this happens at a much faster speed. That is, a target capital structure does exist, and firms may take time to adjust back to the target level when they observe a deviation. Moreover, the results of the prediction model of electric utility's capital structure become more accurate when we consider the energy structure. This allows the more reliable estimation of the speed of leverage adjustment. The use of machine learning methods further improves the accuracy in estimating the target leverage level when compared with the “downward estimation” normally obtained by the conventional econometric methods (Amini et al., 2021). Thus, this finding also contributes to the literature on leverage adjustment speed (Alti, 2006; Amini et al., 2021; Huang and Ritter, 2009).

Finally, this study adopts a novel research method, the machine learning approach, to capture the non-linear relationship between the determinants of capital structure. This allows for a more accurate estimation of the partial nonlinear relationship between the variables as well as the speed of adjustment to the target leverage level. Our work also adds an empirical case on the application of machine learning in financial problems (Bianchi et al., 2021; Gu et al., 2020; Henrique et al., 2018; Yao et al., 2015). We further use the Taylor expansion method to measure the marginal contribution of each variable in terms of their respective change and ranking. This provides additional examples on identifying the relative importance of each variable after obtaining predictions or classifications based on the machine learning approach (Petridis et al., 2022; Wang et al., 2020; Yao et al., 2015; Zhang et al., 2021).

The remainder of this chapter is organised as the following. Section 3.2 undertakes the literature review and develops the research hypotheses. Section 3.3 introduces the methodology. Section 3.4 explains the data source and defines the variables. Section 3.5 discusses the empirical results. Finally, Section 3.6 presents the conclusions of this study along with some useful policy implications.

3.2. Literature Review

3.2.1. Capital Structure Theorems

The theory of modern capital structure has been set up by the famous study of Modigliani and Miller (1958). It states that in a perfect and frictionless capital market, the capital structure is irrelevant to firm value or cost of capital because no benefit can be gained from switching between equity and debt in a perfect market. However, in practice, the capital structure matters. In general, three theorems are widely quoted to offer empirical explanations of capital structure decisions of firms when various assumptions are relaxed.

According to trade-off theory, firms can achieve an optimal capital structure by finding the right balance between debt and equity finance. This can be further illustrated by two versions: static and dynamic trade-off theories. The former suggests that firms may adjust the debt level according to the benefit of tax shield and cost of financial distress to achieve the optimal capital structure and maximise firms' value (Kraus and Litzenberger, 1973). Consequently, any deviation should be adjusted instantaneously to restore the capital structure to the optimal level (Myers, 1984). However, such continuous adjustments can be extremely time consuming and expensive in practice (Myers, 1984). Instead, a debt ratio range can be a more appropriate target for firms; the leverage will be adjusted back to its target only when the deviation costs exceed the adjustment costs (Fischer et al., 1989; Strebulaev, 2007). This is the dynamic trade-off theory. Regarding adjustment speed, while some studies find that firms tend to move back towards the target debt ratios at a slower rate (Kayhan and Titman, 2007), others argue that this adjustment rate can be even exceed 30% annually (Flannery and Rangan, 2006). Such difference may be caused by the different assumptions about adjustment costs (Ai et al., 2021). Furthermore, the chosen method for modelling the target estimation also significantly impacts the speed of adjustment. Specifically, the target leverage predicted by machine learning model is more precise than that of linear models, which results in 10–33% faster speed of leverage adjustment (Amini et al., 2021).

Yet, the trade-off theory has been criticised for its inability to empirically reflect the actual capital structure choices made by firms (Myers, 2001). In particular, as benefits of tax savings are large and certain, while the risks of bankruptcy are rare and unquantifiable, rational firms should rely mainly on debt in their capital structure (Miller, 1977). For instance, highly profitable firms with substantial taxable income to shield should be more motivated to use increased debt finance. However, a different picture is observed in practice: many established, profitable firms with excellent credit ratings have low debt ratios, such as Microsoft and major pharmaceutical companies (Myers, 2001). Therefore, questions have been raised about the relationship between profitability of firms and leverage level (Fama and French, 2002). Some have explained this from the model design perspective. Still, the trade-off theory remains a dominant theory in explaining corporate capital structure decisions in academia (Ai et al., 2021).

The second theory is the pecking order theory, which emphasises the role played by cost of capital and information asymmetry in firms' financing choices (Myers, 2001; Myers and Majluf, 1984). Firms tend to rely first on internal accruals and use equity finance as the last resort. Accordingly, there is no "optimal capital structure". The pecking order theory is particularly useful to explain the negative relationship between firms' profitability and leverage level as firms should have more internally generated earnings to meet their funding gap (Shyam-Sunder and Myers, 1999). However, Fama and French's (2002) empirical work pointed out that the least-levered firms tend to make the largest net new issues of shares, while the small, fast-growing firms are more likely to have large equity. This is contrary to the "order" suggested by the theory. With the emergence of the increased number of small and unprofitable listed firms in the US over the 1990s, the pecking order theory has lost its popularity. This is mainly because these small firms do not behave according to the order suggested by the theory (Frank and Goyal, 2003).

Unlike the former two theories which are built on the costs of different types of finance, market timing theory suggests that the capital structure decision is simply the cumulative outcome of attempts to time the equity market (Baker and Wurgler, 2002). Focusing on the market-to-book ratio, Baker and Wurgler (2002) found that firm's leverage is strongly negatively related to the historical market valuations. Specifically, low-leverage (high-leverage) firms raise funds when their valuations were high (low). The impact of market valuation on the capital structure may persist for a long period, such as at least a decade. Consequently, there is no optimal capital structure again. Using the cost of equity to capture the time-varying characteristics of market conditions, Huang and Ritter (2009) verified the market timing theory. The authors further noted that when the cost of equity capital is low, publicly traded US firms are more likely to use equity to finance a relatively large funding gap; such a decision may create lasting impact on the firms' capital structure. On average, the half-life of firms to adjust their leverage level is 3.7 years. Meanwhile, some argue that the impact of market timing on leverage is short-lived, such as at most two years (Alti, 2006). It is the cross-sectional differences rather than the market timing which can explain the negative relationship between the market-to-book ratio and leverage (Hovakimian, 2006; Mahajan and Tartaroglu, 2008).

In summary, the core difference between different capital structure theories lies in the assumption of a target leverage level. The pecking order and market timing theories argue against the existence of an optimal capital structure and suggest that the adjustment speed of leverage should be zero.[2] In contrast, the static trade-off theory suggests that a target leverage exists; when a deviation happens, firms instantly adjust towards it. Therefore, the expected adjustment speed should be close to one. Next, considering the cost of adjustment, the dynamic trade-off theory concludes that leverage will not adjust immediately, resulting in an adjustment speed ranging between zero and one (Amini et al., 2021). However, one can rarely observe the target leverage ratio directly in practice. This shows the need to comprehensively investigate the key determinants of leverage.

[2] 0 and 1 are used to measure the speed of leverage adjustment. 0 means that firms will not adjust their leverage when a change incurs, while 1 means that firms will instantly adjust their leverage when a deviation happens.

3.2.2. Determinants of Capital Structure

Through investigating the determinants of capital structure, a lot of empirical studies have been done to examine the validity of these capital structure theories. Rajan and Zingales (1995) showed that among public listed firms of G7 countries, tangibility, market-to-book ratio, firm size, and profitability are key determinants of the capital structure. Akhtar (2005) observed similar results for Australian firms. Further, the domestic and multinational firms can differ in their capital structure decisions. A higher value of collateral is associated with higher leverage for domestic firms, while multinationals tend to pay more attention to bankruptcy costs and the level of geographical diversifications. Later, using a sample of US listed firms, Frank and Goyal (2009) identified two additional factors which can affect firms' capital structure decisions: the median industry leverage and expected inflation. Öztekin (2015) confirmed this in a comparative study of firms from 37 countries. Meanwhile, firms from developing countries can also be affected by other factors, including, asset growth, state control, and the largest shareholding (Chang et al., 2014). More recently, Amini et al. (2021) pioneered the study of employing machine learning models to examine the capital structure of listed firms in the US. Analysing a large sample from 1972 to 2018, the authors' best performing model selected the market-to-book ratio, industry median leverage, cash and equivalents, Z-Score, profitability, stock returns, and firm size as key predictors of market leverage.

Over the past decade, with increased environmental awareness, a growing number of studies have examined whether environmental concerns are factored in firms' capital structure decisions. The earlier work of Sharfman and Fernando (2008) noted that firms benefit from enhanced environmental risk management through a shift from equity to debt financing due to decreased firm risk perceived by the market. To tackle climate change, two influential environmental conventions, the Paris Agreement and Kyoto Protocol, have been adopted by major economies across the world and can significantly impact firms financing decisions. Firms facing higher climate risks, like carbon-intensive firms, tend to demand less debt finance compared with their cleaner counterparts (Ginglinger and Moreau, 2019; Nguyen and Phan, 2020). This reduced leverage is caused by both demand (less debt is requested by heavy polluters) and supply side reasons (bankers and bondholders increase the interest rate charged to firm with high climate risks) (Ginglinger and Moreau, 2019). Chang et al. (2021) found similar results for firms with greater environmental liabilities, noting that bank loans tend to account for a smaller percentage in these firms' total loan portfolio as banks are more willing to invest in green innovations.

Thus, with the increasing attention on environmental issues, environmental factors are likely to become an important determinant of capital structure (Ginglinger and Moreau, 2019; Nguyen and Phan, 2020; Sharfman and Fernando, 2008). The omission or ignorance of important factors may lead to noisy target estimations and the violations to existing capital structure theories, as suggested by Amini et al. (2021). Therefore, we need a thorough understanding of the role played by environmental factors, proxied by the energy structure here, in determining the capital structure of electric utility firms.

3.2.3. Energy Structure, Carbon Emission, and Capital Structure

Energy structure often refers to as the energy generation or consumption proportions of various energy types. Globally, the energy structure is being gradually transformed from one dominated by fossil fuels to a renewable energy supported system with the aim of fighting against climate change (Li et al., 2021; Matsumoto, 2015). A cleaner energy structure with more renewables can effectively reduce carbon emissions (Li et al., 2021; Matsumoto, 2015; Yu et al., 2018). As the deployment of different energy resources may lead to different funding needs for the business, the energy structure adopted by firms may directly affect their capital structure.

Some studies have explored the relationship between carbon emission and capital structures (Nguyen and Phan, 2020; Shu et al., 2023). As firms with lower emissions generally deliver better environmental performance and have low compliance costs, they are preferred by the financial institutions. Attracted by the low interest offered, such companies are more likely to have higher leverage (Chava, 2014; Sharfman and Fernando, 2008). However, during the green transition process, firms may also face increased uncertainties due to increased R&D expenses, and additional clean and/or carbon trading fees (Geddes et al., 2018; Nguyen and Phan, 2020; Ni et al., 2022). This can increase the financial risks faced by firms, and hence, reduce their borrowing capacities (Shu et al., 2023; Yang et al., 2022). Therefore, the relationship between carbon emissions and capital structure may vary during different periods and development stages. This dynamic relationship can be better explained by the energy structure transition that drives carbon emission alterations. The cost of carbon emission reduction can be effectively reflected by the energy structure transition cost, which includes investments in renewable energy and carbon compliance cost related to the burning of fossil fuels. This cost is closely linked to the company's capital structure and can be observed through variations in the production of different energy types.

Firms may choose different energy types according to their respective costs, availability, stability, and cleanness. While the energy structure transition is a global social issue, for firms, it is more about an economic challenge as substantial funding needs to be allocated to effectively and efficiently achieve emission reduction targets (Donovan, 2015). As a capital-intensive industry, the development of renewable projects requires large capital inputs (Egli, 2020; Geddes et al., 2018). For instance, achieving the target of 50% of the global energy generation from renewables by 2030 has a projected annual funding gap of $167 billion (Kim, 2015). However, financing for renewable projects has always been challenging given the various risks involved, including complex infrastructure, inadequate technological expertise, and the absence of credit records for nascent projects (Geddes et al., 2018; Polzin et al., 2015).

Although governments have provided various subsidies and soft loans, such as tariffs, grants, and tax incentives, to reduce the financing burden of firms, a large funding gap remains (Curtin et al., 2017; Ng and Tao, 2016). Consequently, bank credit is crucial. For example, from 2013 to 2019, over 100 billion euros in syndicated loans were provided by banks to support European renewable energy projects (Moody's Investor Service, 2019). Some state investment banks even offered guidance and assistance to the financial sector in form of educational programmes. This has effectively reduced the information gap between firms and banks, making it easier for firms to get loans in the future (Geddes et al., 2018). Apart from banks, innovative financial instruments, such as green bonds, have also emerged as effective means to support the development of renewable projects (Ng and Tao, 2016). Moreover, for firms investing into renewable projects, debt financing offers lower costs compared to equity and avoids dilution of ownership; hence, firms prefer debt financing (Geddes et al., 2018; Umamaheswaran and Rajiv, 2015). Thus, when firms transition towards renewables, they may need more debt finance, which increase their gearing.

Moreover, after years of policy and economic support, renewable projects have witnessed a continuous decline in risks (costs); this downward trend is expected to continue (Egli, 2020; In et al., 2022; Shrimali, 2021). Meanwhile, fossil fuels have experienced relatively stable or even increasing costs due to higher costs of mining and transportation, increased costs in pollution management, and additional tax and compliance costs levied (In et al., 2022; Shrimali, 2021). Consequently, the investment risk of fossil fuels now exceeds that of renewable energy (Shrimali, 2021). Therefore, risk-averse capital may naturally divert away from firms relying heavily on fossil fuels.

Clearly, the changes in the consumption of both renewable energy and fossil fuels will reshape the energy structure of electric utility firms. Consequently, this transformation will lead to varying environmental performances, along with diverse financing costs and risks, which are expected to be reflected in capital structure. However, for the electric utility firms who simultaneously deploy fossil and renewable projects, determining the key factors influencing their energy structure becomes crucial. Is it driven by renewable energy, fossil fuels, or a combination of both? Since both elements could potentially alter the environmental performance of these firms, we present the following hypotheses:

Hypothesis I: Renewable energy can significantly affect the capital structure of electric utility firms.

Hypothesis II: Fossil fuels can significantly affect the capital structure of electric utility firms.

Moreover, different types of renewables may also have diverse impacts on firms' capital structure decisions. For instance, solar and wind energy exhibit different level of investment risks and costs (Egli et al., 2018; Feldman and Margolis, 2019; Shrimali, 2021). Compared with wind turbines, technological advancements in solar energy have reduced the global weighted average levelised cost of electricity (LCOE) of solar photovoltaic (PV) by a much larger percentage between 2010 and 2020 (IRENA, 2021). Meanwhile, wind energy generally exhibits a higher risk of resource volatility compared to solar energy (Shrimali, 2021). Consequently, the choice of different renewables may generate different impact on firms' capital structure. Therefore, we propose our third hypothesis as follows:

Hypothesis III: *Different types of renewable energies may have diverse impacts on electric utility firms' capital structure.*

3.3. Methodology

According to previous studies, nonlinear relations have been identified between the leverage and its common determinants (Amini et al., 2021; Graham and Leary, 2011). To gain a preliminary understanding of the relations, we draw the scatter plots for the book leverage and its potential accounting and energy determinants (Figure 3.2, the data has been normalised). The plots depict the nonlinear relationship and this is consistent with the literature.

While the conventional regression method is limited to handling linear problems and a nonlinear pattern has been detected, it is reasonable to conduct the machine learning algorithms that can recognise both linear and nonlinear patterns automatically when the nonlinear relationship cannot be excluded. To provide more accurate predictions by capturing the potential non-linear relationship between the determinants and capital structure, we use machine learning to deal with the proposed problems. Machine learning (Zhou, 2021) is a subfield of artificial intelligence that focuses on utilising data and algorithms to imitate human learning, teaching computers to automatically learn from experience. Past data forms the foundation of machine learning, where the algorithms are trained on historical datasets to automatically learn and make predictions or decisions on new, unseen data. Various machine learning algorithms enable computers to analyse and interpret complex data, identify patterns, and adaptively improve their performance as the number of training samples increases.

Machine learning techniques can be primarily categorised into supervised learning and unsupervised learning. Supervised learning involves training models on known input and output data to generate reasonable predictions for new data. Classification (for discrete responses) and regression (for continuous responses) are the two main techniques in supervised learning. Meanwhile, unsupervised learning aims to discover hidden patterns or structures from unlabelled data. Clustering is the most common unsupervised learning technique. The three machine learning approaches used in this study, SVR, ANN, and RF, are all supervised learning techniques.

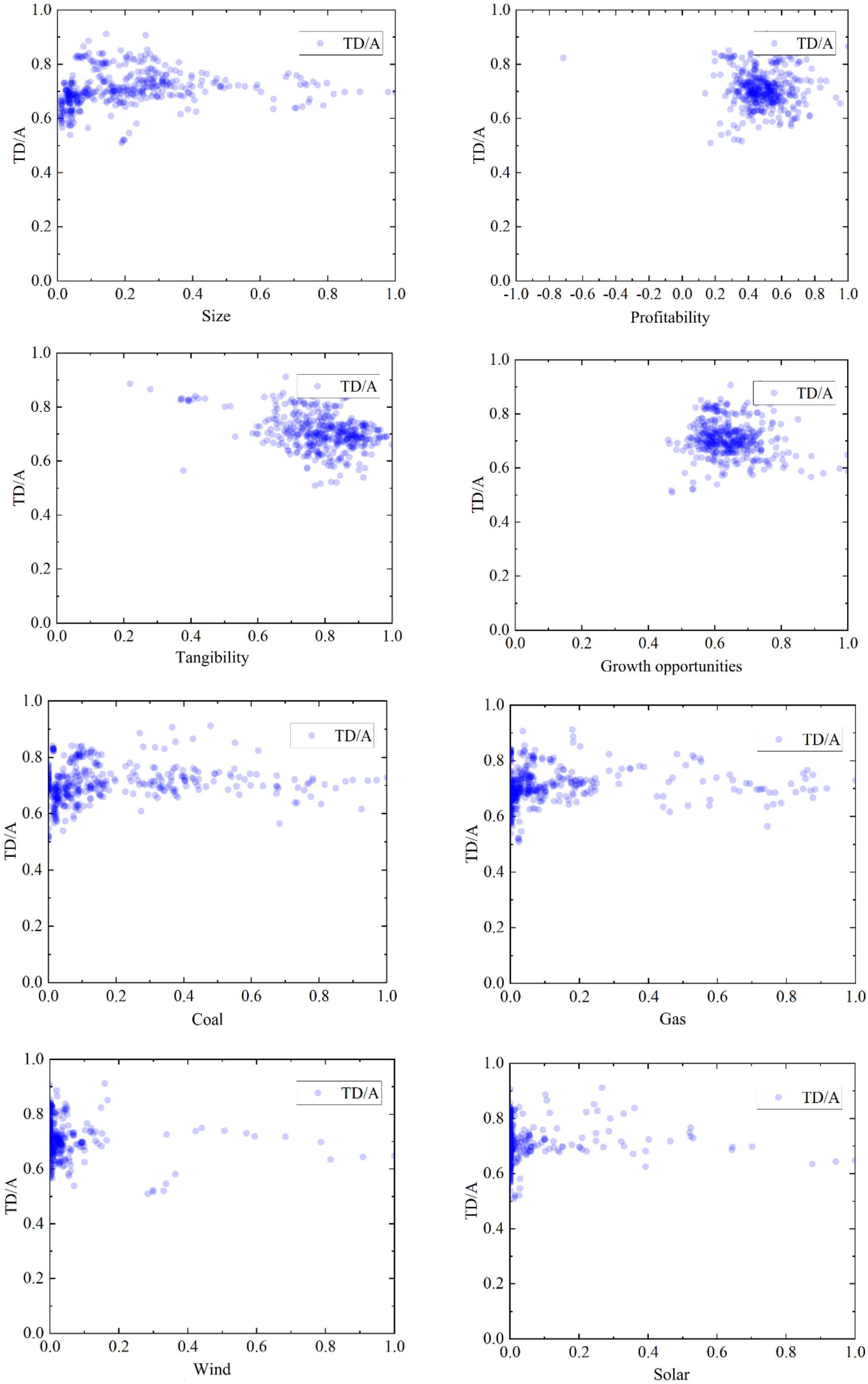

Figure 3.2. Book leverage and potential determinants

Note: The description of selected variables is given in Table 3.1.

The SVR model is a variation of the Support Vector Machine (SVM). First proposed in the 1990s, the SVM is a non-parametric learning technique for solving classification problems (Vapnik, 1998, 1995). As a supervised learning method, the basic concept of SVM is finding a hyperplane to separate training data into two categories according to their different features. Two separating paralleled hyperplanes are set for the nearest sample points, which are the support vectors, and the aim of SVM is to maximise the distance from the support vectors to the hyperplane. In this way, the classification problem is converted to a convex quadratic optimisation problem which can be solved by the Lagrangian function. Furthermore, the SVM is also capable of mapping the input data onto a high-dimensional feature space when they are not linearly separable in the original low-dimensional space.

Moreover, the risk minimisation method of SVM makes it robust with small sample size. Different from other machine learning methods and the linear regression approach, which aim to minimise the empirical risk, the principle of SVM is based on structural risk minimisation. [3] Empirical risk represents the average loss of sample points, while for the population, this average loss becomes the true risk. The true risk encompasses both empirical risk and the confidence interval, which serves as an indicator of the model's complexity. According to the function of confidence interval, it decreases as the sample size grows and increases conversely. Based on the law of large numbers, the empirical risk converges toward the true risk as the sample size goes to infinity (Luxburg & Schölkopf, 2011; Vapnik, 1991). On the contrary, with a limited sample size, especially a relatively small one, the empirical risk may deviate more from the true risk. This situation implies that the constructed model could possess weaker generalization abilities, rendering it less reliable. However, SVM addresses this by

[3] Empirical and structural risks are two important concepts in machine learning used to measure the model's fitting and generalisation abilities, respectively. A lower empirical risk indicates better fitting of the model to the training data, while structural risk considers the potential discrepancy between the training data and true distribution of the data. Therefore, reducing structural risk helps improve the model's generalisation ability (Zhang, 2011).

minimizing structural risk, which aims to minimising both empirical risk and the confidence interval at the same time (Vapnik, 1991). Consequently, SVM exhibits stronger performance with small sample sizes (Mountrakis et al., 2011). It is also less likely to have the problem of overfitting and has a stronger generalisation ability (Yu et al., 2020).

SVR is constructed based on the same principles of SVM but changes the object of the optimisation problem. Since the sample in this study exhibits signs of nonlinearity and is relatively small, SVR is a better choice than the conventional linear regression method. It can recognise both linear and nonlinear relationship between the input and output variables, and it is also robustness with small sample size. Unlike the SVM which tries to maximise the margin between two paralleled hyperplanes to maximise the distance from the nearest sample points, the two paralleled hyperplanes of SVR are set to the farthest sample points. This changes the optimisation problem of SVR to maximise the margin so that it can minimise the distance from the farthest sample points. It can be explained by the following algorithm.

Suppose the training samples are as follow:

$$S = \{(x_i, y_i) | i = 1,2, \dots, n\} \tag{1}$$

where $x_i = (x_{i1}, x_{i2}, \dots, x_{im}) \in R^m$, $y_i \in Y = R$. x_i are the input data, which include the accounting and energy structure variables, such as firm size, profitability, wind, solar, etc. y_i is the leverage, which is the prediction target of the function.

In the general form of SVR, the prediction function is:

$$f(x) = \omega^T x + b \tag{2}$$

where ω is a weight vector and b is a constant. ω and b determine the direction and position of the hyperplane, respectively, which aims to be close to y_i for each input data. They can be calculated by minimising the following regularised risk function:

$$R(f) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n} L_\varepsilon(y_i - f(x_i)) \tag{3}$$

Where C is the tolerance value, which determines the width of the margin.

$$L_\varepsilon(y_i - f(x_i)) = \begin{cases} 0, & |y_i - f(x_i)| \le \varepsilon \\ |y_i - f(x_i)| - \varepsilon, & \text{otherwise} \end{cases} \tag{4}$$

In Eq. (4), $L_\varepsilon(y_i - f(x_i))$ is a loss function. When y_i locates within the ε tube (insensitive tube), it accounts for an accurate prediction of the training point so the loss equals zero. Then, the optimisation problem can be transformed as the following:

$$min \quad \frac{1}{2}\|\omega\|^2 \tag{5}$$

$$s.t. \quad |y_i - (\omega^T x_i + b)| \le \varepsilon, \quad i = 1,2,\dots,n \tag{6}$$

Slack variables (ξ_i, ξ_i^*) are introduced to deal with otherwise infeasible constraints of the optimisaion problem. The values of ξ_i and ξ_i^* define the positive and negative deviations, respectively, out of the ε tube. The optimisation function is reformulated as follows:

$$min \quad \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{7}$$

$$s.t. \quad (\omega^T x_i + b) - y_i \le \varepsilon + \xi_i, \quad i = 1,2,\dots,n \tag{8}$$

$$y_i - (\omega^T x_i + b) \le \varepsilon + \xi_i^*, \quad i = 1,2,\dots,n \tag{9}$$

$$\xi_i \ge 0, \xi_i^* \ge 0, \ i = 1,2,\dots,n \tag{10}$$

Regularisation parameter $C > 0$ is a constant. It determines the trade-off between the training error and model robustness. The larger it is, the less fault tolerance it has.

The following Lagrangian function is constructed to solve the constraint optimisation problem:

$$L = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) + \sum_{i=1}^{n}\alpha_i((\omega^T x_i + b) - y_i - \varepsilon - \xi_i) + \sum_{i=1}^{n}\alpha_i^*(y_i - (\omega^T x_i + b) - \varepsilon - \xi_i^*) - \sum_{i=1}^{n}\mu_i\xi_i - \sum_{i=1}^{n}\mu_i^*\xi_i^* \quad (11)$$

where $\alpha_i \geq 0$, $\alpha_i^* \geq 0$, $\mu_i \geq 0$, and $\mu_i^* \geq 0$ are the Lagrange multipliers.

Then, the dual problem can be derived as follows:

$$min\ \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)x_i^T x_j + \varepsilon\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) - \sum_{i=1}^{n}y_i(\alpha_i^* - \alpha_i) \quad (12)$$

$$s.t.\ \sum_{i=1}^{n}(\alpha_i^* - \alpha_i) = 0, \quad i = 1,2,\ldots,n \quad (13)$$

$$0 \leq \alpha_i \leq C, \quad i = 1,2,\ldots,n \quad (14)$$

$$0 \leq \alpha_i^* \leq C, \quad i = 1,2,\ldots,n \quad (15)$$

The solution of the dual problem provides the value of the optimal solution to the original problem.

For nonlinear problems, SVR introduces kernel function $\kappa(x_i, x_j)$ to map all training points from the original low-dimensional space to a high-dimensional feature space. It can be expressed as follows:

$$\kappa(x_i, x_j) = \phi(x_i)^T\phi(x_j) \quad (16)$$

where x_i and x_j are training points of the sample, and $\phi(x)$ is the map function. The value of kernel function equals the inner production of two vectors in the feature space.

Different kernel functions have been verified as useful, but there are no commonly agreed criteria for choosing a proper kernel function. Following prior research (Yao et al., 2015; Yu et al., 2020), this study also adopts the common radial basis function (RBF) as the kernel function as follows:

$$\kappa(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) = \exp\left(-\gamma\|x_i - x_j\|^2\right) \quad (17)$$

where σ determines the width of the RBF. γ is the gamma term. The larger it is, the smaller the width it has, and the more complex the model becomes, leading to less generalisation ability.

When incorporating the kernel function, the SVR can then be written as:

$$f(x) = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)\, x_i^T x + b = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)\, \phi(x_i)^T \phi(x) + b = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)\, \kappa(x_i, x) + b \quad (18)$$

In SVR, parameters ε, C, and γ should be deliberately set as they determine the overall performance of the model. Particle swarm optimisation (PSO), a popular optimisation technique, is conducted to choose the optimal values of these parameters that can best balance the trade-off between the fitting and generalisation of the model (Sudheer et al., 2014).

As one of the most widely adopted kind of machine learning techniques, SVR has been widely tested as a state-of-the-art predicting technology in various disciplines, such as the electric load forecasting (Luo et al., 2023), gas consumption forecasting (Beyca et al., 2019), electricity price forecasting (Mirakyan et al., 2017), stock price prediction (Henrique et al., 2018), and loss given default prediction (Yao et al., 2015). It has proved to have superior prediction ability compared with traditional linear econometric methodologies (Loterman et al., 2012; Plakandaras et al., 2015; Yao et al., 2015) and other machine learning techniques, such as ANN (Beyca et al., 2019). One possible explanation is that the regression curve obtained by the SVR is mostly defined by the underlying support vectors, and thus, is less affected by the outliers and noise (Luo et al., 2023).

Next, ANN and RF are also frequently used while dealing with nonlinear problems. ANN were originally developed to simulate the functioning of biological neural networks in the human brain (Bishop, 1995; Goodfellow et al., 2016). A typical neural network consists of three parts: an input layer, an output layer, and one or more hidden layers in between. They use interconnected nodes, or neurons, to process information, and make classifications and predictions based on inputs. In empirical tests, the ANN can be further divided into feed-forward and feedback recall architectures. Their performance depends on factors such as the number of neurons and layers, learning algorithm, and transfer function. This study uses the most common learning algorithm of ANN: the backpropagation algorithm (Wang and Ramsay, 1998). It is constructed based on the concept of minimising the sum of squared errors through backward propagation. To accomplish this, the algorithm calculates the gradient of the error for each weight in the network and adjusts the weights accordingly in a direction that reduces the error. By repeating this process iteratively, the algorithm continues to refine the network's weights until a satisfactory level of accuracy is achieved.

Meanwhile, RF is an ensemble machine learning method which builds multiple decision trees using bootstrap (Breiman, 2001). The model can be trained effectively by generating hundreds of thousands of decision trees. The algorithm works by randomly selecting a subset of the input features and bootstrapping a sample to grow each decision tree on this sample. This process is repeated multiple times, resulting in an ensemble of decision trees which generate predictions on their own. When making a final prediction, the new data is passed through each tree in the ensemble, and the output is the average estimate over all trees in the ensemble. Based on the bootstrap method, RF is less prone to overfitting compared to other regression methods and can also provide insights into the relative importance of the input features (Patel et al., 2015).

3.4. Data and Variable Construction

3.4.1. Data Source

This study chose the US electric utility industry as the sample for the following reasons. The country has the largest number of electric utility firms in the world and has successfully implemented electricity market reform in general, resulting in a vibrant electricity market. Moreover, only the US has the most comprehensive disclosure of the energy data required in this research. The US also has one of the most well-developed capital markets, allowing firms to access a wide range of funding sources.

The sample comprises an unbalanced panel data of 42 listed firms in the US electric utility industry over the period 2010–2020. Firm specific data were obtained from the Bloomberg. Originally, 276 firms were selected based on Bloomberg's BICS classification of electric utilities and narrowing the country to the US. This number, however, includes both parent and subsidiary companies. After integrating subsidiary firms into parent companies and eliminating the non-listed firms, only 83 firms remain. This is consistent with the sample employed by Hughes (2000). As the focus of this study is the energy generation sector of electric utility firms, firms that specialise in the distribution and infrastructure were removed. Finally, 42 firms remained after eliminating firms with incomplete data. The accounting and financial data were obtained from Standard and Poor's Compustat North America, while the energy data were extracted from the Global Power Plant Database and US Energy Information Administration (EIA).

The Global Power Plant Database is a comprehensive, open-source database of power plants around the world. Each power plant is geolocated and information related to its capacity, generation, ownership, and fuel type are disclosed. Here, we extracted plants in the US and manually matched them with electric utility firms in the sample. Two methods were used in the matching process. First, the corporate structure of each utility was extracted from Bloomberg and then matched with the owner of the plant to identify the power plants that belong to each electric utility firm.[4] Second, we used information from Find Energy (2022), a professional website publishing the plant information of all US utilities. We then cross-checked data obtained from these two different channels to ensure consistency and accuracy.

In addition, as the generation data covered in the Database only included the period 2013–2019, we collected data from the EIA manually to extend the sample period to 2010–2020. On the energy structure of the utility firms, we choose the power plant's annual output, rather than the installed capacity as the former is considered a more accurate measurement for the utility's current annual output generated by each energy type; for instance, many coal-fired power plants reduce their production over years and operate at levels well below the installed capacity. For a plant whose ownership was shared by two or more utilities, its production was proportionally allocated to each utility in cooperation. Thus, by using the actual annual output data of power plants, we constructed data of the output and proportion of different energy types of 42 US electric utility firms over the period from 2010 to 2020.

[4] A utility firm (say, A) may own several power plants of different energy types, such as coal-fired, hydroelectric, wind power plant, and so on. These power plants may either directly belong to Firm A or be owned by its subsidiary companies. In the Global Power Plant Database, the owner of a power plant is often a subsidiary firm, without indicating the parent utility firm it belongs to. To address this, we downloaded the cooperate structure of all 42 utility firms form Bloomberg and matched the related subsidiary firms back to their parent utility firms.

3.4.2. Variable Selection

We used two datasets of independent (input) variables. The first comprised several firm-level accounting and financial variables, including size (AT), growth opportunities (Tobin's Q), profitability (EBIT/AT), tangibility (PPENT/AT), bankruptcy risk (Z-score), and stock market conditions (Stock_return). The first four variables are widely accepted as firm level determinants of capital structure (Frank and Goyal, 2009; Ginglinger and Moreau, 2019; Nguyen and Phan, 2020). Meanwhile, machine learning methods have revealed the Z-score and stock return variables to be additional reliable determinants of capital structure (Amini et al., 2021). Table 3.1 describes the variables.

Besides the financial and accounting variables, Dataset 2 also includes the energy variables which capture the energy structure of electric utility firms. By comparing the predictive power of two datasets, we can make a preliminary assessment of the role of energy variables in predicting the capital structure of electric utility firms. Unlike studies which often use the proportion of coal or renewables in the total consumption or generation as the proxy for energy structure (Ji and Zhang, 2019; Li et al., 2021), this study used the generation of each energy type of utility firms to capture changes in the energy structure. While the energy structure transition is mainly driven by the development of renewable energy, the changes in other energy sources, especially the reduced use of fossil fuels, also reshape the energy structure. Therefore, inclusion all the energy types of the electric utilities can provide a more comprehensive and accurate assessment of the actual energy structure. It also allows us to further analyse the independent importance of each energy source, particularly renewable energy.

For the dependent (output) variables, we used four measures of financial leverage (Frank and Goyal, 2009; Nguyen and Phan, 2020): long term debts to the market value of total assets (LD/M), long term debts to the book value of total assets (LD/A), as they measure the long-term gearing level of firms, and total debts to the market value of total assets (TD/M), total debts to the book value of total assets (TD/A), as they reflect the overall leverage level of firms. The use of different measurements for leverage is to ensure the robustness of the tested results; further, we included both long-term and total debt leverages to testify whether new Basel III regulations have affected the long-term debt financing for renewable energy.

Table 3.1. Variable description

Variable	Description
Accounting and financial variables (input variable)	
AT	Total assets.
EBIT/AT	Ratio of earnings before interest and taxes to the total assets.
PPENT/AT	Ratio of net property, plant, and equipment to the total assets.
Tobin's Q	Ratio of the sum of the year-end market capitalisation, and the difference between total assets and common/ordinary equity to total assets. (PRCC_F*CSHO+AT-CEQ)/AT
Z_score	Modified Altman Z-score which equals 3.3*EBIT/AT +1.0*Sales/ AT +1.4*Retained/ AT +1.2*WCAP/ AT, where EBIT is earnings before interest and taxes, Sales is total revenue, Retained is retained earnings, and WCAP is working capital which is the difference in total current assets and total current liabilities.
Stock_returns	Cumulative annual stock returns using monthly raw returns.
Energy structure variables (input variable)	
Coal	Annual generation of coal-based energy
Gas	Annual generation of gas-based energy
Hydro	Annual generation of hydroelectric power
Nuclear	Annual generation of nuclear energy
Oil	Annual generation of oil-based energy
Solar	Annual generation of solar energy
Wind	Annual generation of wind energy
Capital structure variables (output variable)	
LD/M	Ratio of long-term debts to the market value of assets, which equals the sum of the year-end market capitalisation, and the difference between book assets and common/ordinary equity
TD/M	Ratio of total liabilities to the market value of assets, which equals to the sum of the year-end market capitalisation, and the difference between book assets and common/ordinary equity
LD/A	Ratio of long-term debts to total assets
TD/A	Ratio of total liabilities to total assets

Table 3.2 lists the descriptive statistics of the selected variables. The mean of wind and solar is not only highly surpass the median but even exceeds the third quartile, indicating significant differences in wind and solar energy among the samples. This may be because the development of wind and solar energy is progressing rapidly, and there are substantial variations in the production of wind and solar energy among different companies. Furthermore, all the independent variables are not highly correlated, which is beneficial for machine learning in accurately identifying their relationships with the dependent variable. The correlation table is available upon request.

Table 3.2. Descriptive statistics

Variable	N	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
Assets	427	32425.371	8053.372	25975.900	45530.000	30285.311
EBIT/AT	427	0.051	0.044	0.050	0.059	0.015
PPEN/AT	427	0.689	0.645	0.699	0.758	0.101
Tobin's Q	427	1.220	1.119	1.201	1.301	0.150
Zscore	427	0.588	0.462	0.567	0.696	0.191
Stock_return	427	0.120	0.025	0.129	0.228	0.157
Coal	427	16972.469	2334.644	8311.292	26460.397	21108.005
Gas	427	13695.616	669.027	4460.515	14746.834	22866.954
Hydro	427	955.295	0.000	145.344	1094.059	1730.852
Nuclear	427	15167.978	0.000	0.000	13904.351	30298.574
Oil	427	495.585	0.000	0.359	14.174	1776.266
Solar	427	370.352	0.000	0.000	123.117	1075.981
Wind	427	2012.966	0.000	343.029	1560.854	5707.777
LD/M	427	0.265	0.222	0.260	0.295	0.068
TD/M	427	0.589	0.535	0.587	0.644	0.087
LD/A	427	0.319	0.277	0.310	0.351	0.077
TD/A	427	0.708	0.672	0.703	0.740	0.065

3.5. Empirical Analysis

Next, we applied the machine learning models to investigate the following research questions: Do changes of the renewable energy and fossil fuels in the energy structure affect the capital structure of electric utility firms? Are the impacts of different types of renewable energies on firm's capital structure consistent? How and at what speed does firms' capital structure adjust? Can existing capital structure theories explain the capital structure of the electric utility sector?

3.5.1. The Predictive Power of Energy Structure on Firms' Capital Structure

To investigate the role played by the energy structure, we employed the three machine learning methods to conduct the five-year rolling prediction on the four different leverages (Amini et al., 2021). Five rolling training and test sets are employed to obtain a reliable result. For instance, data from 2010 to 2015 were used as training set to predict the value of 2016, which is the test set, while the data from 2010 to 2016 were used to predict the 2017 value. This process was repeated to get an out-of-sample prediction over the period 2016 to 2020. Two sets of input variables were employed to forecast the leverage, allowing us to compare the predictivity of the two data sets. The performance of the different prediction models was assessed by the two criteria R_{os}^2 and RMSE, which are defined as follows:

$$R_{os}^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Where N is the number of observations in the out-of-sample subset. y_i is the actual value. $\hat{y}_i$ is the predicted value, and $\bar{y}_i$ is the average value. The larger the R_{os}^2 and the smaller the RMSE, the better the performance of the model. Tables 3.3 and 3.4 report the results when the SVR is applied to all four different types of leverages. Results for the other two methods are in Appendix 1.

Table 3.3. R_{os}^2 of SVR for Datasets 1 and 2

SVR	Dataset 1				Dataset 2 with energy variables			
	LD/M	TD/M	LD/A	TD/A	LD/M	TD/M	LD/A	TD/A
2016	0.42	0.76	0.42	0.50	0.71	0.88	0.65	0.75
2017	0.84	0.69	0.83	0.52	0.83	0.86	0.85	0.81
2018	0.68	0.80	0.69	0.69	0.76	0.87	0.78	0.80
2019	0.62	0.81	0.54	0.67	0.58	0.86	0.60	0.85
2020	0.53	0.84	0.55	0.69	0.60	0.93	0.64	0.87

Table 3.4. RMSE of SVR for Datasets 1 and 2

SVR	Dataset 1				Dataset 2 with energy variables			
	LD/M	TD/M	LD/A	TD/A	LD/M	TD/M	LD/A	TD/A
2016	0.06	0.05	0.07	0.05	0.05	0.03	0.05	0.04
2017	0.03	0.05	0.03	0.05	0.03	0.03	0.03	0.03
2018	0.04	0.04	0.05	0.04	0.04	0.03	0.04	0.03
2019	0.04	0.03	0.05	0.04	0.04	0.03	0.05	0.03
2020	0.04	0.03	0.05	0.04	0.04	0.02	0.05	0.03

Clearly, the inclusion of energy structure variables can increase (decrease) the value of R_{os}^2 (RMSE) in most cases; that is, it can help improve models' predictive power for the capital structure significantly. According to EIA (2021, 2011), from 2010 to 2020, the percentage of renewables in the energy structure of the US electricity utility firms has increased from 10% to 21%. The growing public awareness towards environmental protection and greater regulatory control have forced utility firms to shift their energy structure towards a more sustainable path, which may directly impact their capital structure. Therefore, in the next section, it will calculate the importance of each variable to confirm whether certain energy types have an influence on the capital structure of electric utilities.

For a more detailed explanation and better visualisation, the results of R_{os}^2 are presented in Figures 3.3–3.6. The results for each measurement of leverage are presented separately. In each figure, different colours are used to compare results of the three machine learning methods. The dotted and solid lines stand for the results of Datasets 1 and 2, respectively.

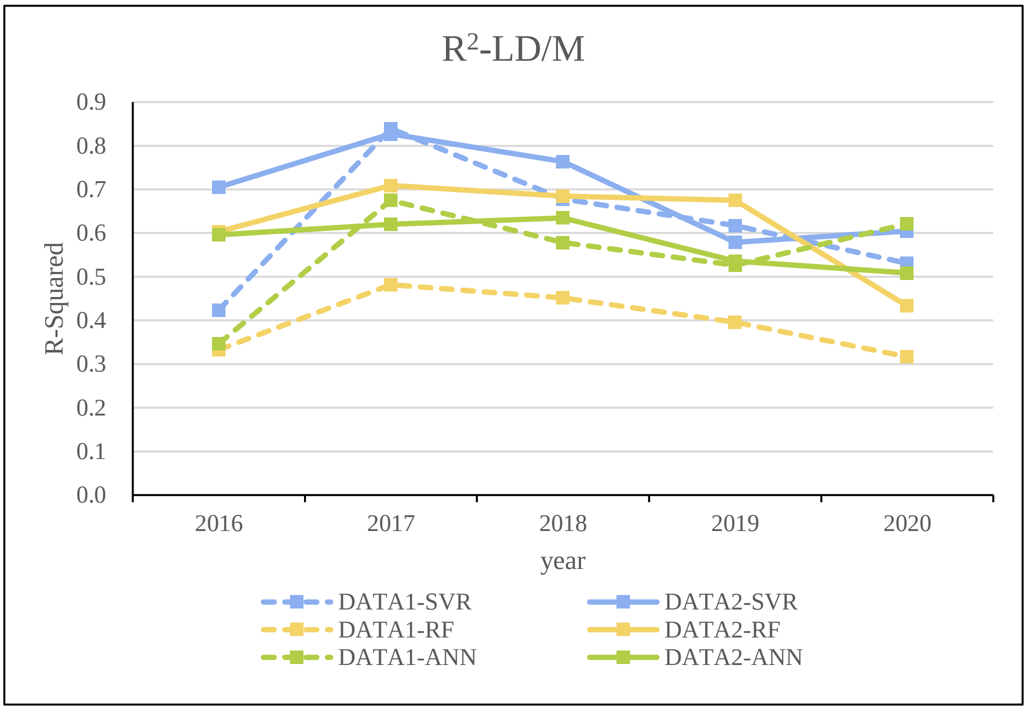

Figure 3.3. R_{os}^2 of long-term debt to market assets

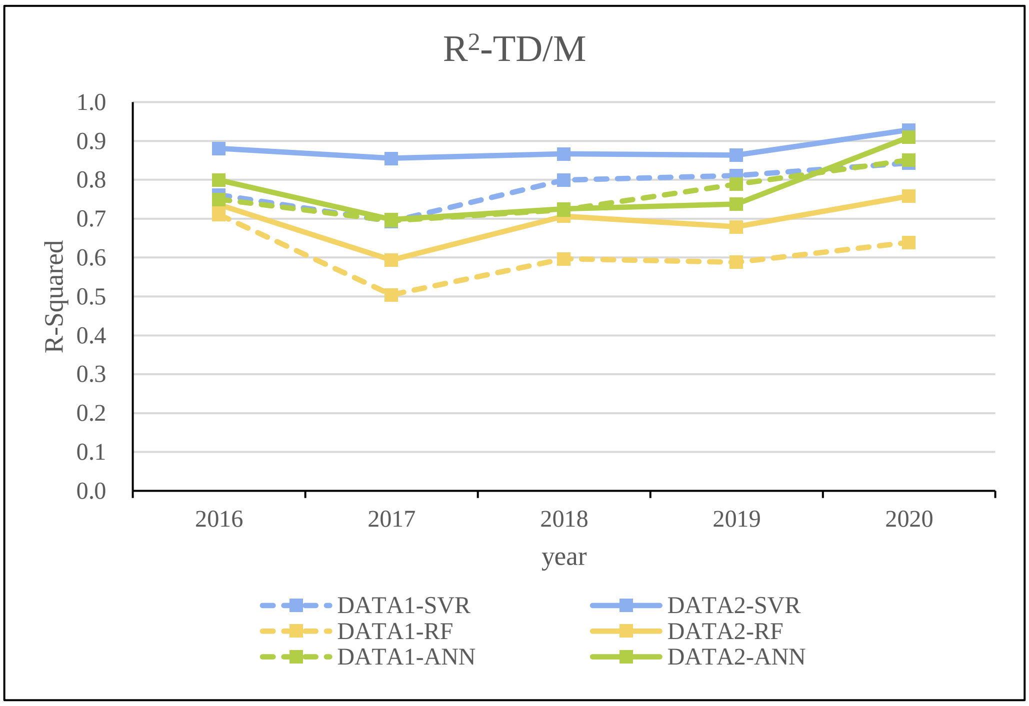

Figure 3.4. R_{os}^2 of total debt to market assets

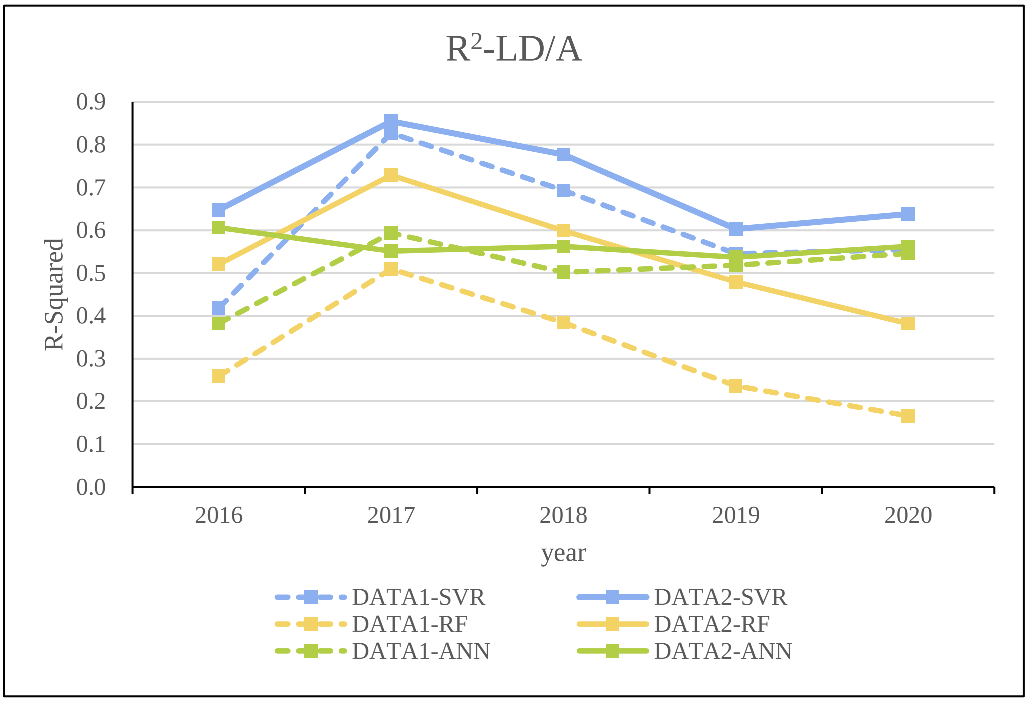

Figure 3.5. R_{os}^2 of long-term debt to book assets

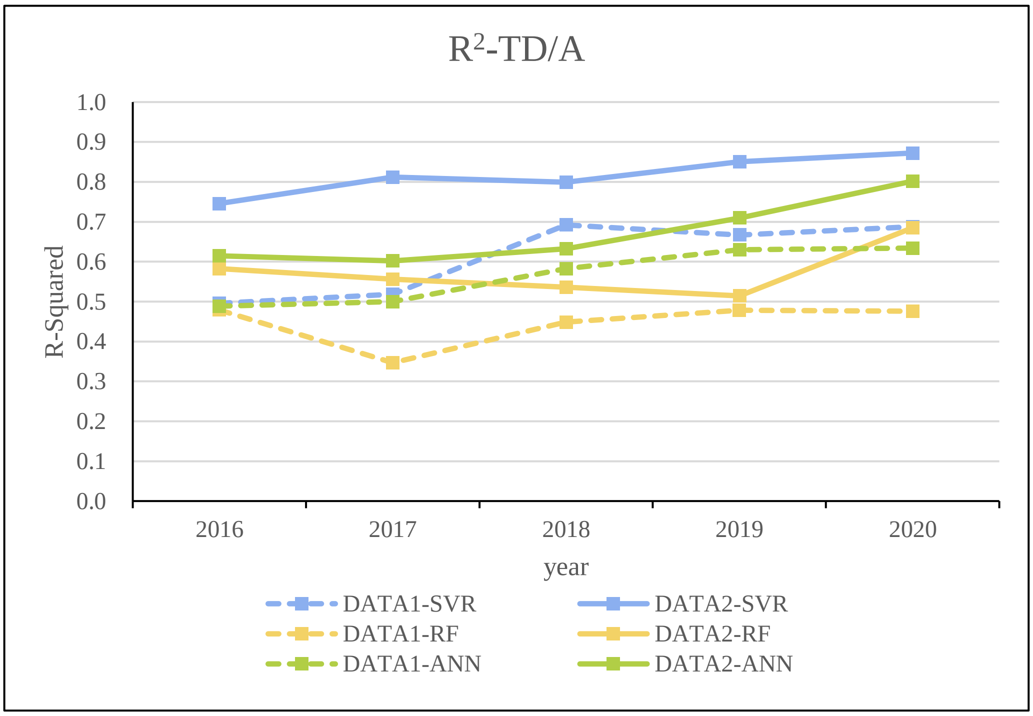

Figure 3.6. R_{os}^2 of total debt to book assets

First, when energy variables are included, Dataset 2 tends to yield higher predictive accuracy than that of Dataset 1 in most cases. The average R_{os}^2 of all Dataset 1 models is 0.56. However, this value increases to 0.68 after including the energy variable in Dataset 2. Meanwhile, the solid lines for each method in all four figures (leverages) are usually above the dotted lines, although the difference between the two types of lines varies when different methods are applied.

Second, on the prediction power of different machine learning methods, the R_{os}^2 of most models exceed 0.55 (the majority of lines in the figures are above the value of 0.55), which verifies the prediction reliability of the machine learning methods. Moreover, when the RF model is used to predict the leverage of TD/M based on Dataset 1, the value of R_{os}^2 is 0.50–0.71 (Figure 3.4). This is generally consistent with Amini et al.'s (2021) conclusions that the best performing model, RF, is capable of achieving a rolling prediction R_{os}^2 value ranging between 45.6% to 58.7% over the sample period. Among the three different machine learning methods, SVR has the best overall prediction performance with both good accuracy and stability for all four leverages (both solid and dotted blue lines are at the top of their respective counterparts in all four figures). The average R_{os}^2 of SVR models for Datasets 1 and 2 are 0.65 and 0.77 (Figure 3.3), respectively, compared with 0.44 and 0.61, respectively, for RF (Figure 3.4) and 0.60 and 0.65, respectively, for ANN (Figure 3.5). This is in line with prior findings that SVR tends to have superior prediction ability when compared with RF and ANN (Baba et al., 2015; Beyca et al., 2019; İskenderoğlu et al., 2020). This may be because the algorithm of SVR has a stronger generalisation ability due to its structural risk minimisation target (Yu et al., 2020; Zhang, 2011). Furthermore, SVR is mostly defined by the underlying support vectors, mitigating the effect of outliers and noise (Luo et al., 2023). Lastly, SVR is more robust at addressing smaller sample size (Mountrakis et al., 2011), while ANN performs better with larger sample in general (Alwosheel et al., 2018). Overall, SVR emerges as the most suitable prediction method for this study. Nevertheless, while RF does not exhibit the best prediction performance, it generates the largest difference in R_{os}^2 between Datasets 1 and 2. This may be because the RF algorithm is sensitive in identifying the decisive variable for prediction (Archer and Kimes, 2008; Strobl et al., 2008). Therefore, it provides valuable evidence in identifying the important energy variables in explaining the leverages.

Regarding the different leverage measurements, the differences in predictions between Datasets 1 and 2 appear to be more noticeable for LD/A and TD/A compared to LD/M and TD/M. In Figures 3.5 and 3.6, the solid and dotted lines of all three models show almost no overlap for LD/A and TD/A. This indicates that the potential impact of energy variables on book leverages (LD/A and TD/A) tends to be relatively stronger. This may be because the book-leverage is a better reflection of loans/debts borrowed for the development of renewables, while the market leverage is more of a forward-looking measurement (Frank and Goyal, 2009).

Moreover, the estimated R_{os}^2 of TD/M and TD/A (Figures 3.4 and 3.6) are increasing over years, but no such trends are observed for LD/M and LD/A (Figures 3.3 and 3.5). This may be because one or more of the influential factors (i.e. input features) for TD/M and TD/A have become more important and relevant in recent years, resulting in a higher predictive accuracy of the model. The R_{os}^2 for both LD/M and LD/A experienced a decline after 2017; this is coincided with the timing of the announcement of the new Basel III (Basel III, 2017). One key objective of Basel III is to enhance banks' liquidity and asset quality to withstand economic stress. However, such requirements may restrict banks' long-term lending capacity, making the long-term funding for capital-intensive renewable energy projects even more difficult (Ang et al., 2017; Ng and Tao, 2016). Consequently, when it comes to the long-term or total leverages, renewables play diverse roles.

3.5.2. Factor Importance Analysis

Next, we applied the factor importance analysis to further investigate each variable's contribution to confirm the influential energy types for the capital structure. The Taylor expansion was used to measure the importance of each variable in determining the capital structure decision of firms (Hoffman and Frankel, 2001)[5].

Assume that the function deduced by the machine learning is:

$$y = f(x_1, x_2, \dots, x_n) \tag{19}$$

When the function has a small increment at x_0, the change can be written as:

$$\Delta y = y_{x_0+\Delta x} - y_{x_0} \tag{20}$$

The change function (Δy) can be expanded by the multivariable Taylor function as the sum of the terms related to the multi-order partial derivatives:

$$\Delta y = \left[\sum \Delta x_i \cdot \frac{\partial}{\partial x_i}\right] f(x) + \frac{1}{2!}\left[\sum \Delta x_i \cdot \frac{\partial}{\partial x_i}\right]^2 f(x) + \cdots + \frac{1}{\kappa!}\left[\sum \Delta x_i \cdot \frac{\partial}{\partial x_i}\right]^\kappa f(x) + \frac{1}{(\kappa+1)!}\left[\sum \Delta x_i \cdot \frac{\partial}{\partial x_i}\right]^{\kappa+1} f(\xi) \tag{21}$$

Where i=1,2,…n, ξ is a value between x_{i0} and $x_{i0} + \Delta x_i$

Δy can be further expressed as the sum of a finite number of partial derivatives and the sum of residuals:

$$\Delta y = \Delta y_{x_1} + \Delta y_{x_2} + \cdots + \Delta y_{x_n} + \mu_{\Delta x} \tag{22}$$

When the decomposed polynomial remainder (k+1) derivative term is ignored, the increment in the variable contains the changes caused by each of the following variables:

[5] Taylor expansion is a mathematical technique used to approximate a function with a polynomial expression; it is useful for coping with the function, such as computing function values and derivatives.

$$\Delta y_{x_1} = \Delta x_1 \cdot \frac{\partial f(x)}{\partial x_1} + \frac{1}{2!}\Delta {x_1}^2 \cdot \frac{\partial^2 f(x)}{\partial x_1} + \cdots + \frac{1}{\kappa!}\Delta {x_1}^\kappa \cdot \frac{\partial^\kappa f(x)}{\partial x_1} \tag{23}$$

$$\Delta y_{x_i} = \Delta x_i \cdot \frac{\partial f(x)}{\partial x_i} + \frac{1}{2!}\Delta {x_i}^2 \cdot \frac{\partial^2 f(x)}{\partial x_i} + \cdots + \frac{1}{\kappa!}\Delta {x_i}^\kappa \cdot \frac{\partial^\kappa f(x)}{\partial x_i} \tag{24}$$

When $\Delta x_i \neq 0$, and the rest $\Delta x_j = 0, j \neq i$, Δy only reflects the effect of the change in x_i on the dependent variable. Therefore, in the multivariate function, the importance of each independent variable on the dependent variable can be investigated separately.

By calculation:

$$y_{x_0} = f(x_{10}, x_{20}, \dots, x_{i0} \dots x_{n0}) \tag{25}$$

and

$$y_{x_i} = f(x_{10}, x_{20}, \dots, x_{i0+\Delta x_i} \dots x_{n0}) \qquad \text{i=1,2,…,n,} \tag{26}$$

Δy_{x_i} can be written as:

$$\Delta y_{x_i} = \frac{y_{x_i} - y_{x_0}}{y_{x_0}} * 100\% \qquad \text{i=1,2,…,n} \tag{27}$$

This can measure the importance of each independent variable separately.

To analyse the contribution made by each energy type in firms' capital structure decisions, we constructed two representative samples with relatively higher and lower proportions of renewables in their respective energy structures. This allows us to analyse the impact of different levels (high and low) of renewables on the capital structure choices of firms. Each variable, including both financial and energy variables, was set to increase by 10% to derive the change of each leverage ratio in every year.

The absolute values of these changes reflect the importance of the input variables. A larger change indicates stronger influence of the input variable on the output variable. Note that these changes represent the variable importance within each model, and no comparisons were made between the changes of different models. When comparing the importance of variables between any two models, the primary focus is on assessing the ranks of the variables, or which variable plays a more significant role in determining the capital structure of firms. Considering the predictive advantage demonstrated by SVR, only the results of SVR are presented in this and subsequent sections. For conciseness, the results of book leverage are presented, as the market leverage provides similar findings. The results are presented in Figures 3.7–3.10.

Combining the results of both samples, among all energy variables, wind, solar, and natural gas have the most significant impact on electric utility firms' capital structure. In contrast, other fossil energy generation, coal and oil, along with other traditional energy, including hydro and nuclear, have small and limited impact. The accounting and financial variables have larger impacts than the energy variables in the low proportion sample but smaller impact in the high proportion sample.

In general, the result support the Hypothesis I and II: both renewable energy and fossil fuels can significantly affect the capital structure of electric utility firms. However, the effects of renewable energy are relatively stronger compared with fossil fuels. This may be because firms' new investments in renewable energy can be substantial (Egli, 2020; Geddes et al., 2018). Nevertheless, the relative impact generated is greatly affected by its proportion in the overall energy portfolio. In short, the larger the share of renewable energy in the overall energy supply, the greater its importance becomes, leading to stronger influence on firm's capital structure. This argument can be verified through the following three dimensions: firm, leverage, and time dimensions.

First, from the firm dimension, renewable energy variables in both LD/A (Figure 3.9) and TD/A (Figure 3.10) of the high proportion sample consistently have significantly higher importance and ranks compared to those of the low proportion sample (Figures 3.7 and 3.8). In most years, wind and solar energy of the high proportion sample rank among the top four, along with the conventional financial indicators, tangibility and growth opportunities, in determining the capital structure of firms. Notably, in over one-third of the years, solar even ranks first as the most important determinant for firms' capital structure, surpassing all financial variables. This is consistent with prior findings that the risk associated with renewable energy decreases as its proportion in the energy mix increases (Tietjen et al., 2016). Consequently, companies with a higher share of renewable energy may experience lower investment risk.

Second, in terms of leverage, compared to total debt, the impacts of wind and solar energy on long-term debt (Figures 3.7 and 3.9) are relatively small and are decreasing over the years (more clearer in the difference between LD/M and TD/M seen in Appendix 2). This aligns with our former inference that the new Basel III (2017) norms have imposed additional restrictions on firms' accessing long-term debt for renewable energy projects (Ang et al., 2017; Ng and Tao, 2016), leading to the prediction difference between the two kinds of leverage. Moreover, when we combine all figures of LD/M in the Appendix 2, wind ranks ahead of solar in almost all years for the long-term debt, while solar ranks higher than wind in the majority of years for the total debt. This is mainly because the construction of PV power plants, depending on the capacity, generally take three months to one year, while building wind farms can take one to three years. Therefore, according to the classification of liabilities, the investments in solar project tend to rely more on short-term funding and this can only be captured by total debt. Consequently, besides the negative impact of Basel III on long-term investments in renewable energy, the varying construction periods of solar and wind projects also partially contribute to the measured difference in renewable energy generated on firms' leverage. Specifically, when the total debt is used to calculate the capital structure, solar tends to play a more significant impact in determining the leverage level of firms.

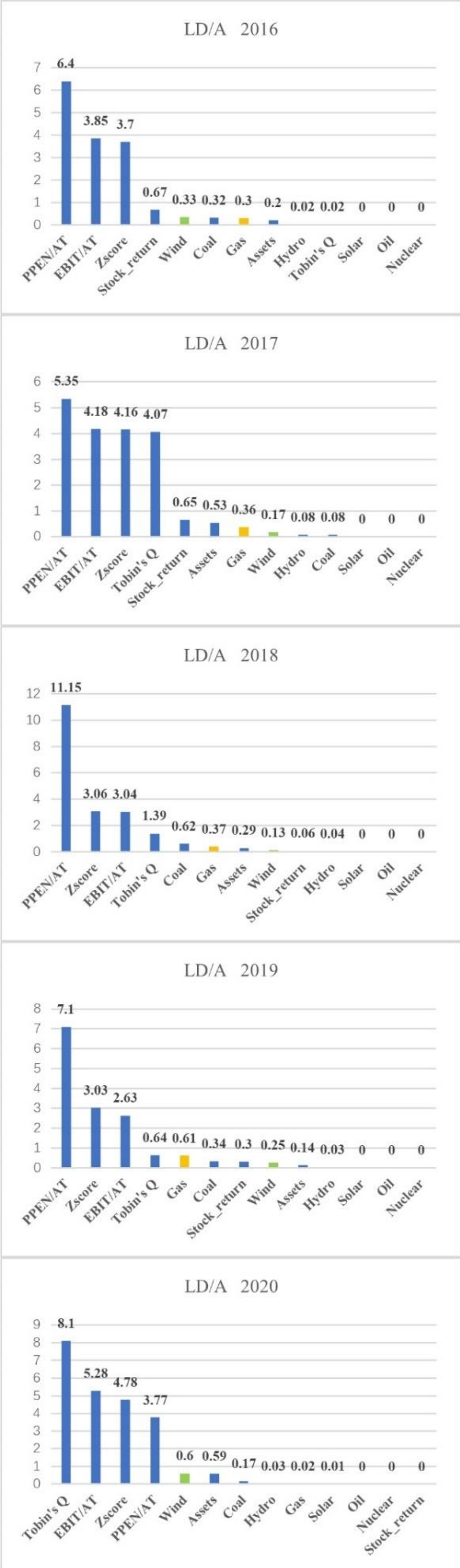

Figure 3.7. Factor importance for LD/A(L) from 2016–2020

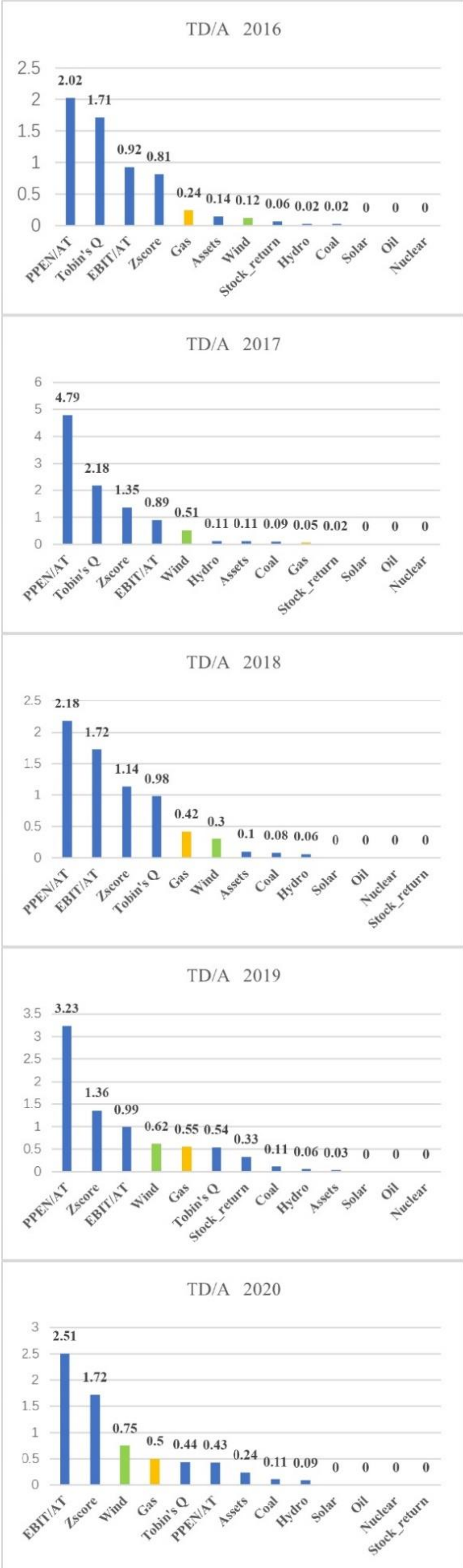

Figure 3.8. Factor importance for TD/A (L) from 2016–2020

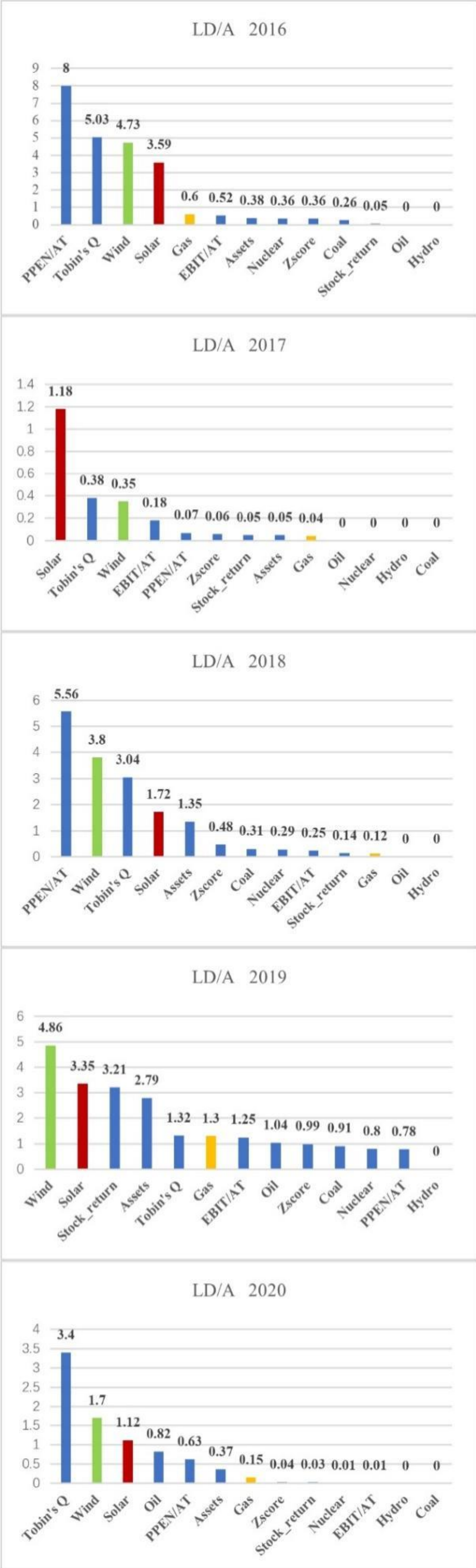

Figure 3.9. Factor importance for LD/A (H) from 2016–2020

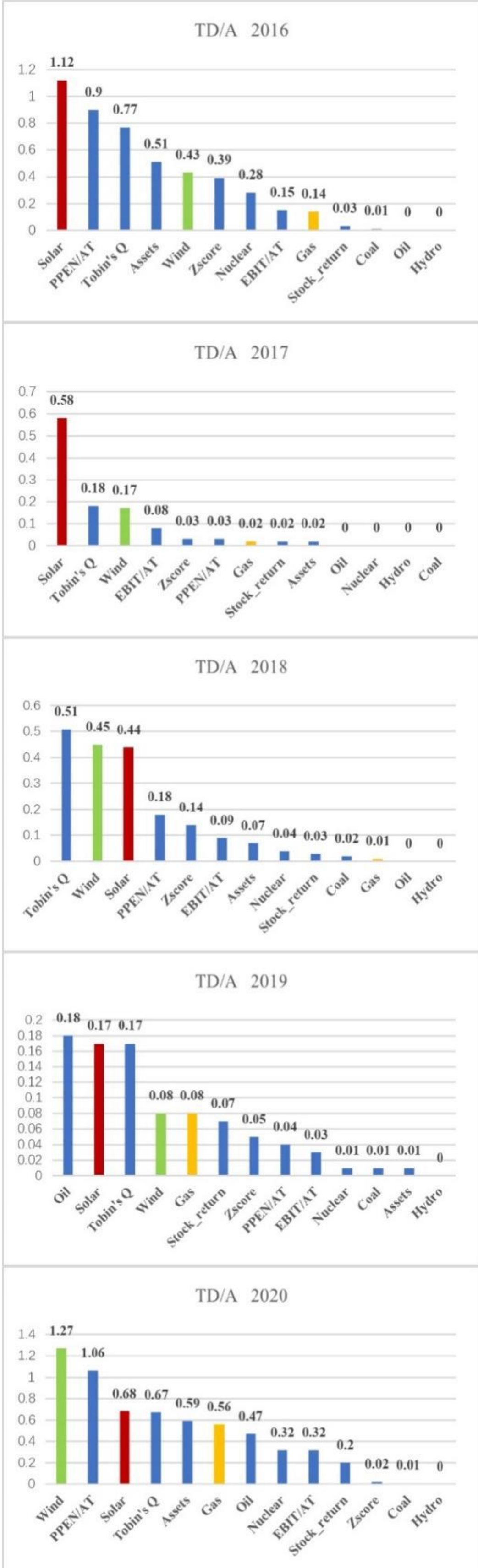

Figure 3.10. Factor importance for TD/A (H) from 2016–2020

Third, the influence of renewable energy on firm's leverage increases over years. The focus is primarily on two total debt estimations (Figures 3.8 and 3.10) as the use of long-term measurement of debt may lead to the omission of investments made on certain type of renewables. For the TD/A of the low proportion sample (Figure 3.8), the rank of wind increases from the seventh in 2016 to the third in 2020. In the high proportion sample (Figure 3.10), solar has always been in the top three, while wind ranks from the fifth to the first. The increased contribution of renewable energy is consistent with previous discussions that along with the decreased risks involved in renewable energy investments, more funding is channelled to support its development (Egli, 2020; In et al., 2022; Noothout et al., 2016; Shrimali, 2021). Consequently, renewables become increasingly important in determining firms' leverage level.

Notably, natural gas significantly affects the capital structure. It is the most influential fossil fuel for both high and low samples. In particular, within the low proportion sample, the impact of natural gas on leverage exceeds that of renewable energy in certain years (Figures 3.7 and 3.8). This is mainly because compared to other fossil fuels, natural gas is a cleaner energy source, emitting nearly 50% less carbon dioxide than coal (EIA, 2022). Furthermore, in the US, natural gas is not only more affordable than coal but has also got lower capital costs compared to wind energy (Feldman and Margolis, 2019; IEA, 2021c). Therefore, from 2010 to 2019, approximately 79% of the new capacity of the conventional US electric generation was natural gas powered (Feldman and Margolis, 2019). Therefore, natural gas will remain a key player in the energy transition process until renewable energy completely replaces fossil fuels as the dominant energy source (IEA, 2019).

Coal-powered generation has significantly decreased in the US. Due to the increasing risks associated with coal, capital has actually flown out from the sector (In et al., 2022; Shrimali, 2021). However, this capital outflow has only generated small impact on firms' capital structure as the infrastructure for coal-fired power generation has been already constructed. Consequently, the cost reduction is mainly due to decreased fuel consumption, which represents a much smaller spending when compared to the total investments needed for renewable energy projects. As a result, the impact of coal on firms' capital structure is relatively minor. Similarly, as oil only accounts for a very small proportion of the overall electricity generation, its impact on firms' capital structure is limited. Finally, as hydro power and nuclear have relatively stable electricity generation throughout the sample period, their influence on firms' capital structure is also marginal, being constantly positioned at the bottom in both of the low- and high-proportion samples.

3.5.3. Impact Directions of Variables

Here, we further analysed the direction of the impact of variables on firms' capital structure. We set the ten firms with the highest renewable energy generation as one group, and the lowest ten as another one. The average value of each variable within each group were used to test their sensitivity. The Taylor (Hoffman and Frankel, 2001) was used to calculate the change in the leverage ratios for each variable. Both changes of 5% and 10% for each input variable were applied to test the nonlinearity of the models. Figures 3.11–3.14 report the directions besides the changes and ranks of the leverage ratios when values of the input variables were changed. As Section 3.5.2 showed that total debt is a better measure for capturing the impact of changes in energy structure on capital structure, only the results of TD/A are reported here. The variables are categorised into three groups for discussion: renewable energy, other energy, and accounting and financial variables.

The degree of impact of wind and solar energy on leverage still indicate a large difference between the low and high renewable generation samples. For the low renewable sample, wind and solar rank among the bottom five variables for both the 5% and 10% changes; meanwhile, in the high renewable sample, wind and solar rank sixth and fourth, respectively. This again verifies that the impact of renewables generated on the leverage is closely related to their proportion in the overall generation.

Interestingly, wind and solar energy impact leverage differently, with wind (solar) energy contributing negatively (positively) to the gearing level of electric utility firms. This is consistent with prior findings that solar energy investments are considered less risky compared to wind as solar experiences a faster decline in the LCOE and less resource volatility risk, resulting in lower costs of capital for solar projects (Feldman and Margolis, 2019; IRENA, 2021; Shrimali, 2021). Meanwhile, wind energy is perceived to have higher investment risks and longer construction period. Consequently, financial institutions are reluctant to lend to companies with a relatively high proportion of wind energy.

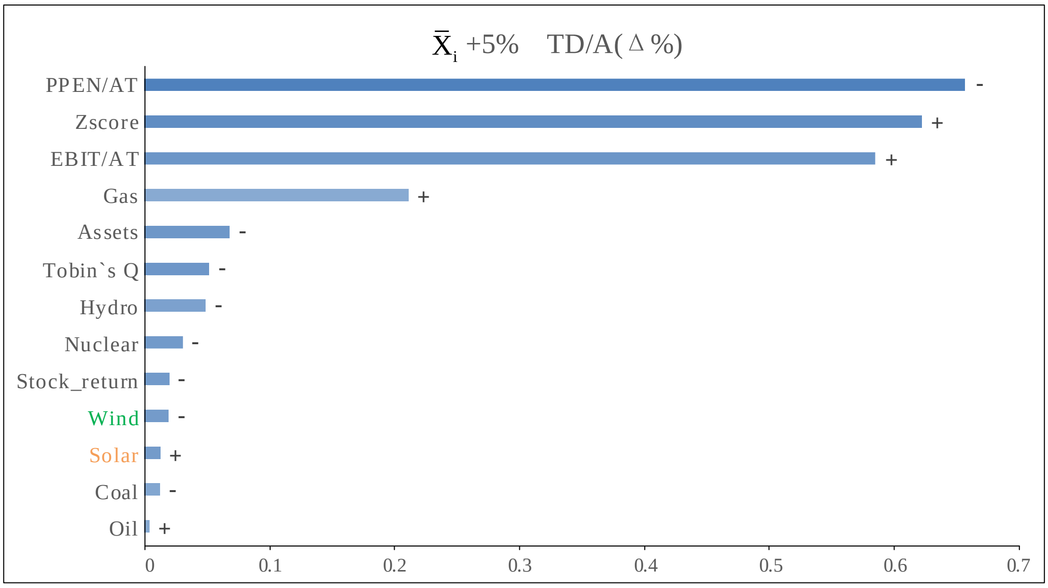

Figure 3.11. Factor directions for TD/A (L) - 5% difference

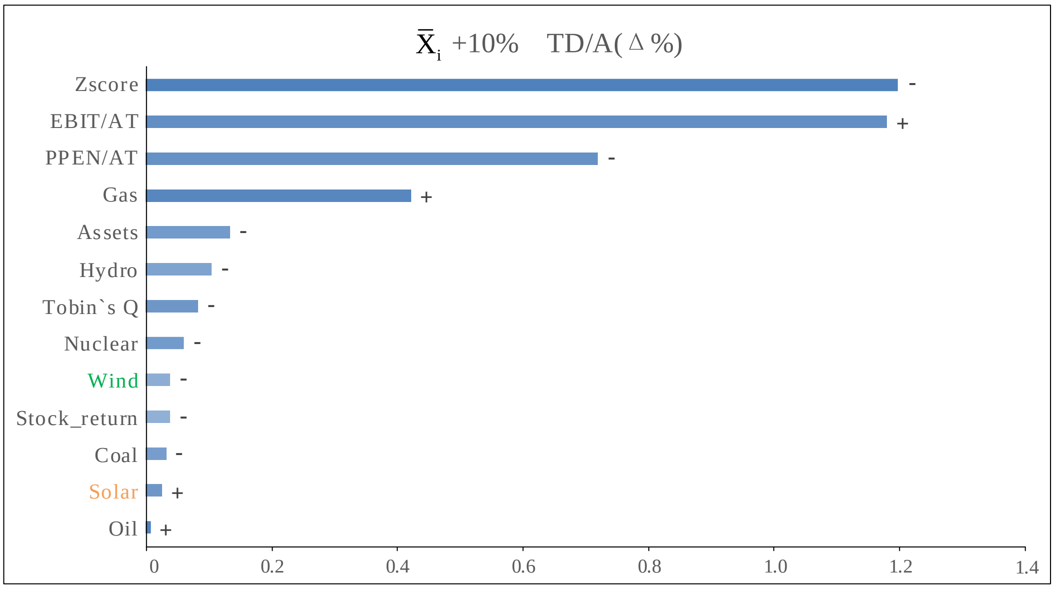

Figure 3.12. Factor directions for TD/A (L) - 10% difference

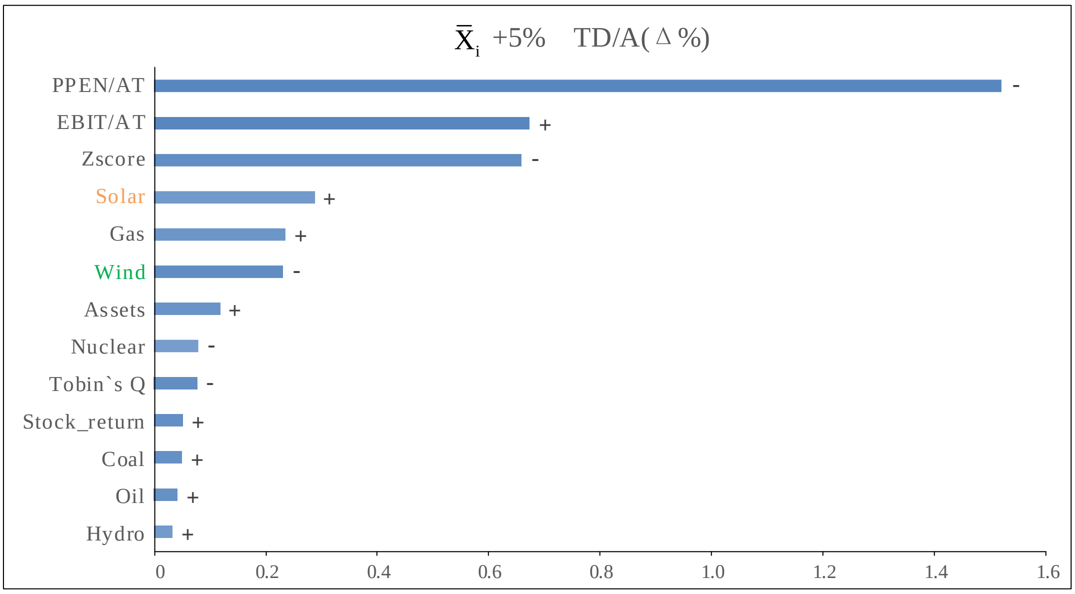

Figure 3.13. Factor directions for TD/A (H) - 5% difference

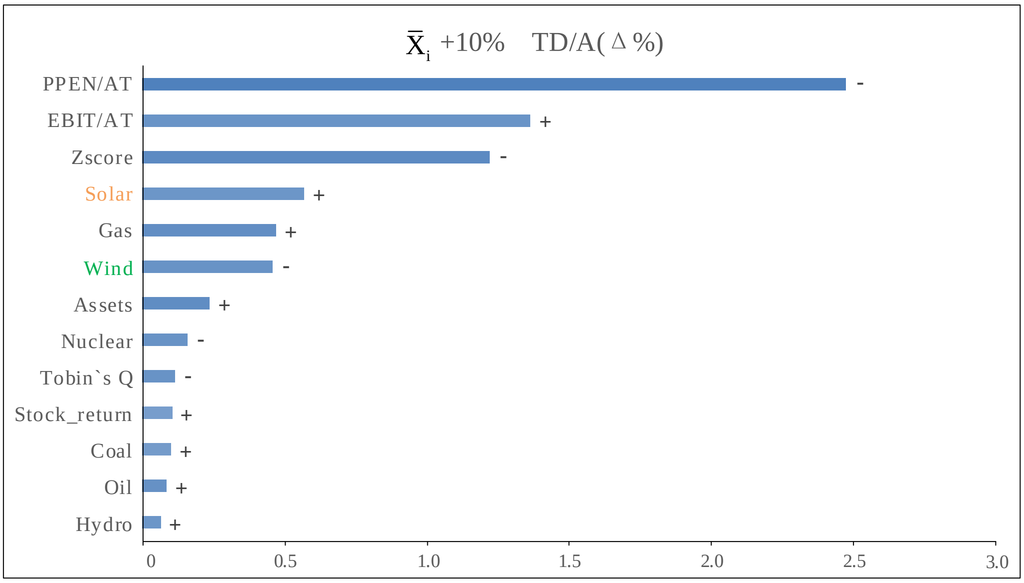

Figure 3.14. Factor directions for TD/A (H) - 10% difference

For other energy variables, gas exhibits a more pronounced influence in both groups. In the low proportion group (Figures 3.11 and 3.12), gas emerges as the most influential energy type among all energy variables, surpassing the combined impact of the remaining energy variables. In the high proportion sample (Figures 3.13 and 3.14), gas ranks the second, following solar but surpassing wind, and its influence is comparable to that of solar and wind. Moreover, in both the high and low proportion samples, gas consistently shows a positive relationship with leverage. This indicates that the lending market holds a favourable view of gas investments and recognises the significance of utilising gas to address the current inadequacy of renewable energy development (IEA, 2019).

Nuclear energy only occupies a middle position in both the high and low proportion samples, with a consistent negative impact. This may be attributed to the perceived potential safety risks associated with nuclear energy, leading both companies and debt investors to adopt a cautious approach towards nuclear energy projects. Meanwhile, hydropower generation holds a middle position in the low proportion group (Figures 3.11 and 3.12) with a negative impact but ranks last in the high proportion group (Figures 3.13 and 3.14) with a positive impact. Coal ranks among the bottom three in both groups, with its impact aligning with that of hydropower in both cases. Oil ranks at the bottom in both groups but with a positive impact. The directions towards hydro and coal are opposite in the two groups. Low proportion companies (Figures 3.11 and 3.12), focusing on traditional fossil energy projects, face higher environmental and financial distress risks, leading to reduced debt investments in such sources. High proportion companies (Figures 3.13 and 3.14), with lower environmental risks, have easier access to debt financing. Furthermore, allocating some traditional energy sources helps mitigate the volatility risks of renewable energy for high proportion companies. However, the impact of the lower-ranked energy variables is minimal. Regardless of the direction of impact, their influence on capital costs is limited.

Among accounting and financial variables, PPEN/AT, EBIT/AT, and Z_score are constantly ranked as the top three determinants of firms' total leverage for both low and high proportion groups (Figures 3.11 to 3.14). The sum changes of the three variables account for more than 50% of all the changes for each model. This means that the tangibility, profitability, and bankruptcy risk are the main influential factors for firm's leverage decision on book leverage. The influence of the remaining accounting and financial variables, firm size, growth opportunities, and stock market conditions, are much smaller, showing the much smaller absolute value of changes and rank after some energy variables.

Besides their importance, the directions of accounting and financial variables are worth discussing. For the most important top three variables, tangibility (-), profitability (+), and bankruptcy risk (-) exhibit almost consistent directions (except the direction of bankruptcy risk is positive for the 5% change of the low proportion group) for both groups, and when 5% and 10% changes are applied. Regarding tangibility, for most companies, having more fixed assets should be interpreted by the lending market as having lower default risks. Consequently, firms tend to borrow more for purposes like corporate investments, and research and development, resulting in a higher gearing level. However, utility investments differ from other types of companies as their primary target is to construct power generation equipment. Therefore, when fixed assets account for a higher proportion of total assets, it implies that there is less need for further investment in building new capacity, resulting in lower leverage. Firms with higher level of profits tend to have lower financial distress cost and can take more advantage of the tax shields, resulting in a higher debt level of firms (Frank and Goyal, 2009). For bankruptcy risk, the results show that in most cases, firms with higher bankruptcy risk are less likely to rely on additional debt financing due to limited additional borrowing capacities.

Regarding the other three accounting and financial variables, except growth opportunity with a consistent negative direction for both groups, firm size and stock market conditions have contractionary impacts on firms' leverage for the two groups. Companies experiencing rapid growth are more likely to suffer financial distress cost and debt-related agency problems. Consequently, they may prefer a lower leverage level (Frank and Goyal, 2009). In the low proportion group, larger firms and firms with high stock returns are more likely to have lower leverage. This is not surprised as large firms tend to have stronger financial resources and stability; if they rely mainly on fossil energy, demand for additional funding is limited, resulting in lower gearing level. Meanwhile, when the stock return is high, firms are more likely to use equity finance to take advantage of the "market timing" (Frank and Goyal, 2009). Here, despite limited demand for additional finance for renewable development, firms will use equity finance whenever needed, leading to a lower leverage ratio.

A different picture emerges for the high proportion group (Figures 3.13 and 3.14). Large firms and firms with high stock returns are more likely to have higher leverage. When companies require significant investments for the continuous development of renewable projects, large firms tend to take advantage of their size effect, borrowing at a cheaper rate from banks to minimise the cost of capital. Meanwhile, for firms with high stock returns, the trade-off theory suggests that to exploit the benefits of low market debt ratios, firms may issue additional debt to move towards the optimum ratio (Frank and Goyal, 2009). Consequently, the gearing level of firms will increase.

Thus, the relationship between the capital structure and its determinants in this study is nonlinear, as shown by the varying changes and rankings of variables. For example, the directions of asset, stock return, hydro, and coal are negative for the low proportion group (Figures 3.11 and 3.12), but positive for the high proportion group (Figures 3.13 and 3.14). Further, even within the low and high proportion groups, when 5% and 10% changes are applied, the rankings of variables are inconsistent. Together, this indicates the nonlinearity of the model, consistent with prior research (Amini et al., 2021).

3.5.4. Adjustment Speed

Finally, we investigated the adjustment speed when the actual leverage deviates from the target level. The partial adjustment framework can be defined as follows (Amini et al., 2021):

$$\Delta y_{i,t+1} = \lambda GAP_{i,t} + \varepsilon_{i,t+1} \quad (28)$$

Where:

$$GAP_{i,t} = \mathrm{E}(y_{i,t+1}) - y_{i,t} \quad (29)$$

GAP represents the gap between the actual and target leverage of firm i. Target leverage is defined as the one predicted by SVR with Dataset 2. Both TD/M and TD/A were tested. λ is the adjustment speed, which should equal zero to one if it fits the prediction of the dynamic trade-off theory. Eq. (28) is estimated as a pooled ordinary least squares (OLS) regression with bootstrapped standard errors (Amini et al., 2021). The results with and without fixed effects are presented in Table 3.5.

Table 3.5. Leverage adjustment speed

	TD/M	TD/M (F)	TD/A	TD/A (F)
GAP	0.126 (***)	0.743 (***)	0.056 (*)	0.645 (***)
	(0.032)	(0.099)	(0.031)	(0.116)
Half-life in years	5.096	0.511	12.158	0.666
Observations	197	197	197	197
Adjusted-R^2	0.065	0.403	0.024	0.331

Note: ***, **, and * indicate statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

Table 3.5 shows that firm fixed effects play a crucial role in determining the adjustment speed. Both market and book leverage adjust more quickly when we control firm specific characteristics. Before controlling for company fixed effects, the adjustment speeds of the market and book leverage are 0.126 and 0.056, respectively. After controlling, these speeds rise to 0.743 and 0.645, respectively. The half-life of market and book leverage are 0.511 and 0.666 years, respectively, after controlling firm fixed effects versus 5.096 and 12.158 years, respectively, without controlling. These findings are consistent with prior research arguing that controlling the firm fixed effect can lead to the faster adjustment speed estimated (Amini et al., 2021).

Note that the adjustment speed identified in this study is much faster than those reported in other studies. This may be because the target leverage is more accurately estimated by the machine learning method (Amini et al., 2021), or perhaps due to the unique sample used in this study. As prior research is normally based on the overall market, the adjustment speed can be viewed as an average speed across industries (usually excluding utilities). However, as our sample only includes firms from the electric utility sector, a much faster adjustment speed suggests that electric utility firms are more sensitive to deviations from the target leverage. This may be because along with the rapid development of renewable energy, utilities need to adjust their financing channels quickly to facilitate the deployment of renewable energy projects. Further, among the two types of leverages, the market leverage tends to adjust 10% faster than that of the book leverage. This is may be because the market leverage is a forward-looking measurement. Market prices adjust quickly to reflect the market's perception of a company's debt levels and risks. Meanwhile, book leverage is subject to the lag in financial reporting and disclosure cycles.

Overall, both types of results are consistent with the predictions of the dynamic trade-off theory, and range between zero and one. In addition, the directions of most accounting and financial variables including, profitability (+), bankruptcy risk (-), growth opportunity (-), firm size of high proportion group (+), and stock market conditions, of the high proportion group (+) are consistent with the predictions of the trade-off theory. That is, the financing decisions for companies with a high proportion of renewable energy tend to align more closely with the trade-off theory, indicating the need for frequent adjustments in capital structure to address the substantial investments required in renewable energy development.

3.6. Conclusion

In order to fight against the climate change, renewable energy is developed and deployed at a much faster speed. As one of the major emitters, electric utility sector must go through the energy transformation process to achieve greener operations. Employing machine learning methods, this study investigates the dynamic adjustments of capital structure in firms in the electric utility sector in response to changes in their energy structure. We ask: 1) Do changes of the renewable energy and fossil fuels in the energy structure affect the capital structure of electric utility firms? 2) Are the impacts of different types of renewable energies on a firm's capital structure consistent? 3) How and at what speed will the firms' capital structure adjust to reflect these changes? 4) Can existing capital structure theories explain the capital structure of the electric utility sector?

We hope to answer these questions by analysing data of 42 listed companies of the US electric utility sector over the period 2010 to 2020 using three machine learning methods (SVR, RF, and ANN). The results show that: First, the introduction of energy structure variables can improve the predictive power of the capital structure models. This provides a sign that certain energy types may affect the capital structure decisions.

Second, we confirm that, among all energy variables, wind, solar, and natural gas have the most significant impact on the capital structure of electricity utility firms. Besides conventional accounting determinants like tangibility, Z-score, and profitability, for firms employing a higher percentage of renewables in the energy structure, wind and solar energy are more likely to have a stronger explanatory power in firms' capital structure. Other conventional fossil fuels have limited impact on firms' capital structure decisions. Moreover, using different proxies of capital structure may yield different results. For instance, compared with the long-term debts, the total debts generally tend to have stronger predictive accuracy. This implies that both short- and long-term debts are used by firms in developing renewable projects.

We further investigated the direction of contribution of each variable. This is the first study to reveal that despite both being renewables, wind and solar energy have opposite effects on the capital structure, with wind (solar) energy contributing negatively (positively) to the gearing level of firms. This may be because compared with wind energy, solar energy investments are considered less risky in debt market, and hence, more likely to attract increased borrowings. Among the three most influential accounting and financial variables, tangibility and bankruptcy risk contribute negatively to leverage, while profitability leads higher debt.

Moreover, based on the target leverage predicted by the machine learning approach, the leverage adjustment speed of electric utility firms is in line with the prediction of the dynamic trade-off theory; rather, it happens at a much faster rate when compared with the overall market. The directions of most accounting and financial variables also conform to the prediction of the trade-off theory.

Our findings have some valuable implications. First, in response to government policies, more green credit and/or green bond should be provided to support firms' green activities. To reduce firms' financial risk exposure, such lending can be priced at a lower rate and backed up by the government. This may encourage more borrowings and increased green investments, particularly for utilities firms operating in regions with favourable natural conditions. Meanwhile, due to higher level of risks involved in wind energy, the government should provide more financial support, and facilitate research collaboration among utility firms and research institutions. This may speed up the industrial transformation process. Finally, given financial institutions preference for solar energy over wind energy, firms could divide their capital more strategically, relying on debt finance more for solar energy plants while using internal accruals more for wind energy plants. This can help optimise the capital structure of utility firms and accelerate the overall green transformation process.

Finally, this study has some limitations. Due to the data availability, this study explores the relationship between energy structure transition and capital structure only in the US market. Future research can consider samples from other markets with distinct energy structure characteristics. For instance, in the Chinese and Indian markets, while renewable energy generation is increasing, the generation of fossil fuels, especially coal, is also on the rise. This stands in contrast to the sample characteristics presented here and may lead to different findings.

Chapter 4: Energy Structure Transition and Firm Risk Exposure: Evidence from the Electric Utility Industry Based on Support Vector Machine

4.1. Introduction

The Paris Agreement, signed in 2015, achieved unanimous consensus to limit global temperature rise to 2˚C.To achieve this goal, global emissions should be halved by 2030 and reach net-zero by 2050 (Climate Analytics, 2022). Accordingly, the energy structure must transition away from fossil fuel-based energy to renewable energy to reduce greenhouse gas (GHG) emissions. As the single largest source of GHG emissions, the electricity industry plays a key role in the energy structure transition (IEA, 2021d). Currently, over 40% of CO2 emissions related to energy come from the combustion of fossil fuels for power generation (World Nuclear Association, 2022). It also contributes to 46% of the global rise in emissions in 2021 (IEA, 2022a). To achieve the net-zero target, nearly 90% of global electricity generation should come from renewable sources by 2050, compared to only 23% in 2015, with solar photovoltaic (PV) and wind contributing to nearly 70% (IEA, 2021d, 2016).

The rapid and extensive transition of the energy structure poses a huge challenge for the electric utilities. After completing the electricity market reform in the 1990s, the electric utilities of major economies have transformed into market-driven operations (Sioshansi and Pfaffenberger, 2006). Instead of requiring direct state intervention, the energy structure transition is now considered more of an economic challenge as substantial funding is needed for the development of renewable energy projects (Donovan, 2015). Under such increased financing pressure, we need to understand the impact of the changes in electric utilities' energy structure on firms' performance. If renewable energy can enhance the financial performance or reduce risk exposure of the electric utility firms, then effective policies should be set up to encourage/speed up this transformation.

The discussion about how electric utilities' energy structure transition influences the corporate performance can be seen as a part of the broader debate about the economic outcomes of firms' corporate social responsibility (CSR) activities. Research often examines the influence of CSR on firm performance from two perspectives, financial performance and risk exposure, with the former receiving much more attention. According to stakeholder theory (Clarkson, 1995; Donaldson and Preston, 1995; Freeman, 1984) and the natural resource-based view (Hart, 1995), investing in CSR can yield several benefits. For instance, it may assist firms to diversify products with enhanced competitiveness, build a positive corporate reputation, and adjust strategies according to the changing business environments (Albuquerque et al., 2019; Aragón-Correa and Sharma, 2003; Miles and Covin, 2000; Miller et al., 2020). These advantages can reduce costs, increase short- and long-term profits, and mitigate firm risk (Albuquerque et al., 2019; Hart and Ahuja, 1996; Liu and Lu, 2021). However, some studies reported contradictory findings. For instance, CSR may be more of a moral obligation used by companies for public relations purpose (Ozdora Aksak et al., 2016). It may also add financial burden and lead to negative firm performance (Barnett and Salomon, 2006; Palmer et al., 1995; Preston and O'Bannon, 1997). Nevertheless, this may be because CSR comprises multiple dimensions and the choice of different proxies may lead to different estimation results (Bouslah et al., 2013; Johnson and Greening, 1999; Rehbein et al., 2004; Ruggiero and Lehkonen, 2017). Consequently, many studies choose to focus on each CSR dimension separately, particularly when it comes to the environmental related impacts (Bouslah et al., 2013; Busch and Lewandowski, 2018; Cai et al., 2016; Correia et al., 2021).

Studies on the impact of energy structure transition on firms' financial performance are quite limited and have diverse conclusions. Employing a cross country sample over the period 2008–2013, Martí-Ballester (2017) found that the adoption of renewable energy does not significantly affect a company's financial performance. However, a positive relationship is observed for European countries, despite the significant inconsistencies among different countries (Correia et al., 2021). Later, Ruggiero and Lehkonen (2017) analysed a sample of utilities from the North America, Europe, and East Asia from 2005 to 2014, and found that firms' transition towards renewables does not promote their financial performance. Therefore, besides firm specific characteristics, the impact of renewables on firms' performance is more likely to be affected by factors including the uneven development of the renewable energy in different regions, study period, and diversified socioeconomic and political backgrounds of different countries.

Some studies have explored the impact of renewable energy on firms' financial performance. However, research about the relationship between energy structure transition, particularly concerning renewable energy, and firms' risk exposure is even more limited. Facing highly volatile international environments, firms' risk management capacity may directly affect their financial performance (Florio and Leoni, 2017; Malik et al., 2020). As suggested by Bouslah et al. (2013), a firm's social performance can influence its financial performance or value if and only if it affects its risk. To fill in this research gap, we investigate the impact of energy structure transition on electric utility firms' risk exposure. While renewable energy is the primary driver of the transition, changes in fossil fuels and other conventional energy also shape the energy structure. Similar to the broader CSR study that acknowledges multiple dimensions may cause biased effects, it is reasonable to conduct separate test to assess the impact of different energy types. This study primarily focuses on renewable energy due to its substantial investment, which has a high potential to influence firm risks. Therefore, it should be clarified that the effect of energy structure transition examined in this study is the part caused by the development of the renewable energy. Considering the different types of risks faced by the electric utility firms, we first test whether and how the development of renewables affects all different types of risks faced by firms.

Furthermore, we explore whether different kinds of renewable energy have consistent impacts on these risks.

To answer these questions, this study employs a sample of 44 US listed electric utility companies during 2010–2020. Unlike other CSR studies which often rely on regression methods, this study adopts the machine learning approach to construct a more reliable classification model for the analysis. We find that the increase in renewable energy is negatively associated with systematic risk but has inconsistent relationship with the idiosyncratic and total risks. This is because that solar (wind) positively (negatively) impact idiosyncratic and total risks. Clearly, in a broader context, it can be concluded that the energy structure transition significantly affects not only the systematic but also idiosyncratic and total risks faced by utility firms. However, it should be noted that deducing the direction of the effect due to the energy structure transition is not appropriate. For instance, despite both being renewable energy sources, wind and solar exhibit different effect direction on firm risks. Therefore, it is highly probable that other energy types may have diverse impact directions.

This study's contributions are fourfold. First, this study integrates the energy structure transition into the broader CSR research framework. It not only contributes to the extensive field of CSR research (Albuquerque et al., 2019; Aragón-Correa and Sharma, 2003; Miles and Covin, 2000; Miller et al., 2020) but also responds to the growing demand for separate testing of specific themes (Bouslah et al., 2013; Busch and Lewandowski, 2018; Cai et al., 2016; Correia et al., 2021). Focusing on the environmental dimension, by analysing the impact of energy structure transition guided by renewable energy on firms' performance, this study provides a more comprehensive understanding about the relationship between CSR and corporate risk exposure.

Second, the majority of studies investigating the relationship between CSR or corporate environmental responsibility (CER) and firms' performance focus on their financial performance and systematic risk exposure only (Albuquerque et al., 2019; Oikonomou et al., 2012; Salama et al., 2011). Electricity utility firms are also generally excluded from the sample due to the uniqueness of their operations. This study fills in these gaps on the important role played by electric utility firms in a country's energy structure transition. Besides systematic risk, we also include the idiosyncratic and total risks into our analysis. This helps us capture the heterogeneous impact of electric utility firm's energy structure transition on its different types of risks exposure.

Third, this study innovatively investigates the respective impacts of wind and solar energy on electric utility firms' risk exposure. We find that both wind and solar energy can reduce the systematic risk. Meanwhile, solar (wind) increases (decreases) idiosyncratic and total risks. Electric utility firms can consider these differences and adjust their future financing plans accordingly.

Finally, this study contributes to the research methods used in the CSR studies. While studies mainly rely on regression methods, this study employs a classification approach, offering a more intuitive understanding of the impact of renewable energy on a firm's market risk. Further, finance studies using the machine learning approach have primarily focused on default and credit risks classification (Härdle et al., 2009; Harris, 2013; Kim and Sohn, 2010; Shin et al., 2005; Zhou et al., 2014). This study extends the research scope by applying these methods to assess the market risk faced by firms.

The rest of this chapter is organised as the following. Section 4.2 reviews the literature and develops the research hypotheses. Section 4.3 introduces the methodology. Section 4.4 describes the data and variables. Section 4.5 discusses the empirical results. Section 4.6 presents the conclusions of this study with some useful policy implications.

4.2. Literature Review

4.2.1. Corporate Social Responsibility, Corporate Environmental Responsibility, and Energy Structure Transition

Many key concepts have been introduced in CSR research, including CER and environmental, social, and corporate governance (ESG). While these concepts are interrelated, they have some distinct characteristics. Therefore, untangling their relations is necessary to obtain a clear understanding of the research landscape, as illustrated in Figure 4.1. The starting point is CSR, which is defined as "a commitment to improve community well-being through discretionary business practices and contributions of corporate resources" (Kotler and Lee, 2005, p. 3). With increased social attention, CSR has evolved to become a widely accepted mainstream business practice (Kitzmueller and Shimshack, 2012). Accordingly, several assessment frameworks have been developed to evaluate firms' CSR performance, such as the ESG principles (Eccles et al., 2012; PRI, 2021)[6]. Subsequently, many data providers, such as Kinder Lydenburg Domini (KLD)[7], offer quantified measurements (scores or ratings) according to the ESG framework.

[6] ESG is a comprehensive criterion of environmental, social, and corporate governance dimensions. Each dimension has their own subthemes. The environmental dimension mainly includes energy usage and efficiency, climate change strategy, waste reduction, biodiversity loss, GHG emissions, and carbon emissions reduction. The social dimension mainly comprises employee wellbeing, workplace safety and health, customer benefits, diversity and equity, product information, and supply chain management. Finally, corporate governance mainly contains bribery and corruption, board diversity, disclosure and transparency, executive pay, and risk management.

[7] The KLD database is recognized as the most extensive and widely accepted data source for CSR research (Bouslah et al., 2013; Mattingly and Berman, 2006). KLD classifies CSR activities into seven categories, each corresponding to one ESG dimension. For every category, CSR activities are ascribed into either "strength" or "concern" types, and a company is rated 0 or 1 for each type (Cai et al., 2016).

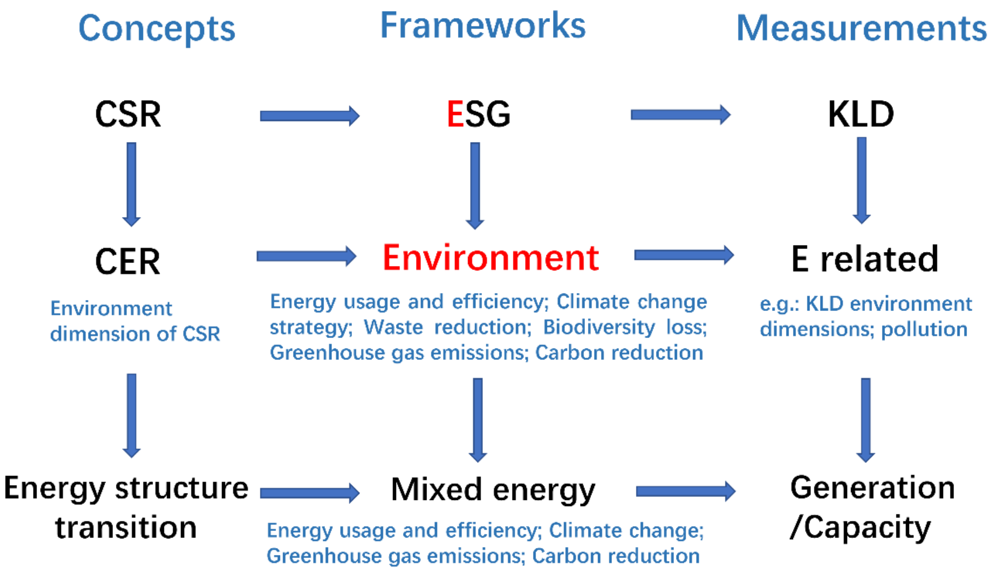

Figure 4.1. Key concepts in CSR Studies

Note: The subthemes of the other two ESG dimensions are in footnote 6.

Indeed, environmental issues have received increased attention in recent years, and the environmental dimension of CSR, CER, has become one of the most prominent topics (Cai et al., 2016; Jo et al., 2015; D. Li et al., 2017; Z. Li et al., 2020; Qin et al., 2019; Wahba, 2008). In Figure 4.1, the framework and measurement of CER can be the environmental dimension of ESG and KLD. Given the different nature and stakeholder involved in different CSR dimensions, each dimension may have distinct effects on a firm's financial and risk performance (Girerd-Potin et al., 2014; Godfrey et al., 2009). Consequently, the aggregate measurement of CSR may muddle the impact of each dimension and lead to biased conclusions (Bouslah et al., 2013; Johnson and Greening, 1999; Rehbein et al., 2004). Separate tests should be conducted for each dimension of CSR to identify its unique impact on firm performance (Bouslah et al., 2013). Therefore, it may not be appropriate to infer the relationship between CER and firms' financial performance or risk exposure simply based on the relationship identified between CSR and them (Cai et al., 2016).

Moreover, the environmental dimension could be further divided into subthemes including climate change strategy, waste reduction, and biodiversity loss (Figure 4.1).

These subthemes may also generate diversified impacts on firms' performance, and thus, should be investigated separately (Busch and Lewandowski, 2018; Correia et al., 2021). Energy, as an important subtheme in the environmental dimension, has constantly attracted wide attention, particularly with the growing public awareness towards environmental protection. Governments have created various policies and regulations to guide firms' practice, while firms are under pressure to develop and invest in green technologies and renewables for more sustainable growth. Renewable energy will undeniably replace fossil fuels gradually as the primary energy source. In this process, the mix of different energy sources is a suitable proxy for the energy structure transition. Among all the energy types, this study mainly focuses on the impact of renewable energy on firm risks due to the significant influx of new investments.

4.2.2. Firm Risk Exposure

While referring to risk, this study focuses on three kinds of risk measures, which are total, systematic and idiosyncratic risks. Total risk can be defined as the volatility of a firm's stock returns over time, often measured by the variance or standard deviation of stock returns from the previous year (Bouslah et al., 2013; Jo and Na, 2012; Sassen et al., 2016). It can be further divided into systematic and idiosyncratic risks (Jo and Na, 2012; Sassen et al., 2016). Systematic risk reflects a company's sensitivity to broad market fluctuations that affect all stocks, while idiosyncratic risk represents company-specific risks that cannot be explained by overall market volatilities (Bouslah et al., 2013; Luo and Bhattacharya, 2009; Sassen et al., 2016; Sharpe, 1964). According to modern portfolio theory, only the systematic risk is relevant to asset pricing as the idiosyncratic risk can be fully diversified away, and hence, not included into the pricing (Markowitz, 1952). Consequently, some studies argue that the CSR (CER) only influences the systematic risk exposure of firms. However, because achieving a fully diversified investment portfolio is nearly impossible in the real market, as a company-specific character, CSR (CER) may still act on the idiosyncratic risks faced by firms (Bouslah et al., 2013; Goyal and Santa-

Clara, 2003; Lee and Faff, 2009; Sassen et al., 2016).

4.2.3. Renewable Energy, Diversification, and Systematic Risk

Researches on the relationship between systematic risk and CSR (CER) often reveal a negative correlation (Albuquerque et al., 2019; Oikonomou et al., 2012; Salama et al., 2011). One important explanation for this relationship is diversification. According to stakeholder theory, besides shareholders, firms should also consider the interests of other stakeholder groups to maximise the value created (Dmytriyev et al., 2021; Donaldson and Preston, 1995; Ruf et al., 2001). As an important dimension of the CSR practice, aligning their environmental strategy with the environmental preferences of stakeholders can create additional competitive advantages for firms (Martí-Ballester, 2017; Rivera, 2002). Transitioning from fossil fuels to renewable energy sources can be viewed as a means to enhance the product diversification of electric utility firms. A higher proportion of renewable energy signifies a stronger ability for diversification. For instance, German customers would like to switch their electricity retailers for environmental reasons (Richter, 2013). The increased loyalty built up could then be transformed into higher profits, leading to reduced systematic risk exposure and more sustained growth (Albuquerque et al., 2019).

For electric utilities, besides the aforementioned benefits, diversification to renewables may also assist firms to have a more stable capital cost and a more reliable energy supply. This can effectively reduce the market risk exposure of firms. Currently, several geopolitical, environmental, and regulatory factors have led to the high volatility of fossil fuel prices, exposing firms relying on fossil fuels to increased risks. Meanwhile, renewable resources have developed rapidly over the past few years. Compared with fossil fuels, investments into renewables, such as wind and solar, is less risky (Shrimali, 2021). This has accelerated the transition from fossil fuels to renewables. Based on the above discussion, a higher percentage of renewables signifies greater diversification, we propose the following hypothesis:

Hypothesis I: *The development of renewable energy negatively affects electric utility firms' systematic risk.*

4.2.4. Renewable Energy and Idiosyncratic/Total Risk

In recent years, an increasing number of studies have investigated the relationship between CSR (CER), and both the idiosyncratic and total risk exposures of firms. A negative relationship is normally detected for idiosyncratic risk when a comprehensive CSR measurement is used (Boutin-Dufresne and Savaria, 2004; Lee and Faff, 2009). Furter, the relationship between a single environmental dimension and firms' idiosyncratic risk exposure becomes inconsistent (Bouslah et al., 2013; Sassen et al., 2016). Meanwhile, total risk has an inverse relationship with CER (Cai et al., 2016). However, for firms with higher carbon efficiency, the total risk remains unchanged despite changes in their environmental performance (Trinks et al., 2020). Regarding the inconsistent outcomes of the relationships between the environmental dimension and idiosyncratic/total risk, one possible explanation suggests that environmental concerns, like climate change, may convey mixed signals to the market (Bouslah et al., 2013). In particular, despite its potential benefits for the business, green investment involves substantial investment upfront. Consequently, shareholders may object and/or some may even choose divestment, such as institutional shareholders (Fernando et al., 2010). Based on this above, we propose the following hypothesis:

Hypothesis II: *The development of renewable energy positively affects electric utility firms' idiosyncratic risk.*

Total risk is the sum of systematic and idiosyncratic risks. Its relationship with renewable energy is likely to be a reflection of the combination of these two risks. Since firms are facing increased social scrutiny nowadays, investments into the renewables can be regarded as firms' response to social requests. However, the investment practices vary significantly among firms, potentially leading to greater volatility in idiosyncratic risk On the contrary, systematic risk reflects the attitude of entire market and tends to be relatively stable compared to idiosyncratic risk. Consequently, the total risk may exhibit characteristics similar to those of the idiosyncratic risk. Based on this discussion, we propose the following hypothesis:

Hypothesis III: *The development of renewable energy positively affects electric utility firms' total risk.*

4.2.5. The Influence of Wind and Solar Energy on Firms' Risk Exposure

Few studies have investigated how wind and solar energy investments individually affect the different types of firm risk exposure. Given the close relationship between cost and risk, this study seeks to make preliminary inferences about their relationship by examining the cost dynamics of wind and solar energy. According to the International Renewable Energy Agency (IRENA, 2021), the last decade has witnessed substantial reductions in the levelised cost of electricity (LCOE) for both wind and solar energy. The LCOE of onshore wind energy has declined from USD 0.089/kWh in 2010 to USD 0.039/kWh in 2020, even surpassing the LCOE of fossil fuels. Meanwhile, solar energy's LCOE has plummeted from USD 0.381/kWh in 2010 to USD 0.057/kWh in 2020. In 2017, the cost of solar energy fell below the cost level of the wind energy in 2010, while the cost of the wind energy itself reached parity with that of fossil fuels at USD 0.05 /kWh. Notably, although solar energy experienced a much rapid decline, its higher initial costs meant that solar energy remained considerably more expensive than wind energy over a long period. Despite the recent narrowing of the cost difference between the two, the cost of solar energy remains high. Furthermore, data from the UK market used by Europe Economics in 2015 and 2018 to assess the capital costs of various energy sources show that both the debt and equity costs for wind and solar energy have declined. Moreover, the equity cost for solar energy exceeded that of wind energy in both 2015 and 2018 (GOV.UK, 2020). Considering the cost trends of wind and solar energy, we propose the following hypotheses:

Hypothesis IIIa: *Wind and solar energy negatively affect systematic risk.*

Hypothesis IIIb: *Wind energy negatively affects idiosyncratic risk.*

Hypothesis IIIc: *Solar energy positively affects idiosyncratic risk.*

Hypothesis IIId: *Wind energy negatively affects total risk.*

Hypothesis IIIe: *Solar energy positively affects total risk.*

As noted before, systematic risk primarily reflects the overall market sentiment. Considering the significant cost reductions in both wind and solar energy, their increased utilisation will contribute to greater diversity of electric utility firms. Therefore, we expect that both wind and solar to have a negative correlation with systematic risk. However, in the context of idiosyncratic risk, the difference in the wind and solar energy costs are linked to individual attributes, directly influencing individual firms. Further, solar has a higher LCOE than wind over the long term. We therefore assume that wind (solar) negatively (positively) affects idiosyncratic risk, and similarly, total risk follows the trend of idiosyncratic risk.

4.3. Methodology

When discussing problems related to risk, the central focus lies in assessing whether the research subject poses a substantial risk. For instance, in scenarios involving default or credit risks, if a borrower’s rating surpasses a specific threshold, it is classified as being of high risk (Harris, 2013; Kim and Sohn, 2010). Our objective is to evaluate whether a firm is exposed to high risk, considering the context of energy structure transition. To tackle such a binary question, a commonly employed approach is classification. The main advantages for using this approach in this study are as follows. First, categorising risks into high and low categories aids in intuitively assessing the level of risks. Second, given the substantial variations in renewable energy development among different companies, extreme values could adversely affect the accuracy of regression models. In contrast, the classification approach relies on categories rather than specific values, thus enhancing the model's robustness by reducing the influence of extreme values. Third, the classification method is better equipped to capture these nonlinear characteristics of renewable energy development.

This study aims to construct reliable classification models to estimate firms' risk exposure by classifying firms into high and low risk categories for each risk type. Based on the reliable classifier, renewable energy values are adjusted to simulate their development trend and further test their influence on the risks.

According to the classification criteria (specific criteria are introduced in section 5.2) of the three risk types, the number of high-risk samples of each risk is less than the low-risk counterpart, leading to an unbalanced dataset. To deal with the unbalanced dataset for high and low risk groups, the adaptive synthetic (ADASYN) algorithm[8] is used for sampling. Then, Support Vector Machine (SVM), a popular machine learning[9] classification approach, is utilised. The dataset is split into two subsets, with a training

[8] ADASYN uses a weighted distribution to generate synthetic data for the minority class. This approach addresses class imbalance by reducing bias and adjusts the classification boundary toward challenging examples (He et al., 2008).

[9] Machine learning (Zhou, 2021) falls within the domain artificial intelligence. It aims to use data and algorithms to teach computers in learning from experience like humans. Algorithms are trained on past data for the purpose of making predictions on new data. This process empowers computers to analyse complex data, identify patterns, and adaptively improve performance as more training data is incorporated.

set comprising 70% and test set comprising 30% of the total sample, respectively.

SVM employs a non-parametric approach to tackle classification problems and falls under the category of supervised learning (Vapnik, 1998, 1995). The primary objective of SVM is to determine a hyperplane that can effectively segregate training data with distinct features into two classes. The sample points nearest to this hyperplane on both sides are termed support vectors, which confirm two separating paralleled hyperplanes. The gap between these two hyperplanes is known as the “margin,” and the key objective of the SVM is to maximise this margin. Furthermore, when the input data cannot be linearly separated in its original low-dimensional space, SVM utilises a kernel function to map the data into a higher-dimensional feature space, rendering it linearly separable.

Unlike other machine learning methods that aim to minimise empirical risk[10], SVM follows an approach that minimises structural risk, endowing the model with robust generalisation capabilities on small sample size. Empirical risk refers to the average loss of empirical data, which is deviated from the true risk of the whole data. The true risk is the sum of empirical risk plus a confidence interval, indicating model complexity. Based on the function of confidence interval, it becomes small when the sample size increases. Following the law of large numbers, the empirical risk converges toward the true risk as the sample size approaches infinity (Luxburg & Schölkopf, 2011; Vapnik, 1991). Therefore, when the sample size is relatively small, it is not reliable to deduce the empirical risk as true risk, indicating that the constructed model has less generalisation ability. In contrast, SVM aims to minimise the structural risk, which refers to minimise both the empirical risk and confidence interval simultaneously (Vapnik, 1991). Hence, SVM demonstrates superior performance on small dataset

[10] Empirical and structural risks are two basic concepts in machine learning, measuring the model's capacities of fitting and generalisation, respectively. A lower empirical risk signifies a superior model fitting to the training data. Meanwhile, structural risk takes into account the potential disparity between the training data and the actual data distribution. Hence, mitigating structural risk helps enhance the model’s generalisation ability. (Zhang, 2011).

compared to other machine learning approaches (Mountrakis et al., 2011).

Many studies have verified SVM's superior classification ability compared with other classification techniques, including Random Forest, Decision Trees, and Logistic Regression, among others (Burbidge et al., 2001; Marjanović et al., 2011; Naji et al., 2021). In financial research, SVM has been widely applied in tackling classification problems, such as bankruptcy, default risk, or credit risk (Härdle et al., 2009; Harris, 2013; Kim and Sohn, 2010; Shin et al., 2005; Zhou et al., 2014).

SVM can be explained by the following algorithm.

Suppose the training samples are as follow:

$$S = \{(x_i, y_i) | i = 1,2, \dots, n\} \quad (1)$$

where $x_i = (x_{i1}, x_{i2}, \dots, x_{im}) \in R^m$, $y_i \in Y = \{-1, 1\}$. x_i is the input data, which are the accounting and energy structure variables (including firm size, profitability, wind, and solar energy), and y_i is the firm risk.

In the general form of SVM, the classification function is:

$$\omega^T x + b = 0 \quad (2)$$

where ω is a weight vector, and b is a constant. ω and b determine the direction and position of the hyperplane, respectively. The aim is to find the farthest distance from the hyperplane to the nearest sample point, which is referred to as the support vector. In two-dimensional space, the distance from (x, y) to line $Ax + By + C = 0$ is:

$$\frac{|Ax+By+C|}{\sqrt{A^2+B^2}} \quad (3)$$

Expanding to the n-dimensional space, the distance from $x = (x_1, x_2, \dots x_n)$ to $\omega^T x + b = 0$ is:

$$\frac{|\omega^T x + b|}{\|\omega\|}, \|\omega\| = \sqrt{{\omega_1}^2 + {\omega_2}^2 + \cdots + {\omega_n}^2} \tag{4}$$

Then, maximising the distance from support vector Xs to $\omega^T x + b = 0$:

$$max \quad \frac{|\omega^T x_s + b|}{\|\omega\|} \tag{5}$$

$$s.t. \quad \frac{|\omega^T x_i + b|}{\|\omega\|} \geq \frac{|\omega^T x_s + b|}{\|\omega\|}, \quad i = 1,2, \dots, n \tag{6}$$

We set $|\omega^T x_s + b| = 1$, then substitute it into equations (5) and (6), and obtain:

$$\frac{1}{\|\omega\|} \tag{7}$$

$$|\omega^T x_i + b| \geq 1, \quad i = 1,2, \dots, n \tag{8}$$

Here, the sum distance from each side's support vector to the hyperplane is $\frac{2}{\|\omega\|}$, and this distance is called hard margin. Removing the absolute value of $|\omega^T x_i + b| \geq 1$, we find:

$$\begin{cases} \omega^T x_i + b \geq 1, & y_i = 1 \\ \omega^T x_i + b \leq 1, & y_i = -1 \end{cases} \tag{9}$$

Combining the two functions of equation (9), we get:

$$y_i(\omega^T x_i + b) \geq 1, \quad \text{i} = 1,2, \dots, \text{n} \tag{10}$$

Thus, the optimisation can be written as:

$$max \quad \frac{2}{\|\omega\|} \tag{11}$$

$$s.t. \quad y_i(\omega^T x_i + b) \geq 1, \quad \mathrm{i} = 1,2, \ldots, \mathrm{n} \tag{12}$$

The maximisation of $\frac{2}{\|\omega\|}$ equals to minimise $\frac{1}{2}\|\omega\|$. For ease of calculation, it can be transformed as $\frac{1}{2}\|\omega\|^2$. Thus, the optimisation can be rewritten as:

$$min \quad \frac{1}{2}\|\omega\|^2 \tag{13}$$

$$s.t. \quad y_i(\omega^T x_i + b) \geq 1, \quad \mathrm{i} = 1,2, \ldots, \mathrm{n} \tag{14}$$

In cases where the data are not linearly separable, slack variables (ξ_i) are introduced to create a soft margin, and ξ_i is subject to a kind of loss function. Then, the optimisation problem becomes:

$$min \quad \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \tag{15}$$

$$s.t. \quad y_i(\omega^T x_i + b) \geq 1 - \xi_i, \quad \mathrm{i} = 1,2, \ldots, \mathrm{n} \tag{16}$$

$$\xi_i \geq 0, \quad i = 1,2, \ldots, n \tag{17}$$

C is a regularisation parameter and a constant larger than zero. It determines the balance between training error and the robustness of the model. The larger it is, the lower its capacity for fault tolerance. When C equals infinity, the margin becomes the hard margin.

To address the constrained optimisation problem, the Lagrangian function is constructed:

$$L = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i - \sum_{i=1}^{n}\alpha_i(y_i(\omega^T x_i + b) - 1 + \xi_i) - \sum_{i=1}^{n}\mu_i\xi_i \tag{18}$$

where $\alpha_i \geq 0$ and $\mu_i \geq 0$ are the Lagrange multipliers.

Then, the dual problem can be derived as follows:

$$max \quad \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{19}$$

$$s.t. \quad \sum_{i=1}^{n} \alpha_i y_i = 0\,, \qquad i = 1,2, \dots, n \tag{20}$$

$$0 \leq \alpha_i \leq C, \qquad i = 1,2, \dots, n \tag{21}$$

The solution of the dual problem consequently yields the value of the optimal solution for the initial problem.

To deal with nonlinear problems, SVM utilises kernel function $\kappa(x_i, x_j)$ to map all training points from their original low-dimensional space to a high-dimensional feature space:

$$\kappa(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{22}$$

where x_i and x_j are training points of the sample, and $\phi(x)$ is the map function. The kernel function's value is equivalent to the inner product of two vectors in the feature space. Different kernel functions have been proven to be effective, but there are no widely accepted criteria for choosing an appropriate kernel function. Following the literature (Hassan et al., 2014; Zuo and Carranza, 2011) we adopt the common Sigmoid Kernel as the kernel function illustrated below:

$$\kappa(x_i, x_j) = \tanh(\gamma x_i^T x_j + r) \tag{23}$$

Where γ is the gamma term and r is the bias term. A larger γ will increase the complexity of the model, which may cause overfitting problem leading to less generalisation ability of the model.

After incorporating the kernel function, the SVM can be written as:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i \, x_i^T x + b = \sum_{i=1}^{n} \alpha_i y_i \, \phi(x_i)^T \phi(x) + b = \sum_{i=1}^{n} \alpha_i y_i \, \kappa(x_i, x) + b \tag{24}$$

In order to find the optimal values for parameters C and γ, particle swarm optimisation (PSO) is utilised (Sudheer et al., 2014). As a popular optimisation technique, it can help determine the optimal parameters for balancing the model performance on both training and test sets.

4.4. Data and Variable Construction

4.4.1 Data Source

For the following reasons, this study focuses on the electricity utility industry in the US as the sample. First, after the completion of electricity market reforms, the US has a vibrant and market-driven electricity market. Second, the US leads the world with the highest number of publicly listed electric utility firms and uniquely provides all the essential energy-related data required for this study. Third, the capital markets in the US are highly developed and sophisticated, facilitating access to a broad range of funding sources for enterprises.

The sample consists of unbalanced panel data of 44 publicly listed companies in the US electric utility sector spanning from 2010 to 2020. Firm data are gathered from the Bloomberg. This study first identifies electricity utilities within the US using Bloomberg's BICS classification, resulting in a pool of 276 firms encompassing both parent companies and their subsidiaries. After eliminating non-listed firms and consolidating subsidiaries under their parent companies, we are left with 83 firms, a count closely matching that of Hughes (2000). Further refinement involved removing firms primarily engaged in transmission, distribution, and power infrastructure while retaining those primarily focused on power generation activities. Subsequently, after filtering out firms with incomplete data, a final sample comprising 44 firms is obtained. The accounting and financial data for these firms are sourced from Standard and Poor's Compustat North America, while risk-related data are obtained from CRSP. Energy data are acquired from the Global Power Plant Database and the US Energy Information Administration (EIA).

The Global Power Plant Database is a comprehensive and open-source repository containing extensive information about power plants worldwide. This information encompasses various details, such as power generation capacity, installed capacity, ownership, and geographical location. This study first extracts data for power plants in the US from this database and subsequently matches them with the electric utility firms in the sample. Each publicly listed company (parent company) may possess multiple power plants of diverse energy types, including coal-fired plants, nuclear plants, solar power plant. These power plants may be directly owned by the parent company or fall under the ownership of its subsidiaries. Notably, the Global Power Plant Database typically provides ownership information for power plants in terms of subsidiary names without specifying the parent company to which these subsidiaries belong. Consequently, this study obtains data on the parent company and subsidiary relationships for the 44 firms from the Bloomberg. Then, matching the information of the subsidiaries that own the power plants with their respective parent companies. Furthermore, Find Energy (2022) has also disseminated information regarding power plant ownership relationships among US electric utility firms. This study employs both data sources for cross-validation, ensuring the reliability and accuracy of the results in matching power plants to their respective electricity companies.

In addition, because the generation data available in the Global Power Plant Database covers the period from 2013 – 2019 only, this study manually collects data from the EIA to expand the sample's period to 2010 – 2020. Moreover, in cases where a power plant is co-owned by two or more electric utility firms, the generated output is distributed proportionally among each of them.

4.4.2. Variables Selection

4.4.2.1. Input Variables

To test whether firms' energy structure could improve the classification accuracy, three sets of data are constructed for three respective models. Model 1 only includes a set of widely accepted firm-level accounting and financial variables. Model 2 adds the energy variables to Model 1. Furthermore, a dimension reduction technique is applied to the input variables of Model 2, creating a new set of composite input variables used for Model 3.

The accounting and financial variables include firm size (AT), measured by total assets (Albuquerque et al., 2019; Benlemlih et al., 2018; Cai et al., 2016), growth opportunities (Tobin's Q), represented by Tobin's Q (Saravia et al., 2021; Schwert and Strebulaev, 2014), profitability (ROA), proxied by the net income divided by total assets (Benlemlih et al., 2018; Cai et al., 2016), investment opportunities (CAPEXP/AT), measured by capital expenditure divided by total assets (Albuquerque et al., 2019; Benlemlih et al., 2018; Cai et al., 2016), leverage (TD/AT), proxied by total debt divided by total assets (Benlemlih et al., 2018; Salama et al., 2011), and sales growth (SALEG), calculated by the rate of sales growth (Cai et al., 2016; Jo and Na, 2012).

Although this study focuses on the impact of renewable energy on the firm risks, it includes the generation and installed capacity of each energy type in the classification model. This helps us in independently identify the distinct characteristics of each energy type. This holistic framework enables a more precise recognition of the impact of renewable energy development on firm risks. Further, including the highly correlated generation and installed capacity variables together allows us to accurately reflect the energy utilisation rate of each energy type. Furthermore, for renewable energy, this rate is closely related to its utilisation risk, which may affect firm risk exposure. Although some studies have verified the robustness of SVM against the multicollinearity issue (Erdogan, 2013; Morlini, 2006), converse outcomes have also been found (Kim and Sohn, 2010). Therefore, the dimension reduction technique is employed to construct new composite variables for comparison. Table 4.1 provides detailed descriptions of the accounting, financial, and energy structure variables. Table 4.2 presents the descriptive statistics of the variables.

To process multivariate data sets that usually consist of many correlated variables, we use principal component analysis (PCA), a common dimensionality reduction technique (Shlens, 2014; Smith, 2002). By extracting the primary features of the data, and eliminating noise and redundant information, PCA reduces the data's dimensionality while preserving its original features as much as possible. In the new lower-dimensional space, each new feature (principal component) is a linear combination of the original features and is no longer highly correlated. The first principal component contains the highest percentage of variance (information) of the data, the second principal component contains the second highest percentage of variance (information), and so on. By retaining the most informative principal components, the dimensionality of the data can be reduced while retaining most of the original information.

Table 4.1. Variable description

Variable	Description
Accounting and financial variables (input variables)	
AT	Total assets.
ROA	Ratio of net income to total assets.
CAPEXP/AT	Ratio of capital expenditure expense to total assets.
Tobin's Q	Ratio of the sum of the year-end market capitalisation, and the difference between total assets and common/ordinary equity to total assets. (PRCC_F*CSHO+AT-CEQ)/AT
TD/AT	Ratio of total debt to total assets.
SALEG	Sales growth rate from t to t-1.
Energy structure variables (input variables)	
Coal	Annual generation of coal-based energy
Gas	Annual generation of gas-based energy
Hydro	Annual generation of hydroelectric power
Nuclear	Annual generation of nuclear energy
Oil	Annual generation of oil-based energy
Solar	Annual generation of solar energy
Wind	Annual generation of wind energy
Coal (IC)	Annual installed capacity of coal-based energy
Gas (IC)	Annual installed capacity of gas-based energy
Hydro (IC)	Annual installed capacity of hydroelectric power
Nuclear (IC)	Annual installed capacity of nuclear energy
Oil (IC)	Annual installed capacity of oil-based energy
Solar (IC)	Annual installed capacity of solar energy
Wind (IC)	Annual installed capacity of wind energy
Risk variable (output variables)	
β	Beta of capital asset pricing model (CAPM)
IR	Idiosyncratic risk of CAPM
TR	Standard deviation of daily stock returns in current year

Table 4.2. Descriptive statistics

Variable	N	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
AT	462	31893.16	7778.2483	24614.0000	45651.5000	30212.59
ROA	462	0.024	0.0185	0.0265	0.0327	0.027
CAPEXP/AT	462	0.069	0.0554	0.0691	0.0813	0.020
Tobin's Q	462	1.223	1.1191	1.1998	1.3031	0.155
TD/AT	462	0.710	0.6717	0.7035	0.7403	0.066
SALEG	462	0.020	-0.0349	0.0141	0.0604	0.109
Coal	462	15809.75	1769.5427	7237.0968	23711.7885	20818.93
Gas	462	12853.13	510.7208	3943.2603	13301.1372	22203.44
Hydro	462	1081.36	0	51.5115	1128.7453	2059.22
Nuclear	462	14462.09	0	0	14620.3188	29318.06
Oil	462	458.58	0	0.1630	11.1583	1712.45
Solar	462	366.60	0	1.7980	150.6133	1050.66
Wind	462	1871.77	0	253.6695	1426.0045	5493.34
Coal (IC)	462	4591.15	1031.7000	2873.5000	6181.7000	5018.93
Gas (IC)	462	4977.42	539.8000	1740.6000	5301.8000	7014.14
Hydro (IC)	462	354.87	0	19.1000	434.2000	633.36
Nuclear (IC)	462	2460.87	0	0	4083.6000	4567.94
Oil (IC)	462	510.15	0	27.0500	335.7000	1068.26
Solar (IC)	462	225.65	0	2.1000	107.2000	582.27
Wind (IC)	462	737.24	0	106.7000	580.6000	1822.04
β	462	0.558	0.3186	0.5649	0.7556	0.3093
IR	462	0.011	0.0081	0.0110	0.0118	0.0059
TR	462	0.013	0.0094	0.0115	0.0137	0.0075

To ensure the feasibility of conducting PCA, we perform the Kaiser-Meyer-Olkin (KMO) test. The estimated KMO value is 0.69, surpassing the cutoff value of 0.5, suggesting that the dimensionality was sufficient for employing dimension reduction (Kaiser and Rice, 1974). We then employ Cattell's scree test and Horn's parallel analysis to determine the number of components to be retained (Naraei and Sadeghian, 2017)[11].

[11] As the Kaiser's eigenvalue rule can lead to severely overestimating the number of components to retain, we only used the other two approaches to determine the number of components that should be retained (Zwick and Velicer, 1986).

Cattell's scree test is a visualised method which helps determine the number of components to retain by examining the "elbow" point in the plot (Cattell, 1966). Figure 4.2 indicates that around six components should be retained. To ensure the suitability of the selection, we employ Horn's parallel analysis, which compares the actual data's eigenvalues with those from a randomly generated dataset and only retains the ones with eigenvalues exceeding the random ones for the analysis (Ledesma and Valero-Mora, 2007). This method can be more reliable than other ones (Henson and Roberts, 2006; Naraei and Sadeghian, 2017). Finally, seven components are retained by parallel analysis, which aligns closely with the scree test result.

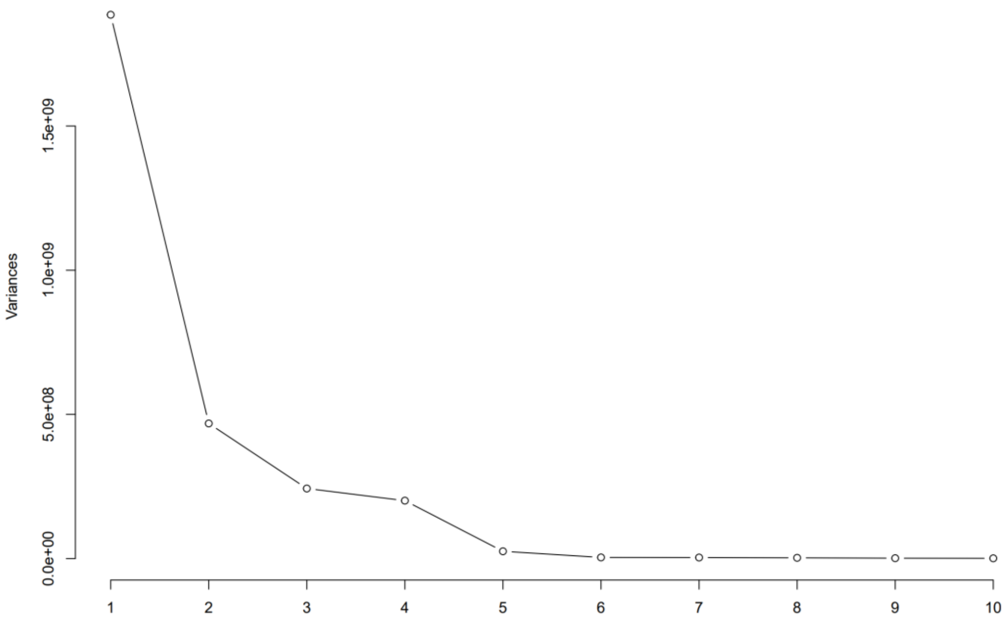

Figure 4.2. Scree plot of components

We then construct seven components by the PCA program. Generally, loadings[12] > |0.4| are assigned to one component (Stevens, 2001). In cases where loadings could be assigned to more than one component, the higher loading is selected. Table 4.3 displays

[12] The loading value represents the weight of the original variable in the principal component. A higher value indicates a greater contribution of that variable. Understanding the composition of the principal component can be facilitated by examining the loading values.

the components along with their respective loadings, arranged in descending order of explained variance proportion. Component one, derived from the generation and installation capacity of solar and wind, explains the largest portion of the variance. In total, approximately 81% of the total variance can be captured by the seven chosen components. Next, scores[13] for the seven components are calculated and integrated into the dataset for further analysis.

Table 4.3. Loadings and components

Component	Variance proportion	Original variables	Loadings
One	0.20	Solar	0.89
		Wind	0.89
		Solar (IC)	0.87
		Wind (IC)	0.86
Two	0.15	Nuclear (IC)	0.96
		Nuclear	0.95
		AT	0.63
Three	0.14	Coal (IC)	0.96
		Coal	0.94
		Gas (IC)	0.66
		Gas	0.55
Four	0.11	Hydro	0.96
		Hydro (IC)	0.95
Five	0.08	Oil	0.72
		CAPX/AT	-0.62
		TD/AT	0.61
		Oil (IC)	0.55
Six	0.07	ROA	0.83
		Tobin's Q	0.76
Seven	0.06	Sale	0.82

[13] Scores are a group of values calculated for each sample data for principal components. It refers to the mapping of original data points onto principal components after the dimension reduction.

4.4.2.2 Output Variables

We use Beta of the famous capital asset pricing model (CAPM) to measure the systematic risk (Albuquerque et al., 2019; Benlemlih et al., 2018; Mossin, 1966; Sharpe, 1964):

$$r_{i,t} - rf_t = a_i + \beta_i(mktrf_t - rf_t) + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return for stock i for period t, rf_t is the risk-free rate, and $mktrf_t$ is the Fama French Excess Return on marketing for period t. $\varepsilon_{i,t}$ is the stochastic error term for period t. The systematic risk for stock i at year t is measured as the estimated value of β_i. The model is captured by the previous year's daily excess returns.

The idiosyncratic risk (IR) is the volatility of the difference between realised and expected returns, which is provided by the CAPM model (Bouslah et al., 2013). Total risk (TR) is calculated directly as the standard deviation of daily stock returns over the previous 12 months (Benlemlih et al., 2018; Bouslah et al., 2013; Jo and Na, 2012).

4.5. Empirical Analysis

We construct reliable classifiers to investigate whether and how the development of renewables affects all different types of risks faced by electric utility firms? Do different kinds of renewable energy have consistent impacts on these risks?

4.5.1. Performance Measures

This study employs the widely used confusion matrix to evaluate the performance of the classification models (Jian et al., 2016; Khemakhem et al., 2018; Liu et al., 2011). Table 4.4 provides the definitions of different classification results. For example, TN represents the number of the correctly predicted low risk firms, while FP indicates the number of low-risk firms that have been wrongly classified into the high-risk category.

Table 4.4. Confusion matrix

	Predicted negative (low risk)	Predicted positive (high risk)
Actual negative (low risk)	True negative (TN)	False positive (FP)
Actual positive (high risk)	False negative (FN)	True positive (TP)

The accuracy rate evaluates the overall classification ability of the models by calculating the number of correctly classified firms divided by the total number of firms:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

However, the accuracy rate may not be adequate to measure the classification performance of each category, especially in the case of an imbalanced dataset (Jian et al., 2016). To address this, two ratios, 'sensitivity' and 'specificity', are calculated as the true positive number to the total positive number and true negative number to the total negative number, respectively. Here, they are the correctly predicted number of high-risk firms to the total number of high-risk firms, and the correctly predicted number of low-risk firms to the total number of low-risk firms, respectively.

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

For the imbalanced dataset, G-mean is another important criterion used to assess the classification balance performance between the majority and minority classes:

$$G - mean = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}} = \sqrt{\text{Sensitivity} \times \text{Specificity}}$$

It considers both sensitivity and specificity. Thus, even if a classifier performs well on one class (e.g. the majority class), the G-mean value remains low (Liu et al., 2011). It only shows a higher value when the model performs well on both classes. In this way, it ensures that accuracy of classification.

4.5.2. Performance of the Classification Models

Here, we test the three models. For the input variables, Model 1 only has accounting and finance variables, Model 2 has both accounting, finance, and energy variables, and Model 3 is estimated by the PCA variables. In terms of the classification criteria, we use the New York University provided US utility industry Beta, 0.64[14], for the systematic risk. This value can represent the average level of systematic risk for US utilities. Furthermore, due to data limitations, we calculated the average values of the idiosyncratic and total risks from the sample data as their respective classification criteria. For each risk type, sample values surpassing the average are categorized into the high-risk group, whereas those falling below the average are classified into the low-risk group.

The classification results in Table 4.5 show that for all three models, the G-mean of the systematic, idiosyncratic, and total risks are higher than 0.6, suggesting that the ADASYN sampling technique has addressed the unbalanced problem of the dataset effectively. That is, the majority samples in both low and high-risk groups are classified correctly.

[14] Data source: https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/Betas.html

Table 4.5. Classification results of the three risk types

Risks	Model	Accuracy	Sensitivity	Specificity	G-mean
Systematic risk	1	0.63	0.67	0.61	0.64
	2	0.68	0.70	0.67	0.69
	3	**0.76**	0.79	0.73	**0.76**
Idiosyncratic risk	1	0.61	0.55	0.64	0.60
	2	0.63	0.64	0.62	0.63
	3	**0.70**	0.77	0.66	**0.71**
Total risk	1	0.66	0.53	0.71	0.61
	2	0.62	0.66	0.60	0.63
	3	**0.68**	0.68	0.67	**0.68**

In terms of accuracy, both systematic and idiosyncratic risks exhibit higher accuracy in Model 2 compared to Model 1, with the former experiencing a more significant increase. Moreover, after using the PCA variables, Model 3 shows further improvements in the accuracy for all three risk types, with the systematic risk achieving the highest accuracy of 0.76. The difference in accuracies between Models 1 and 3 are 0.12, 0.09, and 0.02 for the systematic, idiosyncratic, and total risks, respectively. Thus, the classification accuracy of all three risk types improves after incorporating energy variables, especially after applying PCA technique.

The sensitivity of the high-risk group has increased progressively from dataset one to dataset three among all three types of risks. The systematic risk of the Model 3 has the highest sensitivity of 0.79, which is slightly higher than that of idiosyncratic risk of 0.77 and significantly higher than that of the total risk of 0.68. The largest difference between Models 1 and 3 lies in the idiosyncratic risk, reaching 0.21.

While the specificity of the systematic risk increases progressively from Models 1 to 3, only Model 3 shows a higher specificity in the idiosyncratic risk when compared to Model 1. On total risk, although specificity of Model 3 outperforms that of Model 2, it remains lower than that of Model 1. However, Model 3's accuracy for total risk is still the highest after combining its high sensitivity, suggesting that the classifier for the total three remains reliable.

4.5.3. The Impact of Renewable Energy on Firms' Risk Exposure

After confirming the reliable classifier, the impact of renewable energy on firm risks can be examined. According to the IEA, global renewable energy (including the US) is expanding annually, and this growth is expected to further accelerate in the upcoming years[15]. Figures 4.3–4.4 shows the installed capacity of PV and onshore wind energy in the US from 2005 to 2027, illustrating the patterns of this growth trend. To ensure the congruence of our study with real-world trends, we employed a yearly escalating rate to simulate the growth of renewable energy with greater accuracy. We assume that the installed capacity of renewable energy of each sample increases by k% in the first year, followed by an annual increase of n times k% (n=1,2,…, 11) thereafter. Accordingly, the changed value of the generation variable equals to the changed value of the installed capacity variable multiplied by the ratio of original value of the wind generation variable to the original wind installed capacity variable. For samples without wind energy, their values are substituted by the average value of samples with the wind energy. The rate (k%) is set at 0.5%, 1%, and 2% to simulate the three different development scenarios of slower, medium, and faster speed of deployment. An even higher growth rate would not align well with the actual situation, hence there is no need to test for a higher growth rate at the moment.

[15] Full reports can be found at the website of IEA: https://www.iea.org/reports/renewables-2022/renewable-electricity.

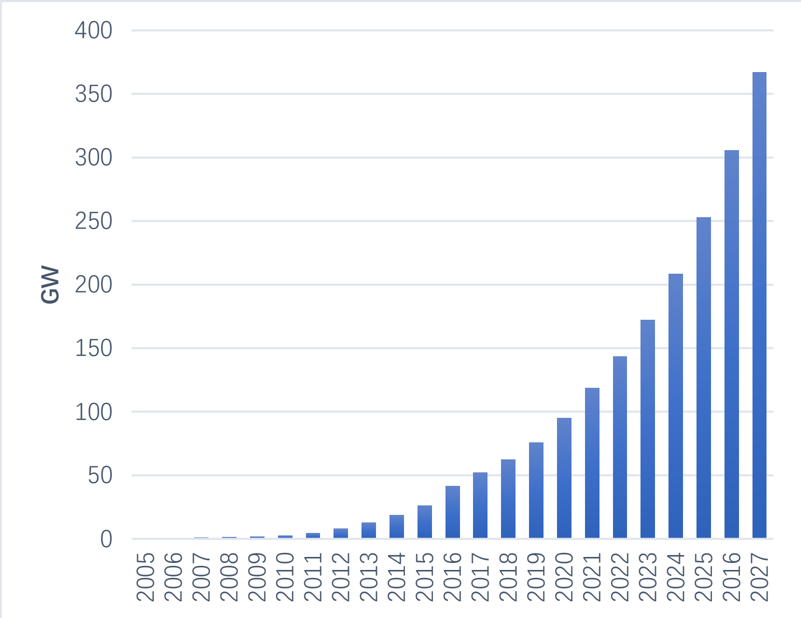

Figure 4.3. PV capacity, United States, 2005–2027

Data source: https://www.iea.org/reports/renewables-2022/renewable-electricity.

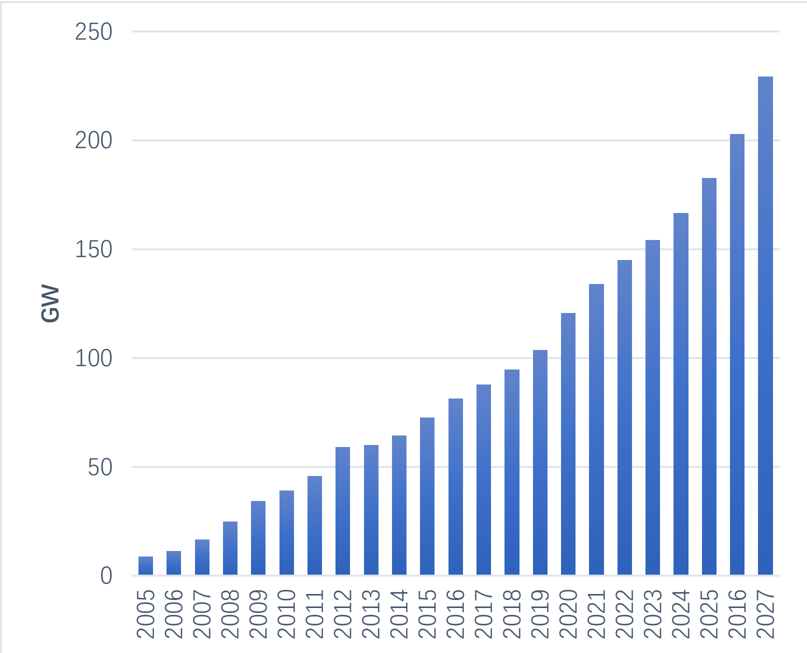

Figure 4.4. Onshore wind capacity, United States, 2005–2027

Data source: https://www.iea.org/reports/renewables-2022/renewable-electricity.

To simulate the real-world scenario of inconsistent growth rates in wind and solar better, three different growth ratios, 1:1, 3:1, and 1:3, are applied. The actual growth ratio of wind and solar energy is hard to confirm as it varies depending on different companies and countries. Therefore, the choice of 1:3 and 3:1 ratio is primarily aimed at reflecting the impact of these two distinct trends, where wind energy's growth is greater than that of solar energy or *vice versa*, on different types of risk exposure of firms. For example, when renewable energy increases by 1%, following the 1:1 ratio, both wind and solar energy increase by 0.5%. When the ratio is 3:1, wind and solar energy increase by 0.75% and 0.25%, respectively, and *vice versa* if the ratio is 1:3. The same logic applies to the cases of 0.5% and 2% increase in renewables.

For each adjusted sample, PCA is performed to derive a new set of components. To make comparisons, PCA and the SVM classifier are applied to the entire original sample as well. Given that the primary focus is on high-risk firms, the presented results are ratios of the predicted number of high-risk firms to the total firm number. A higher ratio indicates that more firms are categorised into the high-risk group, suggesting a higher risk.

Figure 4.5 displays the proportion of high-risk firms in the total sample after increasing the installed capacity and generation of renewable energy at different rates. Higher proportions indicate a larger number of firms are classified into the high-risk group and are subject to higher risk exposure. Nevertheless, as the three risk types are measured differently, making direct comparisons between them are invalid. For instance, we cannot conclude that a systematic risk of 0.5 implies a higher level of risk than an idiosyncratic risk of 0.3. We therefore use the blue, yellow, and red lines to represent the systematic, idiosyncratic, and total risks, respectively.

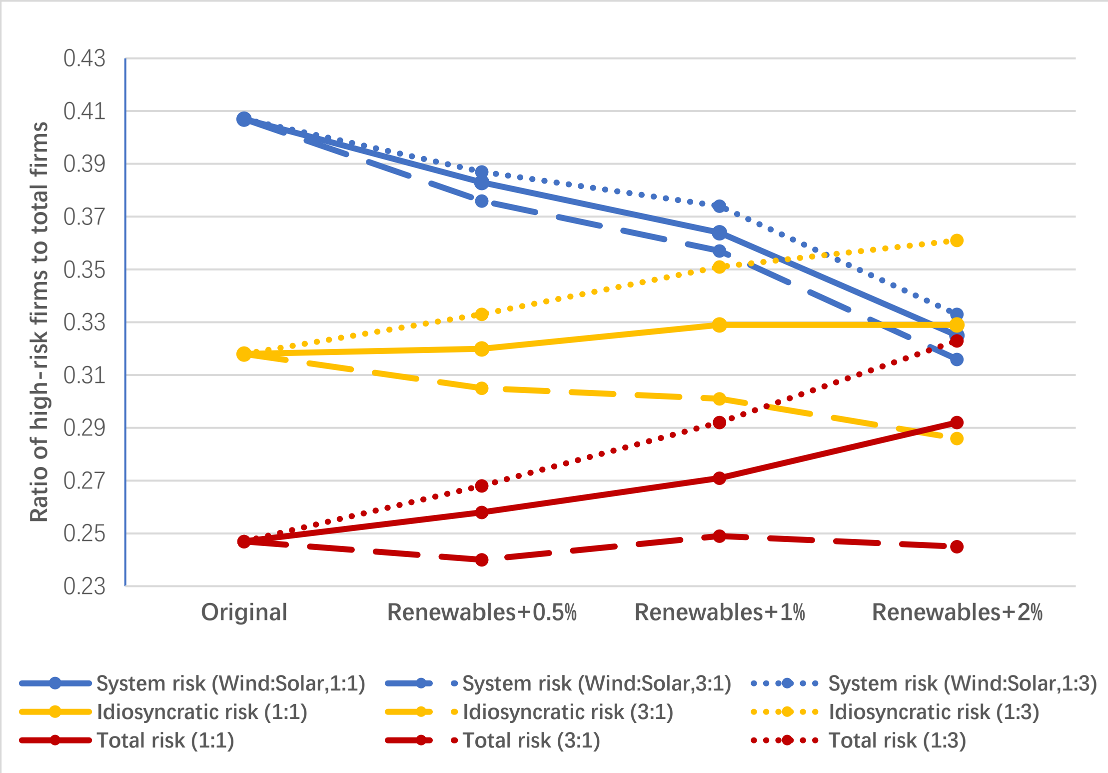

Figure 4.5. Results of high-risk firms' proportions with different renewables growth

Note: The solid, long-dashed, and short-dashed lines correspond to the results of wind and solar energy increases in the ratios of 1:1, 3:1, and 1:3, respectively

Clearly, systematic risk and renewable energy are significantly negatively correlated. Thus, the introduction of more renewables reduces the systematic risk exposure of electricity utility firms. This relationship is consistent across all three wind-solar growth ratios applied. Thus, hypothesis I is supported. It also aligns with prior research showing that environmental performance is negatively correlated with systematic risk (Albuquerque et al., 2019; Oikonomou et al., 2012; Salama et al., 2011). Firms with more renewables tend to be better diversified, and thus, more immune to external volatilities (Shrimali, 2021). Moreover, when the proportion of solar energy exceeds that of wind energy, the short-dashed blue line is positioned above both the solid and long-dashed lines. This indicates a higher ability of the renewable energy to decrease systematic risk when wind energy grows faster than solar energy. This may be the result of the current US power generation landscape, where wind energy is playing a much more important role than the solar energy. In 2020, the percentage of wind energy generation in the total generation was around four times that of solar energy [16]. Therefore, with a much more mature market, investors may consider investments in wind power to be less risky. Consequently, when the development of the wind energy outpaces that of solar energy, electric utility firms are more likely to experience a reduction in systematic risk exposure.

Idiosyncratic risk's relationship with renewables is directly affected by the different growth ratios assigned to wind and solar energy. This is not fully consistent with our hypothesis II that renewable energy is positively correlated with the idiosyncratic risk. The solid yellow line remains relatively flat throughout, while the long- and short-dashed lines show negative and positive trends, respectively. Thus, if wind and solar energy increase proportionally, the impact on idiosyncratic risk is not substantial. However, if the increase in wind energy surpasses that of solar energy, renewable energy and idiosyncratic risk positively correlated. Conversely, the correlation is negative. Moreover, the distance between these lines and the solid line is much greater than that of the systematic risk, indicating that idiosyncratic risk is highly sensitive to disproportional changes in wind and solar energy increments. This may be because although wind energy exhibits a more robust capacity to reduce systematic risk than solar energy, the market still perceives that both energy sources have the potential to mitigate the risk exposure of utility firms. Consequently, the disparity in the impact of varying growth ratios between the wind and solar energy remains relatively small when they have the same impact directions. On the contrary, the results suggest that wind and solar energy have opposite impacts on the idiosyncratic risk exposure of firms. Therefore, when the growth rate of one surpasses the other, individual companies may perceive the changes in their risk profile more sensitive and initiate actions accordingly. This is consistent with the literature which emphasises that environmental factors are the unique characteristics of individual companies, thereby influencing their

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[16] Data are available on the website of U.S. Energy Information Administration: https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T07.02B#/?f=A&start=2010&end=2022&charted=14-13.

idiosyncratic risks (Bouslah et al., 2013; Goyal and Santa-Clara, 2003; Lee and Faff, 2009; Sassen et al., 2016). The specific impact directions, extent, and reasons of the wind and solar energy are further analysed and discussed in the subsequent section.

Importantly, renewable energy's contrasting impact on the idiosyncratic risk with varying wind-solar growth ratios offers a potential explanation for the discrepancies observed in prior research regarding the influence of environmental factors on idiosyncratic risk (Bouslah et al., 2013; Sassen et al., 2016). In previous studies, where renewable energy data were part of comprehensive environmental variables; hence, variations in wind-solar ratios across different samples meant that the seemingly uniform "renewable energy" variable actually exhibited distinct characteristics which will generate different outcomes. This also highlights the importance of thoroughly dissecting environmental factors when studying such issues (Busch and Lewandowski, 2018; Correia et al., 2021).

Next, total risk exhibits comparable trends to the idiosyncratic risk concerning the three distinct wind-solar growth ratios. In essence, when the solar energy experiences a higher growth ratio, the total risk increases decreases. In contrast, renewable energy has almost no impact on total risk when wind energy undergoes a faster growth ratio. As total risk comprises systematic and idiosyncratic risks (Jo and Na, 2012; Sassen et al., 2016), it reflects their comprehensive characteristics. We find that the relationship between idiosyncratic risk and renewable energy has more influence compared to the relationship between systematic risk and renewable energy. Therefore, the total risk displays similar trends to the idiosyncratic risk. This is partially consistent with hypothesis III. This could potentially explain the inconsistent results in prior studies on the relationship between CER and the total risk (Cai et al., 2016; Trinks et al., 2020), as the influence of total risk is a combination of the other two types of risk.

Overall, the short-dashed lines of the three risk types are all positioned above the other two lines. This indicates that when solar and wind energy develop simultaneously, the risk associated with solar energy is greater than that of the wind energy. Therefore, when solar energy increases faster than wind energy, all three types of risks show an upward trend. In fact, many companies may only be able to develop either solar or wind energy in practice due to various reasons, such as natural constraints. In addition, to eliminate potential interactions between wind and solar energy, the following section separately examines their individual impacts on the three types of risks.

4.5.4. The Impact of Wind and Solar Energy on Firms' Risk Exposure

To precisely evaluate the individual effects of wind and solar energy, this section examines their individual impacts on the three types of risks at different growth rates and presents the results in Figure 4.6. Clearly, the growth of wind and solar energy has a consistent negative impact on systematic risk, indicating that investments into the renewables lower firm risks. This is consistent with hypothesis IIIIa. However, the influence of wind energy is more obvious, resulting in a smaller number of firms being classified into the high-risk groups.

Furthermore, wind and solar energy generate opposite impacts on idiosyncratic risk, as wind energy is negatively correlated and solar energy positively correlated with it. In other words, electric utility firms with more wind energy tend to have lower idiosyncratic risk, whereas the adoption of more solar energy may increase firms' idiosyncratic risk exposure. This finding is consistent with hypotheses IIIIb and IIIIc.

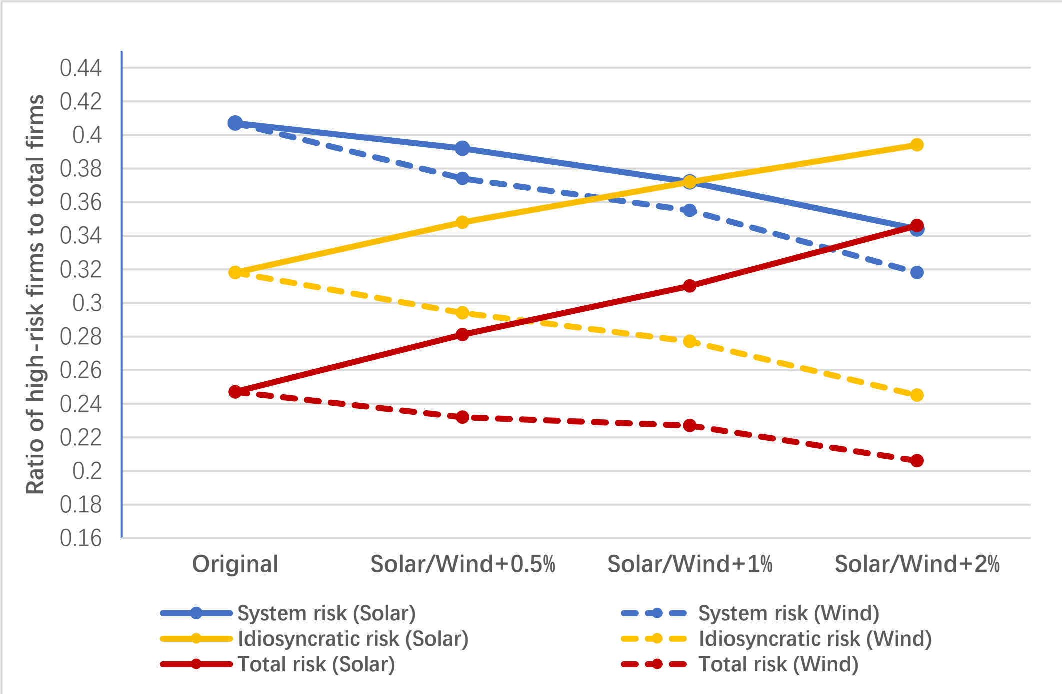

Figure 4.6. Results of high-risk firms' proportions with different solar and wind growth

Note: The blue, yellow, and red lines represent systematic, idiosyncratic, and total risks, respectively. Meanwhile, the solid and dashed lines correspond to solar and wind energy, respectively.

According to IRENA (2021), solar energy consistently had a higher LCOE than wind energy throughout the sample period. Furthermore, based on reports of the UK government in 2015 and 2018, the equity cost of solar energy exceeded that of wind energy in both years (GOV.UK, 2020). Although solar energy experienced a greater reduction (85%) in LCOE compared to wind energy (56%) from 2010 to 2020, its LCOE remains much higher than that of wind over a long period due to high initial costs. Notably, by 2020, the LCOE of wind had even dipped below that of conventional fossil fuels. As the idiosyncratic risk is linked closely with its investment costs, the observed results of increased idiosyncratic risk for solar energy and decreased risk for wind energy could be explained as the differences in LCOE and equity costs between these two renewable sources.

Meanwhile, as the total risk reflects a combination of systematic and idiosyncratic risks, and the latter seems to have a more pronounced influence, the total risk demonstrates a trend which is consistent with that of idiosyncratic risk when additional investments are made in the solar and the wind energy. This is in line with hypothesis IIIId and e. The magnitudes and directions of wind and solar energy's impact on different types of risks are different. Hence, using renewable energy, which includes both wind and solar, as a single variable to assess its relationship with firms' risk exposure may lead to biased conclusions. These biases might arise from the mutual offsetting or compounding effects of wind and solar energy, leading to upward or downward biases. In particular, for the systematic risk, although both wind and solar energy share the same impact direction; meanwhile, wind energy has a stronger risk reduction ability compared to solar energy. Hence, using the composite renewable energy variable may not reveal these distinctions. In terms of the idiosyncratic risk, due to the opposite influence directions of wind and solar energy, the composite renewable energy variable could potentially yield unreliable outcomes. Furthermore, this effect could subsequently contribute to the total risk.

Next, we further investigate whether the influence of wind and solar energy on firms' risks varies over time. The data from 2010 to 2020 are divided into six groups. The first five groups consist of data of two consecutive years each, while data of 2020 is classified as the last group. Within each group, wind and solar energy are again increased by 0.5%, 1%, and 2%, respectively. Figure 4.7 displays how the impacts of wind and solar energy on the systematic risk change over time. Clearly, in the original data (represented by the grey bars), the systematic risk decreases over time from 2010 to 2019. However, in the year 2020, there is an abnormal rebound to the level observed ten years ago. This may be because of the dislocations caused by the COVID-19 pandemic, leading to crisis in the energy sector (IEA, 2020b).

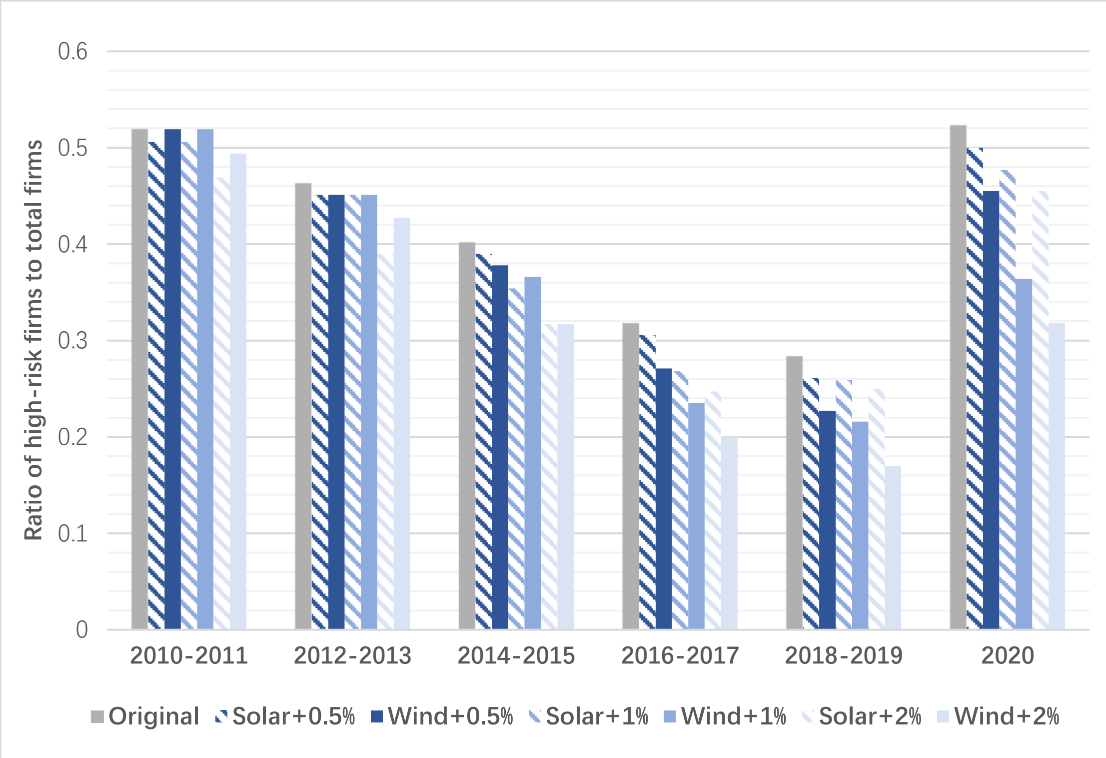

Figure 4.7. Impacts of wind and solar energy on the systematic risk over time

Note: Solid and dashed bars represent wind and solar, respectively

First, except for the year 2020, the systematic risk decreases over time as the use of both wind and solar energy increases. The negative impact is more significant in recent years, and when more wind and solar energy are used. Compared with solar, firms using wind tend to experience a faster reduction in their systematic risk exposure. For example, from 2016 to 2019, for all three increase scenarios, firms with wind energy experience lower systematic risks compared with solar energy. This may be because after 2016, the installed capacity of wind energy has been much higher than that of solar. Hence, scaling up wind energy on a larger basis may be recognised by the market as a more stable choice, leading to a more rapid reduction in the associated systematic risk. Finally, although the data for the year 2020 may be influenced by the COVID-19 pandemic, increasing the utilisation of wind and solar energy can effectively reduce systematic risk to a certain extent.

Figure 4.8 depicts the variations in idiosyncratic risk. Even when the anomalous year, 2020, is excluded, the original idiosyncratic risk faced by firms is increasing gradually over years. After adjusting the proportion of wind and solar energy to firms' original energy portfolio. The idiosyncratic risk rises over time for all three increments of solar. This rise is also positively correlated with the size of the increase of the proportion of the solar energy. This aligns with the higher LCOE of solar energy (IRENA, 2021).

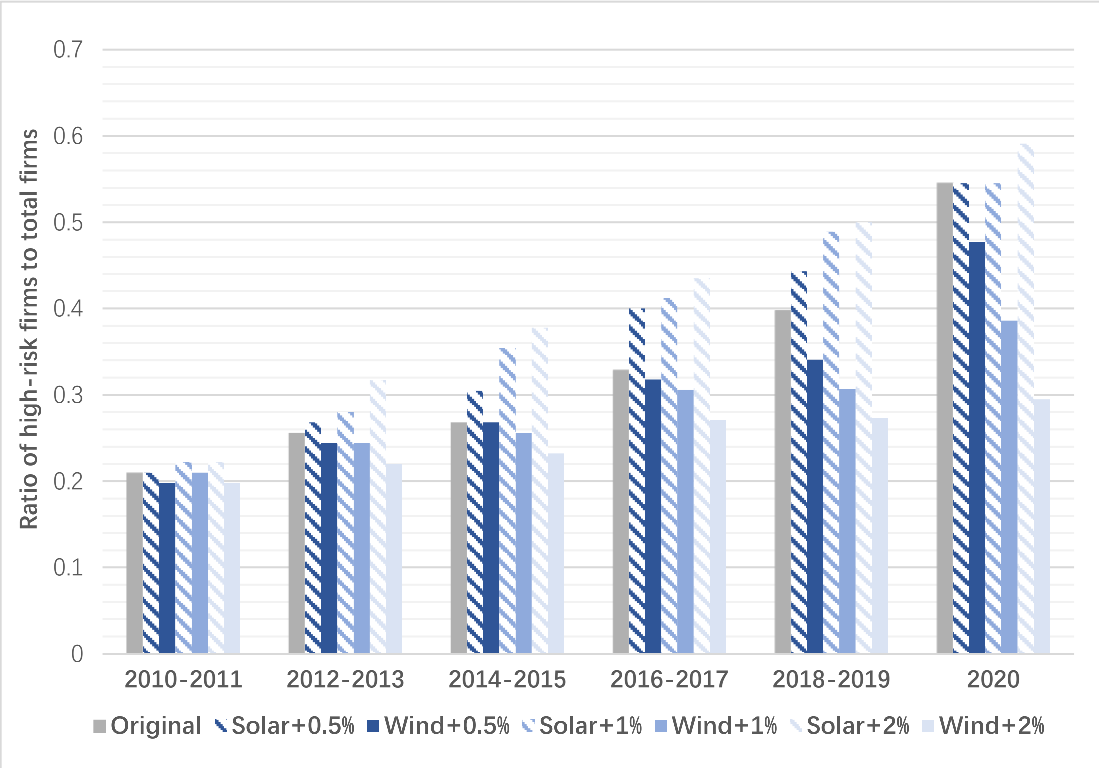

Figure 4.8. Impacts of wind and solar energy on the idiosyncratic risk over time

Note: Solid and dashed bars represent wind and solar, respectively

Meanwhile, each increment of wind energy reduces the original idiosyncratic risk within the study period, while the magnitude of reduction in risks increases when more wind energy is used. However, the idiosyncratic risk still increases over time at a slow speed after an increase in wind energy in three different rates. This indicates that wind energy can mitigate the rise in idiosyncratic risk, but the extent of reduction is not large enough to fully alter the trajectory of risk progression. This is consistent with the fact that financing renewable energy projects is challenging, especially in the earlier development stage (Geddes et al., 2018; Polzin et al., 2015).

Total risk (Figure 4.9) remained relatively stable from 2010 to 2019. However, it exhibited a noticeable increase in the abnormal year of 2020. As the total risk exposure of firms equals to the sum of the systematic and idiosyncratic risks, the converse growth of the two risks during normal years offset each other, resulting in firms' relatively stable overall risk exposure. However, when variations in wind and solar energy are considered, solar energy's changing pattern follow that of the idiosyncratic risk as it shows a stronger influence degree compared to the systematic risk. Although wind energy mitigates the idiosyncratic risk compared to the original one, it still experiences a slow increase over time. Further, such an increase is offset by the decrease in the influence of systematic risk. Consequently, wind energy shows no obvious impact on total risk.

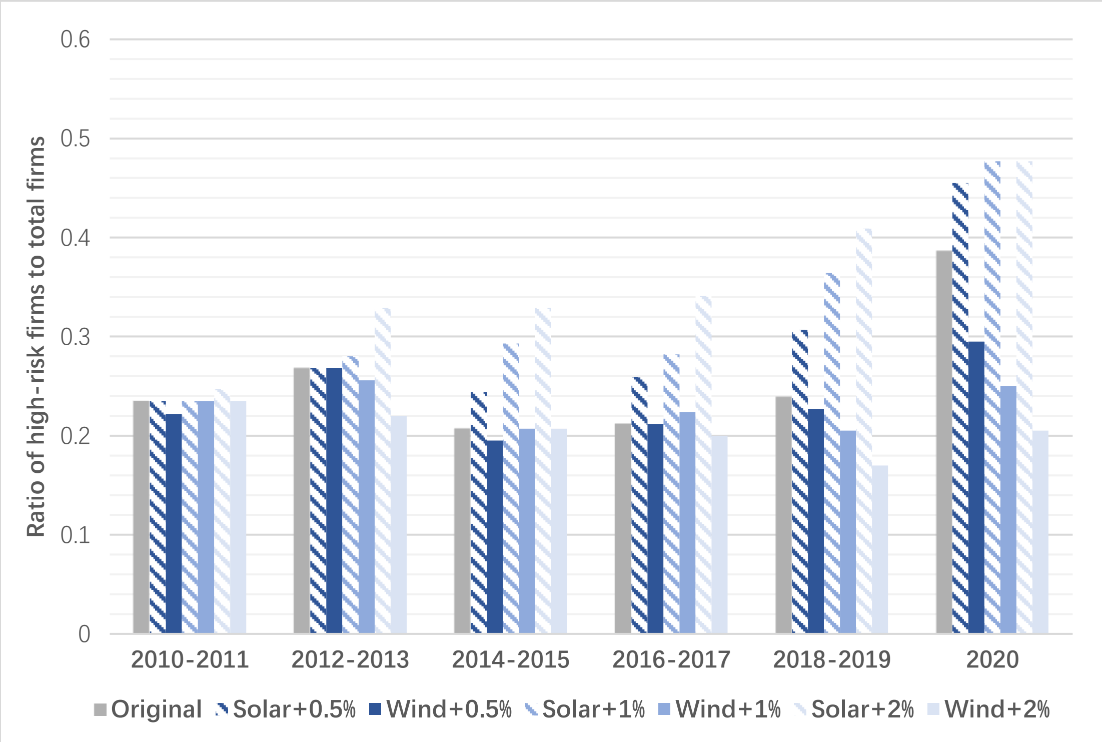

Figure 4.9. Impacts of wind and solar energy on the total risk over time

Note: Solid and dashed bars represent wind and solar, respectively

4.6. Conclusion

Reacting to the challenges of climate change, the electric utility industry has directed substantial financial resources toward its energy structure transition. Then, one may ask whether this significant investment affects the fluctuations in their market risk. Using a dataset consisting of 44 listed companies operating in the US electric utility industry from 2010 to 2020, we ask: Whether and how does the development of renewables affect the systematic, idiosyncratic, and total risk exposures of firms? Is the impact of different kinds of renewable energy consistent on different types of risk exposure?

Employing the machine learning classification approach, SVM, we show that the inclusion of energy variables improves the classification accuracy of systematic, idiosyncratic, and total risks, constructing a more reliable classifier. Second, we simulate the increase in the growth in renewables at different rates of 0.5%, 1%, and 2%. Further, to better simulate the real-world scenario of inconsistent growth ratios within the renewables, three different growth ratios, 1:1, 3:1, and 1:3, are applied to wind and solar energy for each rate. We find that first, systematic risk and renewable energy are significantly negatively correlated. That is, the introduction of more renewables reduces the systematic risk exposure of electricity utility firms. This relationship is consistent across all three wind-solar growth ratios. Notably, the reduction in systematic risk is more pronounced when wind energy has a larger proportion compared to solar energy. This may be due to the current US power generation landscape, where wind energy is playing a much more important role than solar energy; consequently, investors feel more confident about further expanding wind energy capacity. In contrast, idiosyncratic risk exhibits positive relationships with renewable energy when solar develops at a faster pace than wind, and *vice versa*. This finding offers a potential explanation for the discrepancies observed in former research regarding the influence of environmental factors on idiosyncratic risk (Bouslah et al., 2013; Sassen et al., 2016). Specifically, when the renewable energy data are part of comprehensive environmental variables, variations in wind-solar ratios across different samples may be simply ignored. This divergence strongly implies the necessity of considering different outcomes in such research. In addition, as the total risk encompasses both systematic and idiosyncratic risks, it follows a similar pattern to idiosyncratic risk, which exhibits a stronger influence compared to the systematic risk.

Third, the independent effects of wind and solar on the three risks have been examined. Both wind and solar are negatively correlated with the systematic risk due to their continually decline LCOE, which leads to lower risk perception by the market as the energy product diversifies. For the idiosyncratic risk, wind and solar exhibit opposite effect. Since the LCOE of solar remains higher compared to wind, firms perceive a higher (lower) risk associated with solar (wind), resulting in a positive (negative) relationship with idiosyncratic risk.

Besides examining the individual effects of wind and solar on the three risk types, we explore whether these effects change over time. The results show that in terms of systematic risk, although both wind and solar have negative impacts over time, wind leads to a much faster decline compared to solar. Meanwhile, solar (wind) significantly increases (decreases) idiosyncratic and total risks. In other words, electric utility firms with more wind (solar) energy tend to have lower (higher) idiosyncratic risk. This is mainly due to the lower costs of wind energy compared with solar energy. Furthermore, the degree of influence of solar is much larger than that of wind, suggesting that the same amount of wind is insufficient to offset the risks brought about by an equivalent amount of solar. This implies that the firm may be more sensitive to the higher cost compared to the lower cost.

To sum up, it can be stated in a broader concept that the energy structure transition significantly affects not only the systematic but also idiosyncratic and total risks faced by utility firms. However, it needs to clarify that it is not proper to deduce the influence direction of whole energy structure transition as each energy types may have diverse impact direction.

Our findings have some valuable implications. First, considering idiosyncratic risk in asset pricing is reasonable as this risk is significantly influenced by both wind and solar. Second, as the impacts of wind and solar on the systematic and idiosyncratic risks vary in direction and degree, a rational allocation between the two should be considered to minimise the total risk exposure of firms. Third, given the higher risk associated with solar energy, companies can explore diversified financing sources for developing solar energy projects, rather than relying on the equity financing only. For instance, some other financial instruments, like green bonds, could be used to mitigate the impact of market fluctuations. Finally, governments should consider the diversified conditions of different regions while formulating subsidy policies. For instance, in areas where wind energy development is restricted by geographical and climatic factors, more support could be provided to assist firms' development of solar projects. This can facilitate the better utilisation of state funding, reducing the risk exposure of electricity utility firms while improving their overall financial performance. In turn, this can promote the steady development of the green energy industry and accelerate the energy structure transition of the whole country.

This study has some limitations. This study only investigates how energy structure transition influences firm risks in the US market, which exhibits a moderate level of renewable energy development. Future studies could be extended to regions with high renewable energy proportion in the energy mix, such as Germany and Northern European countries. Furthermore, developing countries undergoing rapid renewable energy expansion should be considered as well, such as China and India. Comparative studies can further reveal interesting and comprehensive insights.

Chapter 5: The Cost Optimisation of the Electricity Retailers with the Integration of the Cloud Energy Storage

5.1. Introduction

Along energy supply structure adjustments and higher requirement for energy efficiency, many countries, including the US, Australia, European countries, and the UK, started reforming the electricity market since the 1990s. The goal has been to unbundle the traditional vertically integrated electricity market into four sectors, generation, transmission, distribution, and supply, and induce competition via privatisation, restructuring, and deregulation (Sioshansi and Pfaffenberger, 2006). With this market liberalisation process, the majority of electric utilities in many countries are now investor-owned (EIA, 2019). Electric utilities in the supply sector are often referred to as electricity retailers. Acting as an intermediary, retailers purchase electricity from the generators and resell it to the end users. The prosperity of the electricity retail market has offered customers with more choices and helped the whole power industry in improving its efficiency.

Contrary to normal commodities, electricity can neither be stored on a large-scale nor can the supply-demand relation be simply adjusted via inventory management. The production and consumption of electricity must always be balanced to avoid power wastage and extremely high electricity prices (Griffin and Puller, 2005; Müsgens et al., 2014). When electricity supply and demand are unbalanced for a substantial amount or period, it may lead to additional maintenance expenses, lower energy efficiency, and even market failure, such as the California crisis (Joskow, 2001). To appropriately balance electricity supply and demand, and survive under tough competition, retailers need to work carefully with both the consumer and wholesale sides of the market. Extensive research has used various angles to examine how the balance program can be addressed, including consumer load forecasting, energy procurement strategies, and related risk management.

Several studies have explored load forecasting. For instance, various techniques, such as Artificial Neural Network (Alhussein et al., 2020; Cecati et al., 2015; Li et al., 2016), linear regression model (Hong and Wang, 2014), semi-parametric additive model (Goude et al., 2014), statistical method (Hong et al., 2014), and fuzzy regression (Hong and Wang, 2014; Song et al., 2005) have been proposed to forecast the short-term load (up to several weeks). Moreover, the long-term load forecasting models (up to a few years) are often developed based on short-term models (Hong et al., 2014; Hyndman and Fan, 2010; Nalcaci et al., 2019; Xie et al., 2015; Yang et al., 2018).

In terms of the energy procurement strategies, various internal and external factors, including the electricity price volatility, price elasticity of demand, and market competition, are considered while making the optimal purchasing decision from different sources, such as the spot market, forward contracts, call options, and self-production facilities (Yang et al., 2018). Several models have been proposed to capture electricity price volatility, such as the generalised autoregressive conditional heteroskedasticity (GARCH) and GARCH-jump models (Ciarreta et al., 2020; Hatami et al., 2009; Liu and Shi, 2013), the mean-reverting Ornstein-Uhlenbeck stochastic process (Kettunen et al., 2010), and the envelope bound model (Charwand and Moshavash, 2014). Meanwhile, two main types of models are widely used for energy procurement optimisation: the stochastic (Safdarian et al., 2015) and bi-level optimisation models (Nazari and Akbari Foroud, 2013). The demand side responses are often considered in the purchasing models (Feuerriegel and Neumann, 2014; Khan et al., 2015; Zugno et al., 2013).

Finally, on the risk management of electricity retailers, some studies have focused on the trade-off between the expected profit and risk (Carrion et al., 2007; Charwand and

Gitizadeh, 2020; Mahmoudi-Kohan et al., 2010; Sun et al., 2021). Others have analysed the hedging strategies that can be adopted by the electricity generators and retailers (Boroumand et al., 2015; Deng and Oren, 2006; Stevenson et al., 2006). However, some hedging choice could be inefficient, and the seasonal variation of the electricity consumption may cause systematic mismatch in hedging demand (Junttila et al., 2018).

Among all available tools that electricity retailers have to balance supply and demand, the development of energy storage brings new possibilities. Energy storage is a set of technologies that transform one kind of energy which is hard to store to other kinds of energy which can be easily stored and used at a later time (IEA, 2023a). This time difference in electricity production and consumption can significantly reduce the imbalance between energy supply and demand. The rapid development of energy storage has come along with the increasing penetration of renewable energies. As a sustainable and environmentally friendly energy source, renewable energy is projected to account for nearly 90% of global electricity generation by 2050 (IEA, 2021a). However, the nature of renewable energy makes it unstable and intermittent. Energy storage technologies can help address this intermittency and have indeed developed rapidly in recent years. Energy storage facilities can be installed flexibly in any place on the power system—from the generation supplier, through the transmission network, and to the final consumer—to integrate them in the comprehensive operation of the power system (Ding et al., 2019; Locatelli et al., 2015). Notably, using energy storage techniques to maintain grid balance in the power system is not a new research topic. Studies have typically focused on the integration of stored energy into the grid from the aspects of electricity generation, transmission, and distribution sectors (Després et al., 2017; Di Cosmo and Malaguzzi Valeri, 2018; Scorah et al., 2012). To our knowledge, little attention has been paid on the role played by electricity retailers, probably because the energy storage technologies were not that well developed at the time. With energy storage technology advancements, the lower cost and faster response of storage technologies has now made it possible for retailers to utilise energy storage devices to balance the load deviation and optimise the procurement strategies. Since then, an increasing number of models have been proposed to simulate this optimisation process.

Hu et al. (2019) built a purchase model of an energy storage system and distributed renewable energy to control the load forecast deviation risk and increase the total profit of the power-selling company. Wei et al. (2015) proposed a two-stage two-level optimisation model for the retailers to cope with the procurement problems incorporating storage units. In the first stage, the consumer's attitude to the retail price was reflected by the demand response. This phenomenon was characterised by a Stackelberg game in which the leader of the market moves first, and then the followers move. In the second stage, retailers worked on dispatching energy storage and executing the energy contracts. Using case studies, the authors showed that building larger storage units may help retailers maximise their profits. Ju et al. (2020) proposed a new two-stage demand response for electricity retailers with an energy storage system and a corresponding two-layer coordinated optimal model for purchase and retail transactions, respectively. The results showed that higher energy storage capacity with proper dimension can enhance the demand response efficiency. Yang et al. (2020) constructed a multi-objective stochastic optimisation model of electricity retailers with energy storage system to minimise the cost of electricity retailers and maximise the consumption of clean energy power generation considering the uncertainties of clean energy power generation and demand response in four different scenarios. Liu et al. (2021) established an optimal planning model for multiple electricity retailers who shared energy storage and analysed the cost-benefit for them of doing this. The electricity retailers were screened and classified into groups with high or low matching degree based on the correlation degree of their load curves. Their results demonstrated that energy storage can effectively reduce the cost for all groups and the groups with higher matching tend to benefit more. Sun et al. (2022) built a data-model hybrid driven bi-level optimisation model to maximise the profit of the electricity retailer by combining real-time price and energy storage system as demand response strategies.

The authors found that the retailer's profit extra increases by 7.19% after integrating the energy storage system.

Together, these studies show the feasibility of using energy storage for cost cutting and profit maximisation by electricity retailers from different angles. Moreover, a higher level of energy storage capacity and more flexible consumption patterns are more likely to lead to higher profit and efficiency. However, Liu et al. (2017) noted that despite these potential benefits, in practice, high maintenance cost, policy restriction and low control efficiency mean that many domestic and small users are reluctant to invest in energy storage devices. To address this issue, a new business concept, cloud energy storage (CES), was developed (Liu et al., 2017). In this virtual energy storage service system, the CES operator invests and operates centralised energy storage facilities. Different kinds of energy storage devices can be deployed according to different situations to optimise the operations. CES users can make a virtual request of their load demand to the central operator, and store or withdraw real electrical energy to and from central energy storage facilities connected to the power grid. Due to the sharing of storage resources and economies of scale, CES can help in achieving higher social benefits at lower social costs.

The amount of energy that needs to be charged or discharged by energy retailers to deal with supply and demand fluctuations is volatile. Hence, renting CES capacities seems a better choice as it is more flexible and cheaper in the short term. Due to tough competition, it is important for the electricity retailers to limit costs. Therefore, we believe that the adoption of CES may offer new business opportunities to retailers. Then, one question naturally arises: How can we fully utilise the CES system to balance electricity supply and demand while maximising retailer profits? We construct a new business model to estimate the optimal CES rental amount required to achieve a balanced supply and demand on a daily basis. Based on this, we further calculate the minimal costs incurred. Data from the advanced PJM[17] market from the US are used to test the feasibility of the model.

The contributions of this study are fourfold. First, to the best of our knowledge, this is the first study which try to link the two agents, electricity retailers and CES suppliers, for potential collaborations. Compared with individuals, these agents have more resources to gather comprehensive market information. Further, compared with the power system, they tend to be more flexible. Consequently, if these two agents can collaborate, a win-win situation can be created for more efficient resource allocation and more stable power supply.

Second, this study proposes a new energy storage model for electricity retailers. Unlike previous studies that require electricity retailers to purchase the energy storage devices, this model proposes a dynamic renting mode, allowing the electricity retailers to rent the energy storage capacities from CES suppliers according to their daily needs. In this way, the idle energy storage devices can be fully utilised, and the financial burden of the electricity retailers can be significantly reduced. With a much higher capital utilisation rate, returns generated from investments in energy storage can be greatly improved.

Third, The CES-based business model requires the estimation of a set of energy storage devices' overall cost (Liu et al., 2017). This study advances this business model by providing a more accurate estimation of the single rental price of CES. It considers all key factors including the time value of the capital, battery life, and charge-discharge cycle times. In practice, to maximise profit, electricity retailers can use this estimated single rental price as a key reference while searching for electricity supplies from different sources.

[17] PJM, the Pennsylvania-New Jersey-Maryland Interconnection, is a regional transmission organisation (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia in the United States.

Finally, the proposed business model is very practical and can be easily adapted in different electricity markets with minor adjustments. The case study uses data from the PJM electricity market, and demonstrates that the proposed method can significantly reduce the total cost of the electricity retailers and improve their operational efficiency. As electricity consumption behaviours, electricity price trend, and battery price share many common characters in different countries and regions, our proposed business model can also be applied in different markets with reasonable confidence. In addition, as the costs of the electricity retailers decrease over the long term, the electricity price would be lower. This may save energy and reduce carbon emissions.

The rest of this chapter is organised as follows. Section 5.2 describes the cooperation between electricity retailers and CES suppliers and establishes the business model for the electricity retailers to incorporate CES. Section 5.3 builds the model to calculate the single rental cost of the CES and confirm its optimal rented amount of the CES. Section 5.4 explains the data selection and analysis approaches. Section 5.5 presents the case study to demonstrate the effectiveness of the proposed model in different scenarios. Section 5.6 highlights the contributions and draws the conclusions of this chapter.

5.2. Cooperation between Electricity Retailers and CES Suppliers

5.2.1. Electricity Retailers Operations

To understand the relationship between electricity retailers and CES suppliers, we first discuss the purchasing process of electricity retailers. In general, retailers' purchasing decision is determined by consumer demand, which can be highly volatile sometimes. To reduce the uncertainties, electricity retailers often divide the purchasing amount into the fixed and variable components, and engage in transactions on both medium-to-long term financial markets and the short-term spot market (Nazari and Akbari Foroud, 2013). For the fixed component, electricity retailers can sign procurement contracts with the generators directly at a relatively low price. They can also use futures and other financial derivatives to hedge against the potential risk exposure. In practice, this fixed amount is often estimated conservatively as any deviation from this figure may lead to penalties or high balance fee cost (Hu et al., 2019). Meanwhile, generators and electricity retailers also bid and offer in the short-term spot market, where the price is constantly fluctuating. Consequently, under the widely adopted time-of-use (TOU) pricing scheme, the electricity retailers would bear the price risks from the spot market. In particular, if it is very close to the electricity consumption time, a very high cost could be incurred to balance the supply and demand (Byström, 2005). This can incentivise the development of energy storage, which can be used to effectively balance supply and demand on both medium-to-long term markets and the short-term spot market (Bradbury et al., 2014; Hu et al., 2019; Zhang et al., 2013). The electricity retailers can purchase a certain amount of electricity when the price is low and then discharge it when needed. This can reduce the demand for high cost electricity on the spot market while absorbing the additional electricity generated from the medium-to-long-term market. Meanwhile, the increased demand in the medium-to-long term market may encourage large scale energy generation from renewable sources; this can further lower the overall electricity generation costs.

5.2.2. Business Model

As shown in Figure 5.1, the flow of the electricity can be explained from both physical and economic aspects. From the natural science perspective, the entire process of electricity production, transmission, and consumption is completed almost simultaneously. Generators produce the electricity, the power grid transmits the electricity to consumers, and then the electricity is immediately consumed. This process can be regarded as a physical chain of electricity flow. Meanwhile, from an economic perspective, a business chain exists for electricity consumption. The central platform of the business chain is the electricity market, which incorporate all parts of the physical chain.

As a professional agency, electricity retailers do not exist in this physical chain but are inevitable in the business chain. Renting storage capacity from the CES suppliers can significantly improve the adjustment ability of the electricity retailers. In the following section, we propose an optimisation model for the electricity retailers with the CES (ER-CES). To ensure the balance between electricity supply and demand, ER-CES will rent certain amount of energy storage capacities from the CES for charging or discharging. However, as the real-time electricity price may be cheaper than the cost of the CES in some periods, it is not advisable to balance all the supply-demand imbalance by renting the CES. Understanding the optimal rental amount of CES is essential. Hence, the model first calculates this amount and then determines the total minimal cost.

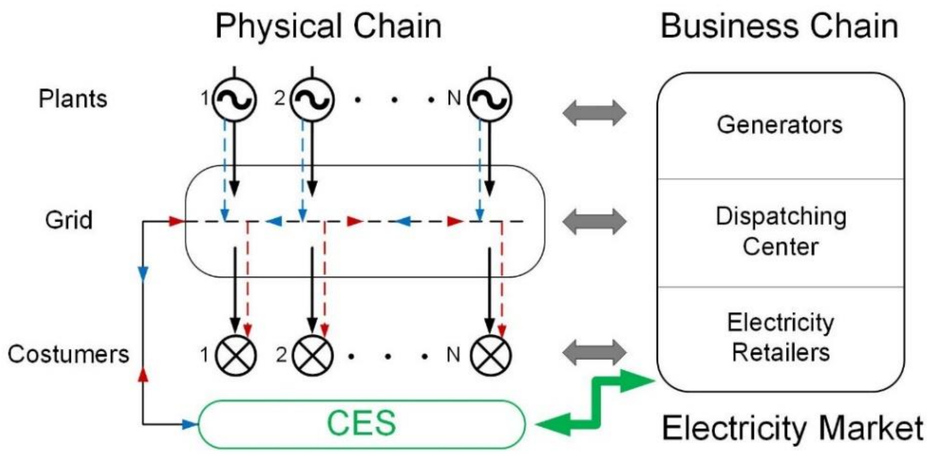

Figure 5.1. ER-CES model

5.3. Methodology

5.3.1. Flow of the ER-CES Model

Essentially, electricity retailers purchase electricity from the electricity market based on customer demand and then sell it to customers, taking advantage of the wholesale-retail arbitrage. However, customer demand is dynamic, leading to a difference between the amount of electricity purchased in advance and actual customer demand. Consequently, there is always a load deviation between the predicted and real loads. Taking one day's load data of the PJM power market in the United States as an example, Table 5.1 shows the predicted load, real load, and load deviation ratio of one load area on December 11, 2020. The load deviation ratios vary from -9.43% to 6.31%. The parts of positive deviation should be purchased from the spot power market to compensate for the shortage, while the negative deviation should still be paid according to the contract.

Table 5.1. Load data from the PJM on December 11, 2020

Time	Predicted Load / MW	Real Load / MW	Load Deviation Ratio
12 am	1290	1352.5	4.62%
1 am	1258	1292.9	2.70%
2 am	1244	1277.6	2.63%
3 am	1243	1249.8	0.54%
4 am	1266	1262.1	-0.31%
5 am	1326	1284.0	-3.27%
6 am	1418	1355.7	-4.60%
7 am	1494	1446.8	-3.26%
8 am	1522	1509.5	-0.83%
9 am	1537	1539.2	0.14%
10 am	1538	1525.2	-0.84%
11 am	1527	1496.1	-2.07%
12 pm	1514	1493.7	-1.36%
1 pm	1499	1478.0	-1.42%
2 pm	1481	1452.1	-1.99%
3 pm	1470	1423.1	-3.30%
4 pm	1487	1408.0	-5.61%
5 pm	1548	1414.6	-9.43%
6 pm	1532	1509.0	-1.52%
7 pm	1499	1501.6	0.17%
8 pm	1458	1486.7	1.93%
9 pm	1408	1465.5	3.92%
10 pm	1345	1417.5	5.11%
11 pm	1276	1361.9	6.31%

Figure 5.2a shows electricity retailers' actual processing procedure for the load deviation in practice, which has no CES (No-CES); the aim is to solve the load deviation by purchasing electricity in the spot power market. The purchase price is the spot price for that day and is cleared by the end of the day. In general, the spot price is much higher than the contract price; if the load deviation is too large, the retailer may have to pay a penalty.

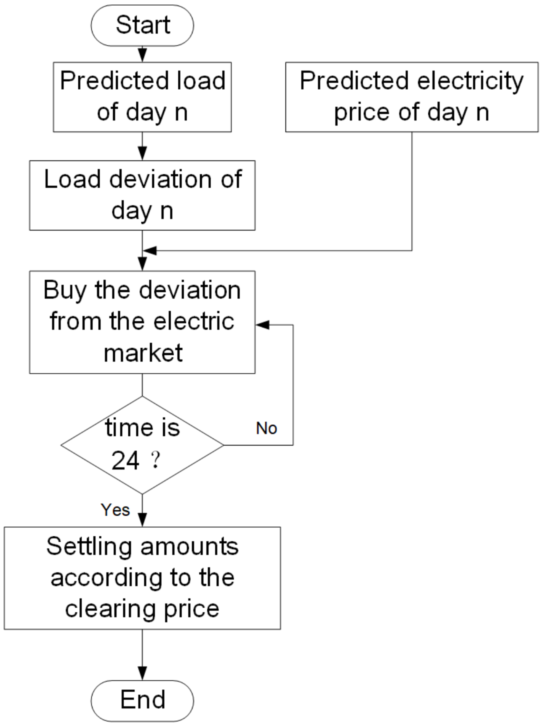

Figure 5.2a. Flow chart of the No-CES Model

Figure 5.2b below illustrates how an electricity retailer can minimise its costs after incorporating the CES. The predicted load, predicted electricity price, and single CES price of day n are obtained first. Then, they are used for computing the total cost of ER-CES and optimal CES rental amount. When a positive deviation occurs on day n, the CES will discharge for compensation; for a negative deviation, the CES is charged to absorb the extra power.

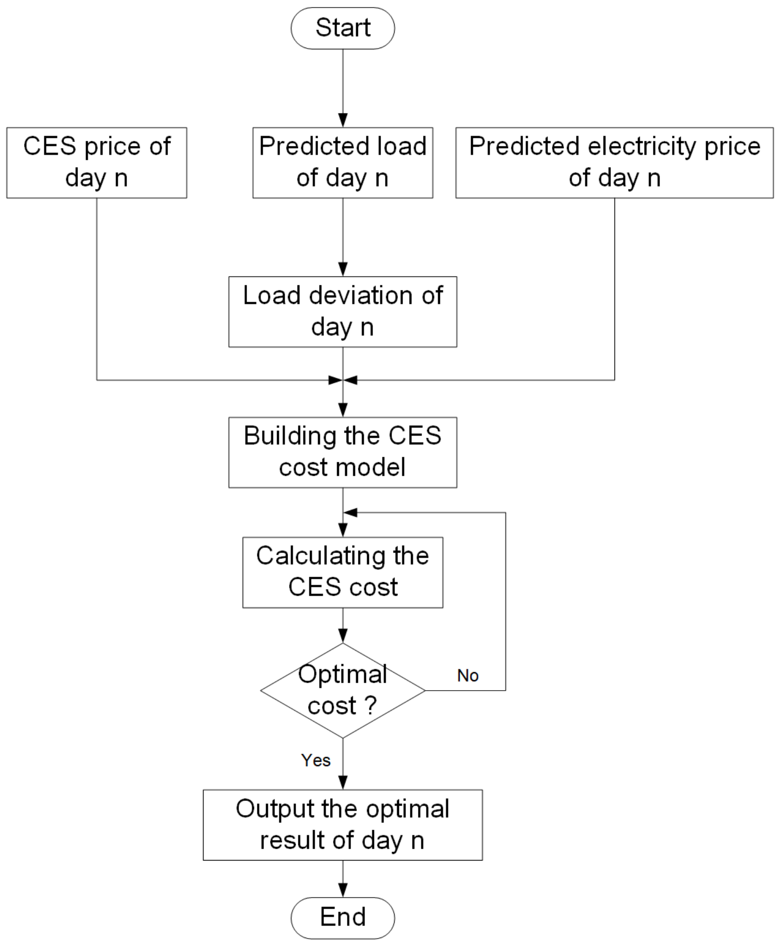

Figure 5.2b. Flow chart of the ER-CES Model

5.3.2. Definition of Load Deviation

The price of energy storage devices is determined by two factors: power (P) and capacity (Q) (Q = PΔt). To rapidly respond to charging and discharging needs, and avoid the repeated charging and discharging of the same equipment, two sets of energy storage devices are normally required to compensate and absorb the load deviation, respectively. If an hour is set as one trading period, there will be 24 trading periods in a day. The estimated load for period t of day n can then be represented by $P_{Lp(t)}$. Assuming the actual load as $P_{L(t)}$, the deviation $P_{K(t)}$ is:

$$P_{K(t)} = P_{L(t)} - P_{Lp(t)} \tag{1}$$

The size of $P_{K(t)}$ depends on the accuracy of load forecasting. However, a prediction error is inevitable due to the randomness of electricity consumption. As load forecasting is not the research object of this study, the load deviation curve of day n will be estimated in a simple way. From Figure 5.3, when $P_{K(t)} > 0$ in period t, it is called the positive load deviation, implying that the actual load is greater than the estimated load (Hu et al., 2019). The optimal discharging CES capacities should then be calculated to compensate the deviation. Assume that the power discharged is $P_{ESD(t)}$, then, for all periods t with a positive $P_{K(t)}$, the total capacity is Q_{ESD}. When $P_{K(t)} < 0$, it is called a negative load deviation, implying that the actual load is less than the estimated load (Hu et al., 2019). The optimal charging CES capacities should then be calculated to absorb the load deviation. Assume that the power of absorption is $P_{ESC(t)}$, then, for all periods t with a negative $P_{K(t)}$, the total capacity is Q_{ESC}. Consequently, the remaining positive and negative deviations, represented by the yellow parts in Figure 5.3, would be traded directly in the real-time electricity market.

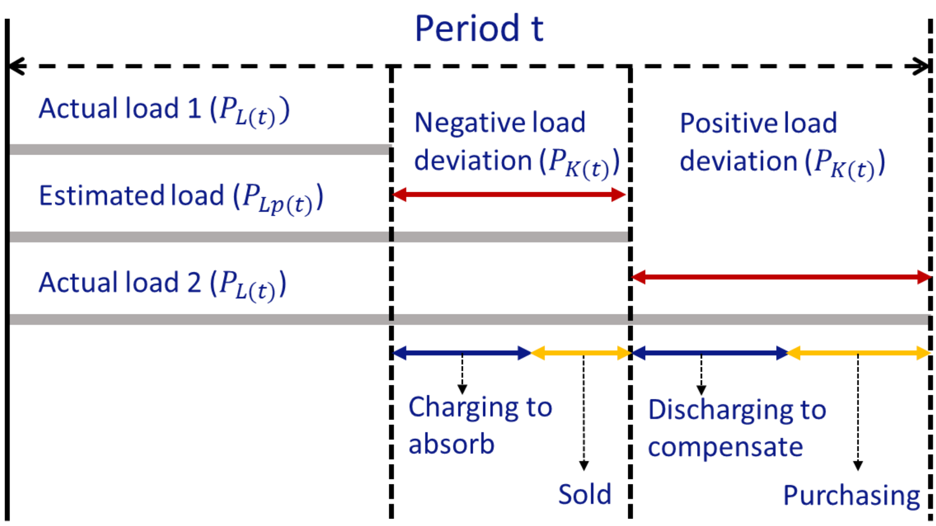

Figure 5.3. Load deviation

5.3.3. Electricity Cost of ER-CES

To balance the daily load deviation though CES, the cost of electricity charging and discharging should be separately calculated. The charging electricity needs to be purchased, while the discharging electricity can be sold. Assuming N periods for charging and M periods for discharging; then, the difference between the two parts can be positive or negative. Referring to the electricity price curve of day n, set $\gamma_{(t)}$ as the estimated real-time electricity price for day n. Then, the cost is:

$$C_{ES} = \sum_{t=1}^{N}(P_{ESC(t)} \times \Delta t \times \gamma_{(t)}) - \sum_{t=1}^{M}(P_{ESD(t)} \times \Delta t \times \gamma_{(t)}) \tag{2}$$

According to the model, the optimal charging and discharging amount may not fully match the deviation. Then, the unfulfilled component must still be traded in the spot market. Using $\gamma_{(t)}$ as the trading price, the difference cost for charging and discharging is:

$$C_{ES}^{+} = \sum_{t=1}^{M}[(P_{K(t)} - P_{ESD(t)}) \times \Delta t \times \gamma_{(t)}], \quad P_{K(t)} > 0 \tag{3}$$

$$C_{ES}^{-} = \sum_{t=1}^{N}[(-P_{K(t)} - P_{ESC(t)}) \times \Delta t \times \gamma_{(t)}], \quad P_{K(t)} < 0 \tag{4}$$

Then, the total electricity costs after using the CES is:

$$C_{ES}^{E} = C_{ES} + C_{ES}^{+} + C_{ES}^{-} \tag{5}$$

5.3.4. Equipment Cost of ER-CES

The total equipment cost includes two parts: the energy ($/kWh) and power capacities ($/kW):

$$C_{ESP} = (\alpha_{ES} Q_{ESM} + \beta_{ES} P_{ESM}) \tag{6}$$

α_{ES} and β_{ES} are the unit investment cost of the energy ($/kWh) and power capacities ($/kW), respectively. Q_{ESM} and P_{ESM} are the purchased energy capacity and power capacity of energy storage.

After considering the time value of capital, the annualised equipment cost (C_Y) over Y years can be estimated as follows, assuming r is the discount rate (Liu et al., 2017):

$$C_Y = \frac{r}{1-(1+r)^{-Y}} \times C_{ESP} = \frac{r}{1-(1+r)^{-Y}} \times (\alpha_{ES} Q_{ESM} + \beta_{ES} P_{ESM}) \tag{7}$$

The single rental price is related to the service times of equipment that has limited number of uses. Setting the circle times for charging and discharging as K, one year's usage days as ρ, and one circle for one day, the service life of the energy storage equipment is:

$$Y = \frac{K}{\rho} \tag{8}$$

The single rental price of energy and power capacities, α and β, respectively, can be represented as：

$$\alpha = \frac{\left(\frac{r}{1-(1+r)^{-\frac{K}{\rho}}}\right) \times \alpha_{ES}}{\rho} \tag{9}$$

$$\beta = \frac{\left(\frac{r}{1-(1+r)^{-\frac{K}{\rho}}}\right) \times \beta_{ES}}{\rho} \tag{10}$$

Next, P_{ESCM} is defined as the rental power capacity for charging, and it should meet the largest one:

$$P_{ESPCM} = \max\{P_{ESC(t)}\},\ t = 0,1,2\ldots23 \quad (11)$$

P_{ESDM} is the rental power capacity for discharging, and it also should meet the largest one:

$$P_{ESPDM} = \max\{P_{ESD(t)}\},\ t = 0,1,2\ldots23 \quad (12)$$

Then, the rental energy capacity for charging is:

$$Q_{ESC} = \sum_{t-1}^{N}(P_{ESC(t)} \times \Delta t) \quad (13)$$

The rental energy capacity for discharging is:

$$Q_{ESD} = \sum_{t-1}^{N}(P_{ESD(t)} \times \Delta t) \quad (14)$$

Because the charging and discharging capacities are rented separately, charging and discharging only complete half of one charge-discharge cycle. This means that only half of the full cost should be calculated for charging (C_{ESC}) and discharging (C_{ESD}) separately:

$$C_{ESC} = \frac{1}{2} \times (\alpha Q_{ESC} + \beta P_{ESCM}) \quad (15)$$

$$C_{ESD} = \frac{1}{2} \times (\alpha Q_{ESD} + \beta P_{ESDM}) \quad (16)$$

The total equipment cost for using CES is:

$$C_{ESP} = C_{ESC} + C_{ESD} \tag{17}$$

5.3.5. Upfront Cost of ER-CES

The charging equipment prepared for absorbing the electricity should be kept empty. Meanwhile, the discharging equipment should be charged in advance to guarantee the supply. The amount is determined based on the optimised energy and power capacities. Then, the cost for day n is:

$$C_{ESD'} = \gamma_{(p)} \times Q_{ESD} = \gamma_{p1} \times \sum_{t=1}^{M} (P_{ESD(t)} \times \Delta t) \tag{18}$$

γ_{p1} is the clearing price of day n-1. Furthermore, the electricity that is absorbed in day n-1 can be traded at the clearing price of day n (γ_{p2}), generating an income from the absorbed electricity. Thus, the actual cost incurred is:

$$C_{ESD'(n-1)} = \gamma_p \times Q_{ESC(n-1)} = \gamma_{p2} \times \sum_{t=1}^{N} (P_{ESC(n-1)} \times \Delta t) \tag{19}$$

The upfront cost of CES is:

$$C_{ESQ} = C_{ESD} - C_{ESC(n-1)} \tag{20}$$

5.3.6. Total Cost of ER-CES

The total cost of the ER-CES is the sum of all three parts, which are the real-time electricity, equipment and upfront electricity costs:

$$C_{total} = C_{ES}^{E} + C_{ESP} + C_{ESQ} \tag{21}$$

5.4. Data Collection and Analysis

To test the feasibility of our model, data from the PJM electricity market of the US are used. Two sets of 15 days of data are chosen in December 2020 and May 2021, respectively. As this study intends to balance the load deviation on a daily basis, we purposely use data from winter as the season tends to have a higher demand for electricity due to increased heating needs. This may also result in a larger fluctuation in the load and price curves, making it ideal to verify the feasibility of the proposed model. For the rest of the year, the load curve tends to be relatively smooth (the summer is not hot in the sample area, which means that demand for electricity tends to remain stable). To further test the model validity in such a lower load fluctuation period, data from May 2021 are used for comparative analysis.

In total, three types of data are collected for the case study: users' load data, electricity price in the spot market, and parameters of energy storage devices. The former two are collected from the PJM electricity market[18], while the third one comes from the literature (Liu et al., 2017; Sloane, 2019). Data from PJM are chosen for the following reasons. First, PJM is a regional transmission organisation (RTO) in the US serving eastern several states, including Pennsylvania, New Jersey, and Maryland. It was the world's largest competitive electricity market until the development of the European Integrated Energy Market in the 2000s. The successful operation of PJM has made it a research case for many studies (Ott, 2003; Sioshansi et al., 2009; Walawalkar et al., 2008).

Second, PJM provides high quality data. As it is impossible for one electricity retailer to serve the whole country, the load data at the city level or even a smaller scale would be suitable. The load data of PJM are released by load areas, which can be a very small town or area. This provides us with a relatively precise estimation of the service

[18] http://dataminer2.pjm.com/feed/da_hrl_lmps/definition

coverage of an electricity retailer. Meanwhile, except for the actual load and price data, the predicted load and price data are also readily accessible in the PJM market. Therefore, the quality of data ensures that the proposed model's results are reliable, and hence, reasonably generalisable. Valuable lessons may also hold for countries like China, which is trying hard to build up its own electricity market.

Finally, as big and well-developed cities tend to have sound infrastructure and well-educated labour force, they are also more likely to invest into new technologies and adopt new business models. Duquesne, in the metropolitan area of Pittsburgh (the second largest and second-most populous city in Pennsylvania, known as "the Steel City", and is a leader in manufacturing, computing, electronics, and the automotive industry), is a suitable choice to demonstrate the validity of our business model.

We also employ data from the power market of New South Wales (NSW), Australia, as a robustness test for the adaptability of the proposed model in different regions. The load data for November 1, 2022, are randomly selected and scaled down to simulate the scale of an electricity retailer. For simplification, we directly present the results of the NSW power market in the Finding and Discussion rather than showing the detail of their various types of data in the following parts as we did for the PJM market.

5.4.1. Load Data

The daily predicted (Figure 5.4) and actual load curves (Figure 5.5) of 15 days in December 2020 in Duquesne, Pittsburgh, with a time interval of one hour, were collected from the website of PJM. The data covered the period from December 4 to 18. The Christmas was not included, because the commercial and industrial load demand is very low during the holiday period.

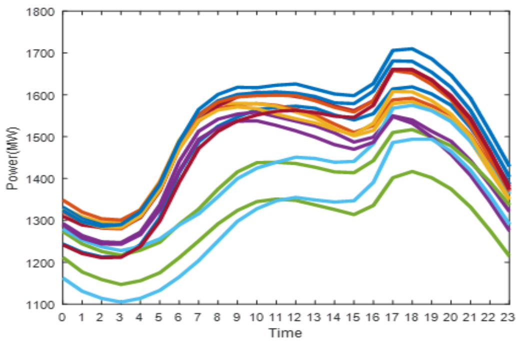

Figure 5.4. Predicted load curve (December)

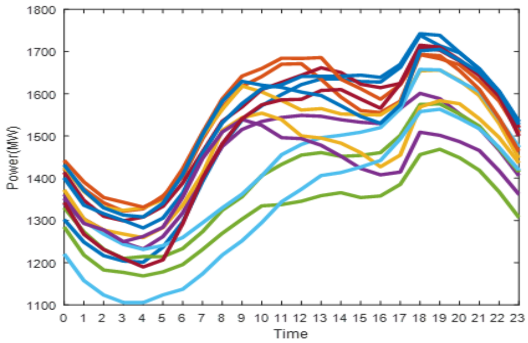

Figure 5.5. Actual load curve (December)

The load deviation curve for each day can be calculated based on the two sets of loads (Figure 5.6). Considering the different load characteristics of weekday and weekend, the load curves of the weekday are more representative as there is less commercial and industrial demand during the weekend. Moreover, Monday is not suitable as day n, as the electricity data of day n-1, which is Sunday, will be used for calculation of upfront cost. Hence, one day from Tuesday to Friday can be randomly chosen as day n. Finally, 18 December 2020 (Friday) was chosen as day n because it is the last day of our data period. For simplicity, the mean value of the former two Friday's load deviation (4 December and 11 December) was used as the predicted load deviation for day n (Figure 5.7).

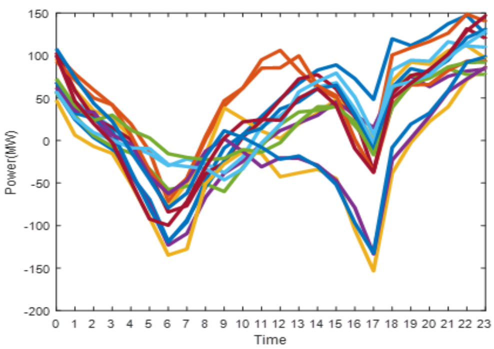

Figure 5.6. Load eviation curves of 15 days (December)

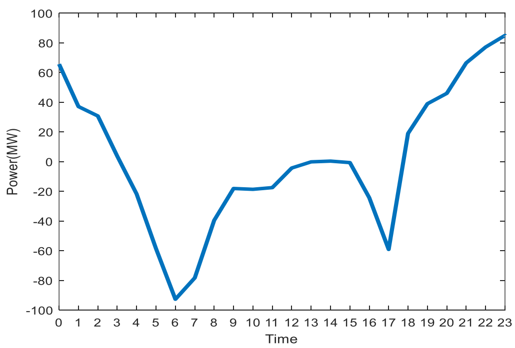

Figure 5.7. Predicted load deviation curve of day n (December)

For the comparative sample, data from 7 to 21 May 2021 were chosen randomly and May 21 (Friday) was chosen as day n. Figures 5.8 and 5.9 are the predicted and actual load curves of May respectively. Figure 5.10 shows the load deviation curves and

Figure 5.11 is the predicted load deviation of day n (mean value of May 7and 14). Clearly, the majority of load curves of May are more stable than that of December.

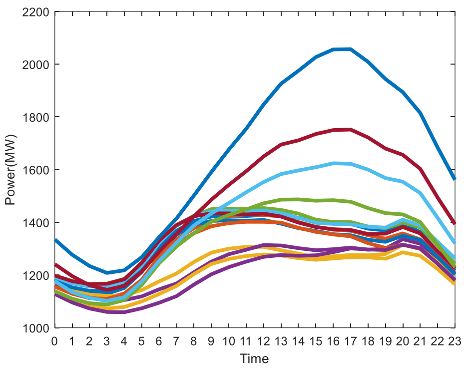

Figure 5.8. Predicted load curve (May)

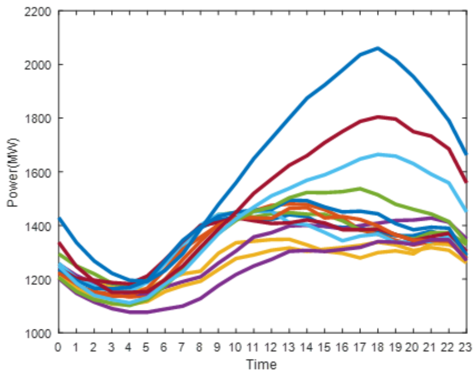

Figure 5.9. Actual load curve (May)

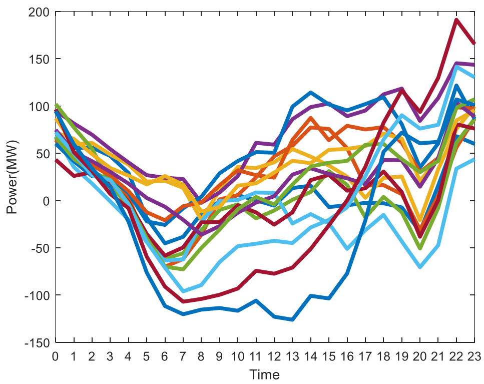

Figure 5.10. Load deviation curves of 15 days (May)

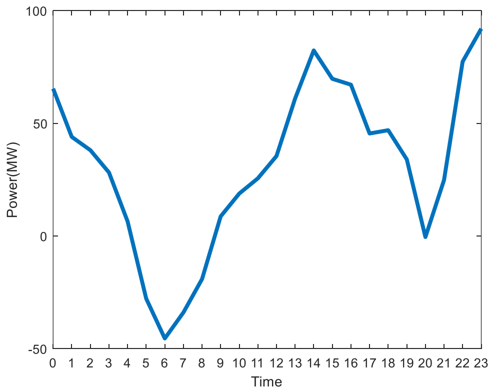

Figure 5.11. Predicted load deviation curve of day n (May)

5.4.2. Electricity Price

The real-time electricity prices of day n-1 were collected, and the price of the last period was chosen as the clearing price. Figures 5.12 and 5.13 represent the data of December 2020 and May 2021, respectively. The price curve of May 2021 is less volatile than that of December 2020. Figures 5.14 and 5.15 are the predicted real-time electricity prices curve of day n in December and May, respectively.

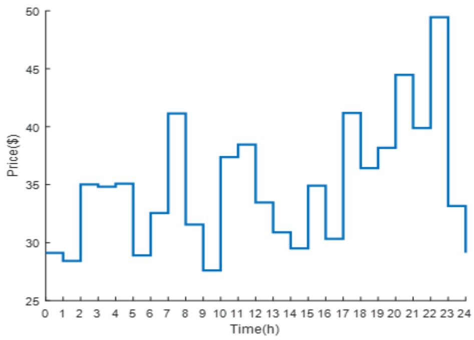

Figure 5.12. Real-time electricity prices of day n-1 (December)

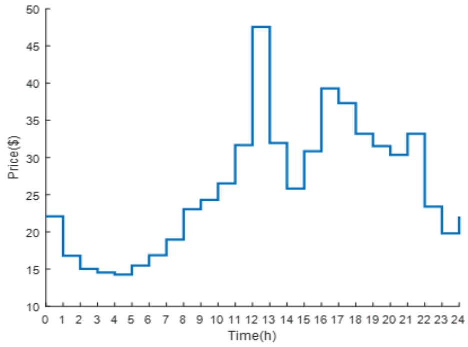

Figure 5.13. Real-time electricity prices of day n-1 (May)

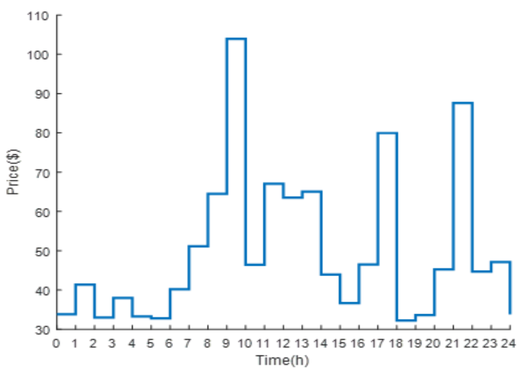

Figure 5.14. Predicted real-time prices of day n (December)

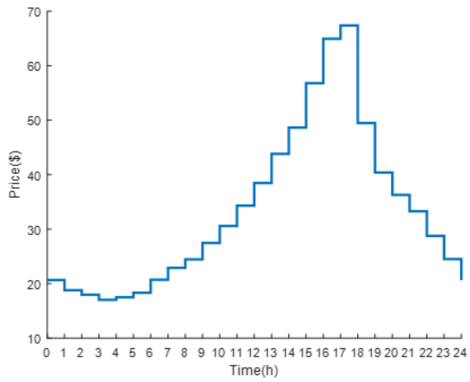

Figure 5.15. Predicted real-time prices of day n (May)

5.4.3. Energy Storage Parameters

Lithium-ion batteries are widely used for energy storage because of their high energy density, small size, fast response speed, and flexible regulation, make it convenient to deploy them on the user side. According to the literature and the price trend of the lithium-ion battery (Liu et al., 2017; Sloane, 2019), two sets of costs were assumed for comparison: 1) $293.7/kWh for energy capacity (kWh) and $154.8/kW for power capacity (kW); and 2) $180/kWh for energy capacity (kWh) and $100/kW for power capacity (kW). In practice, the latter is more closely related to the actual average price of the battery. The discount rate, usage days of a year, and the cycle index were assumed to be 6%, 300, and 3000, respectively (Liu et al., 2017). Finally, lithium-ion batteries were selected as an example to validate the proposed business model. Electricity retailers can choose any other more suitable energy storage devices in the real market just by changing the relevant parameters in the model.

5.5. Results and Discussion

5.5.1. PJM Power Market in December 2020

This section tests the effectiveness of the ER-CES model in the PJM market in December 2020. The condition without CES is set as the baseline model, which is then compared with the model with CES. To evaluate the models with varied CES costs and electricity prices, three scenarios are examined: 1) higher CES cost and lower electricity price; 2) lower CES cost and lower electricity price; and 3) lower CES cost and higher electricity price.

5.5.1.1. No-CES Baseline Model

When electricity retailers do not have energy storage configurations, all load deviations should be traded in the real-time electricity market to achieve supply and demand balance. This situation without CES is set as the baseline model. Figure 5.16 shows a bar chart of the load deviation on day n. After calculation, it would cost $45,231 for the electricity retailers to balance supply and demand.

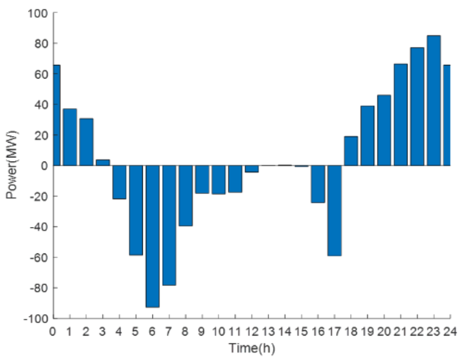

Figure 5.16. Load deviation of day n in bar chart

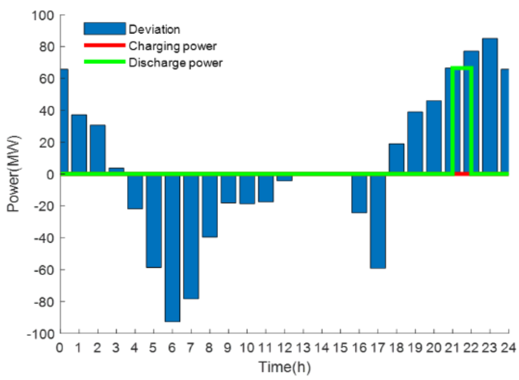

Figure 5.17. Application of energy storage in scenario 1

5.5.1.2. ER-CES Model – Scenario 1

In scenario 1, the investments in energy and power capacities were set as \$293.7/kWh and \$154.8/kW respectively; and r, ρ, and K were assumed to be 6%, 300 and 3000 respectively. Then, α and β are \$133/MWh and \$70/MW. The clearing price is \$33.16 /MWh on day n-1 and \$47.13/MWh on day n. Based on our calculation, the optimised charging capacity is 0 and discharging capacity is 66.5 MWh (Table 5.2). The total cost is \$44,864, which saves \$367 than the situation without energy storage devices. Figure 5.17 shows that the positive deviation is not completely compensated by the energy storage capacity for most time periods and all negative load deviations are sold in the real-time market. The results suggest that investment in energy storage is less cost-effective in most time periods when the cost of energy storage is relatively higher than the real-time electricity prices.

5.5.1.3. ER-CES Model – Scenario 2

In scenario 2, the cost of the energy storage devices was assumed to be \$180/kWh and \$100/kWh, while other parameters remain the same. Then, α and β are \$81.5/MWh and \$45.3/MW, respectively. With a decrease in battery price, the optimised charging and discharging capacities increase to 189.9 MWh and 286.65 MWh, respectively (Table 5.2). The total cost decreases to \$37,651, representing a saving of \$7,580 (C_{saving} =16.8%). Clearly, a lower cost battery can significantly enhance the amount of the energy storage capacities in the purchase strategy, lowering the total costs further. While the discharging capacity increases with the amount of load deviation, the charging capacity remains roughly the same across all periods (Figure 5.18).

Table 5.2. Charging and discharging capacities of the three scenarios

Time	Charging capacity /MW (Scenario 1)	Discharging capacity /MW (Scenario 1)	Charging capacity /MW (Scenario 2)	Discharging capacity /MW (Scenario 2)	Charging capacity /MW (Scenario 3)	Discharging capacity /MW (Scenario 3)
0	0	0	0	0	0	65.70
1	0	0	0	37.1	0	37.10
2	0	0	0	0	0	30.75
3	0	0	0	3.7	0	3.70
4	0	0	18.65	0	21.80	0
5	0	0	18.65	0	58.60	0
6	0	0	18.65	0	58.60	0
7	0	0	18.65	0	58.60	0
8	0	0	18.65	0	39.55	0
9	0	0	18.1	0	18.10	0
10	0	0	18.65	0	18.65	0
11	0	0	17.5	0	17.50	0
12	0	0	4.3	0	4.30	0
13	0	0	0.15	0	0.15	0
14	0	0	0	0.35	0	0.35
15	0	0	0.65	0	0.65	0
16	0	0	18.65	0	24.30	0
17	0	0	18.65	0	58.60	0
18	0	0	0	0	0	0
19	0	0	0	0	0	11.10
20	0	0	0	46.00	0	46.00
21	0	66.5	0	66.50	0	66.50
22	0	0	0	66.50	0	77.15
23	0	0	0	66.50	0	77.15
Sum	0	66.5	189.9	286.65	379.4	415.5

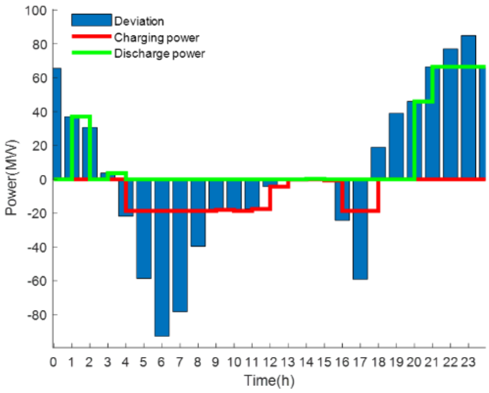

Figure 5.18. Application of energy storage in scenario 2

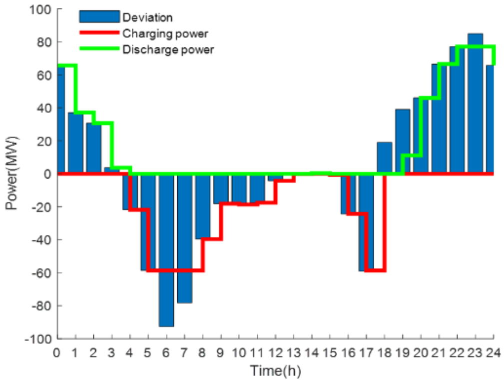

Figure 5.19. Application of energy storage in scenario 3

5.5.1.4. ER-CES Model – Scenario 3

In scenario 3, to simulate the power shortage that might be caused by some natural disasters, such as snowstorm and hailstone, a higher predicted real-time electricity price of $5 increase per hour on day n is assumed. Setting all other parameters the same as scenario 2, the cost without the CES increases to $49,751. Further, the optimised charging and discharging capacities increase further to 379.4 MWh and 415.5 MWh, respectively (Table 5.2). The total cost decreases to $37,549, representing a saving of $12,202 ($C_{saving}$ =24.5%). According to Figure 19, when the real time electricity price is higher, the majority of positive and negative load deviations are traded with CES.

5.5.2. Comparative Test – May 2021 of the PJM Power Market

For comparison purposes, all parameters and scenarios are set the same as the December figures apart from the data of load and electricity price. The clearing electricity prices of days n-1 and n are $19.82/MWh and $24.51/MWh, respectively. The results are presented by Figures 20-23 below. Without the use of CES, the balancing cost of the load deviation is $36,292 (Figure 5.20).

Figure 5.21 (scenario 1) shows that both the optimised charging and discharging capacities are 0. Thus, adopting the energy storage system is not suitable under this situation. This is due to the low clearing price and relatively high CES cost.

In scenario 2 (Figure 5.22), when the CES cost falls, the optimised charging capacity is 0 and discharging capacity is 345 MWh. This can reduce total cost to \$32,218, or a saving of \$4,074 (C_{saving} =11.2%). Because of the lower CES cost, the model chooses to discharge when the electricity price is relatively high on day n and trade in the real-time market for the remaining periods when the electricity price is relatively low.

Finally, as for scenario 3 (Figure 5.23), when the predicted real-time electricity price increase by \$5 per hour, the cost without the CES increases to \$41,284. The optimised charging is still 0, while the discharging capacity increases to 381 MWh. Consequently, the total cost decreases by \$5,877 (C_{saving} =14.2%), reaching \$35,407.

A comparison reveals that even when the load and price fluctuations are relatively stable, our proposed model remains effective on cost saving. However, when the cost of energy storage devices is higher, such positive effect tend to be less significant.

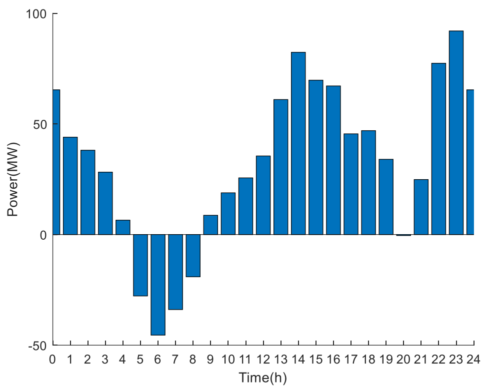

Figure 5.20. Load deviation of day n in bar chart (May)

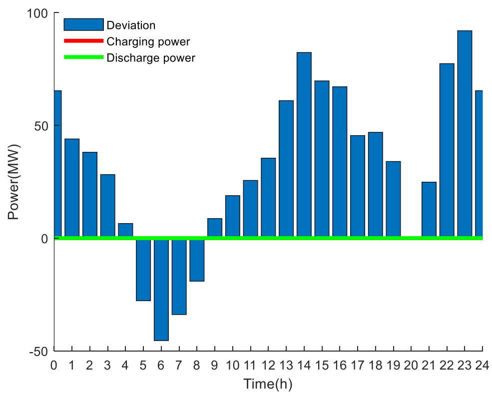

Figure 5.21. Application of energy storage in scenario 1 (May)

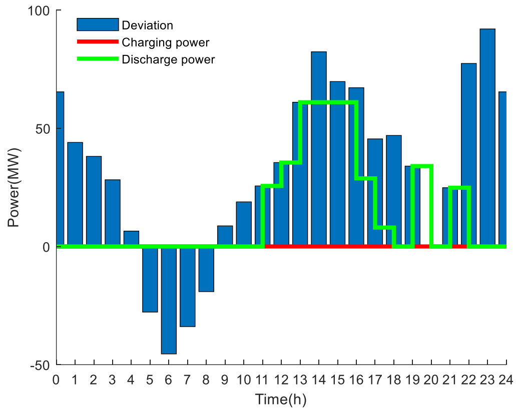

Figure 5.22. Application of energy storage in scenario 2 (May)

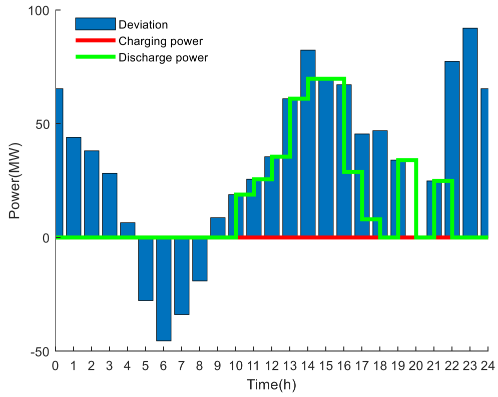

Figure 5.23. Application of energy storage in scenario 3 (May)

5.5.3. Comparative Test – November 2022 of the NSW Power Market

To verify the adaptability of the proposed model in different regions, the data from NSW, Australia, are used. Data were obtained from the Australian power market operator AEMO's website.

The load data of November 1, 2022, were randomly selected and scaled down to simulate the scale of an electricity retailer. The load deviation (Figure 5.24) and electricity price curves (Figure 5.25) of this day are obtained by the same method described above. For simplification, only scenario 1 with the higher CES cost is tested to compare with the scenario without CES. The clearing electricity prices of days n-1 and n are \$128.25 /MWh and \$149/MWh, respectively. All other parameters remain the same as in the PJM market.

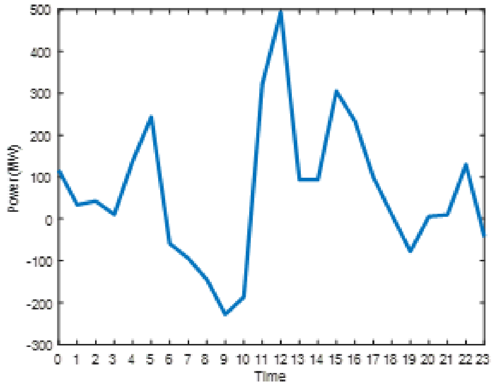

Figure 5.24. Predicted load deviation curve of day n (Nov)

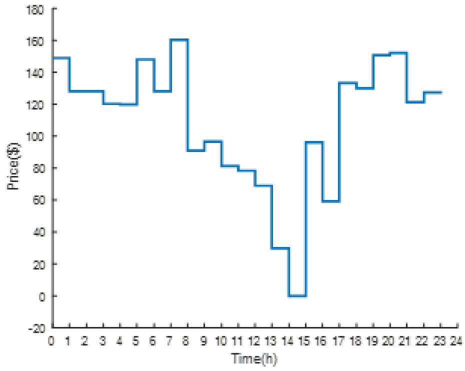

Figure 5.25. Predicted real-time prices of day n (Nov)

As shown in Figure 5.26, the cost of balancing without the use of CES is $30,948. After incorporating the CES, Figure 5.27 shows the optimised charging capacity is 1204.8 MWh and discharging capacity is 625.5 MWh. In general, the CES discharges when the load deviation is positive, while it charges with negative load deviation. During the period 11-12, the electricity price is relatively high; hence, no compensation is given. Meanwhile, for the period 13-14, the discharge should be made; however, the electricity price fell to the lowest point at this time. Hence, the optimal decision is to charge during this period to obtain greater benefits. The total cost decreases to $20,378, or a saving of $10,569 (or C_{saving} =34.2%). Although the electricity price in the Australian power market is much higher than that in the PJM power market, a satisfactory profit can still be obtained by renting the CES.

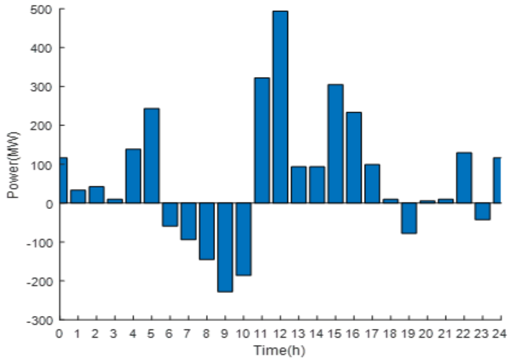

Figure 5.26. Load deviation of day n in bar chart (Nov)

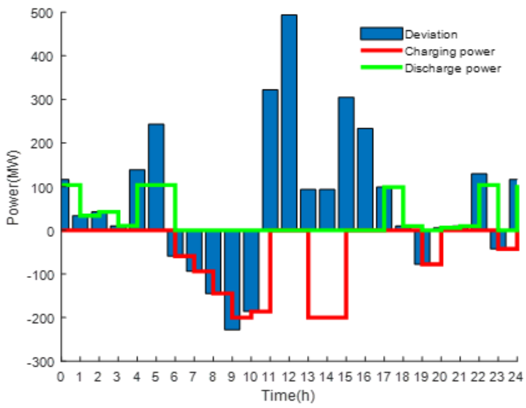

Figure 5.27. Application of energy storage in scenario 1 (Nov)

These experiments verify that the decision variables of the proposed model are only related to factors like user demand, electricity price, battery price, and battery parameters. The model can be employed in different seasons and regions with good results, and can significantly reduce the cost of electricity retailers and improve their ability to respond to different customers.

5.5.4. Comparison Analysis

(1) No-CES baseline and ER-CES models (PJM market)

Table 5.3 compares the No-CES baseline model with the ER-CES model in the three scenarios. The savings continuously increase with the decrease in CES costs and increase in electricity prices. Thus, the ER-CES model can effectively smoothen the fluctuations and lower the risk of some extreme situations, such as the power shortage caused by some natural disasters, with robust cost saving for electricity retailers.

Table 5.3. Comparison between the No-CES baseline and ER-CES models (PJM)

Scenario	**Cost**		
	No-CES baseline model	ER-CES model	C_{saving}
1	$45,231	$44,864	0.8%
2 (CES cost decrease)	$45,231	$37,651	16.8%
3 (electricity price increase)	$49,751	$37,549	24.5%

(2) Co-investment energy storage and ER-CES models

Liu et al. (2021) proposed an approach to optimally plan the energy storage shared by multiple electricity retailers to minimise their electricity procurement cost; specifically, the procurement cost can be reduced through arbitraging the shared energy storage in the day-ahead and real-time markets. Different from the proposed strategy in this study, this scheme of co-investment and co-use of energy storage pursues overall optimisation;

however, it may not be an optimal choice to compensate the load deviation of individual electricity retailers. Furthermore, as the load pattern of electricity retailers changes over time, the investment optimisation circumstance will change accordingly. Consequently, the flexibility of such fixed investments may deteriorate, and the investment income may face uncertainties. Meanwhile, in this study, the independent electricity retailer rents CES, which relieves it of the burden of fixed asset amortisation and generates stable cost savings.

5.6. Conclusion

The energy supply-demand imbalance has always been a critical and extensively debated issue. Acting as intermediaries, the electricity retailers have tried hard to balance supply and demand. Energy storage can serve as an effective solution to this load imbalance problem. However, the majority of electricity retailers have not developed a practical business model to leverage energy storage at scale. Based on the development of a new business concept, CES which is a virtual energy storage service system, this study discusses the cooperation between the electricity retailers and CES suppliers, and proposes a novel ER-CES model that can effectively leverage the CES to reduce the load deviation and realise cost efficiency. The main results are summarised as follows:

First, by renting the CES, the electricity retailers can flexibly use the energy storage resources and real-time electricity price mechanism to achieve a dynamic balance between power purchase and sale, and maximise profits. This option eliminates the need for electricity retailers to make upfront investments in fixed assets (energy storage devices) or endure their amortisation pressure. They can flexibly adjust the amount and duration of renting energy storage in response to changes in customer demand for electricity. Second, we consider the cost of renting CES, time value of investment, price of power on the market, and other factors before establishing an optimisation model using the CES rental amount as the decision variable. This model can not only give the total amount of the next day's rented CES, total cost, and total profits, but also the charge and discharge plan of CES for each period of the next day, which is convenient for the electricity retailers to execute things as planned. Third, a decision method of separately renting charge and discharge energy storage is adopted to simplify the optimisation model and solve the optimisation decision problem when there are both positive and negative load deviations. Fourth, testing the model in both the PJM market in the United States and NSW market in Australia verified the effectiveness of the model. This demonstrates that renting CES can significantly reduce the costs for electricity retailers in different seasons and regions.

Our findings have several practice implications. Policy makers should further encourage the development of the energy storage industry. This may speed up technological progress, lowering the battery price and application costs further, similar to the case of solar energy. With lower costs, electricity retailers can purchase more energy storage capacities and enjoy better cost efficiency brought by CES. In turn, this could allow retailers to gain better control over the load deviation, and help them in more flexibly adjusting the balance of supply and demand. Furthermore, successful cooperation between electricity retailers and CES suppliers will not only create a win-win situation for themselves, but also decrease the electricity cost for consumers, strengthen power system stability, and more importantly, improve energy efficiency. Higher energy efficiency and renewable penetration are critical for the energy transition and the fight against climate change. Next, the successful application of the proposed business model could expand the business scope for CES suppliers, help them in achieving much higher return on investments. Consequently, more investors can be attracted into the market, leading to more competition, and hence, more rapid technological progress in the energy sector.

Finally, although the feasibility of the proposed model has been demonstrated here, it should be tested in more electricity markets to identify the boundary of application and other potential limitations. In addition, over the longer term, studies could compare the cost efficiency of electricity retailers between renting CES capacities and purchasing energy storage equipment themselves.

Chapter 6: Conclusion and Policy Implications

This thesis investigates the influence of the energy structure transition on electric utility firms. Chapter 1 introduces the research background, develops research questions, and outlines the key contributions of the thesis. Chapter 2 reviews the primary theoretical foundations and literature. Chapters 3 and 4 examine whether energy structure transition affect firms' capital structure and risk exposure, respectively. Chapter 5 develops a useful business model for the utilisation of energy storage to assist the energy structure transition. This chapter (Chapter 6) summarises the major findings of the three studies, and then proposes the policy implications, limitations, and future research directions.

6.1. Conclusion

Utilising data from the US electric utility sector between 2010 and 2020, Chapter 3 extensively explores the relationship between the energy structure transition and firms' capital structure. Machine learning approaches are used to capture the nonlinear relationships between them. For robustness, three machine learning methods, Support Vector Regression (SVR), Artificial Neural Network (ANN), and Random Forest (RF), are employed to conduct a five-year rolling prediction on four different measures of leverage (Amini et al., 2021). Two sets of input variables are used to compare their prediction accuracy for these leverage measures. Dataset 1 comprises a group of widely accepted firm-level accounting and financial variables for determining capital structure. Dataset 2 further adds energy structure variables. The out-of-sample R-squared (R_{os}^2) and root mean squared error (RMSE) are used to assess whether energy variables improve the prediction ability for capital structure. A higher (lower) value of R_{os}^2 (RMSE) indicates greater prediction accuracy.

The outcomes of all three methods consistently show that the R_{os}^2 (RMSE) of Dataset 2 is significantly higher (lower) than that of Dataset 1 in most cases (Table 3.3). For instance, the average R_{os}^2 of Dataset 2 is 12% higher compared to Dataset 1. Among the three machine learning methods, SVR outperforms the other two in both accuracy and stability for all four leverage measurements.

Chapter 3 further applies Taylor expansion to analyse the importance contribution of each variable. Among the energy variables, wind, solar, and natural gas exert the most significant influence on electricity utility firms' capital structure. Moreover, their influence becomes stronger over time. Natural gas has interesting results. Despite being a fossil fuel, it is much cleaner with nearly 50% less carbon emissions compared to coal (EIA, 2022). It is also more cost-effective compared to both coal and wind energy (Feldman and Margolis, 2019; IEA, 2021c). Therefore, it is expected to continue playing a pivotal role in the ongoing energy transition process until renewable energy fully replace fossil fuels as the dominant energy source (IEA, 2019). Conversely, other fossil fuels, like coal and oil, as well as other traditional energy sources, like hydro and nuclear, have small and limited impact. Importantly, the influence of renewable energy on capital structure grows as its proportion in the total generation increases. The ranks of wind and solar energy increase from ninth and twelfth in the low percentage sample to sixth and fourth in the high percentage sample, respectively (Figures 3.12 and 3.14).

Furthermore, different measurements of leverage exhibit different outcomes. Total debts yield higher prediction accuracy compared to long-term debts over time. This is due to the relatively small and declining impacts of wind and solar energy on long-term debt over the years. One potential reason for this trend is the implementation of new Basel III in 2017, which imposed additional constraints on firms' long-term debt financing for renewable energy projects (Ang et al., 2017; Ng and Tao, 2016). Specifically, wind (solar) energy has a stronger impact than solar (wind) energy on the long-term (total) debt. This is primarily because PV power plants have shorter construction periods, whereas wind farms take longer. Consequently, investments in solar projects often rely more on short-term funding, which is better represented by total debt. In conclusion, total debt is a more accurate measure of leverage in this context.

Chapter 3 further examines each variable's direction contribution. The results reveal, for the first time, that the influence of wind and solar energy on electric utility firms' capital structure are opposite, with wind having a negative impact and solar having a positive impact on firms' gearing levels. This may be because solar investments are perceived as less risky in the debt market compared to wind energy, thanks to their faster cost decline and less resource volatility risk, making them more attractive for borrowing.

Moreover, according to the target leverage predicted by the SVR, the adjustment speeds of the market and book leverage are 0.743 and 0.645, respectively, after controlling company fixed effects. When converted to half-life values, they are 0.511 and 0.666 year, respectively. This adjustment speed is much faster than that of the overall market, indicating that electric utility firms quickly respond to market changes related to renewable energy, and hence, actively adjust their leverage according to the target capital structure. Furthermore, both adjustment speeds align with the expectations set by the dynamic trade-off theory, falling within the range of zero to one. The impact directions of most accounting and financial variables also support the trade-off theory.

Employing data from the US electric utility sector from 2010 to 2020, Chapter 4 comprehensively explores the impact of energy structure transition on firms' systematic, idiosyncratic, and total risks. Support Vector Machine (SVM) is utilised to build dependable classification models for estimating firms' risk exposure, categorizing firms into high and low risk groups for each type of risk. Moreover, as the number of the high and low risk groups are uneven, the adaptive synthetic (ADASYN) algorithm is employed for sampling. The dataset is divided into training and test sets, each comprising 70% and 30% of the total sample, respectively. Confusion matrix is used to evaluate the performance of the classification models (Liu et al., 2011). It provides four performance criteria. Accuracy assesses the model's overall classification ability. Sensitivity (specificity) is the correctly predicted number of high (low)-risk firms to the total number of high (low)-risk firms. $G - mean$ evaluates the balance between the high- and low-risk class performance, with higher values indicating good performance across both classes.

For each risk, Model 1 only uses accounting and finance variables, Model 2 adds energy variables to Model 2, and Model 3 adds variables reconstructed after applying principal component analysis (PCA) to Model 2. As for the classification criteria, US utility industry Beta = 0.64, provided by the New York University, is used for the systematic risk. The other two risks use the average Beta values calculated form the sample data. All models exhibit a G-mean higher than 0.6 (Table 4.5), indicating the effectiveness of the ADASYN sampling technique in balancing the classification performance of both groups. The accuracy differences between Models 1 and 3 are 0.12, 0.09, and 0.02 for systematic, idiosyncratic, and total risks, respectively (Table 4.5), confirming significant increase in the prediction accuracy for these risks.

To examine the influence of renewable energy variables in the energy structure, Chapter 4 employs a yearly escalating rate to simulate their growth. The installed capacity of renewable energy in each sample is initially increased by k% (k = 0.5, 1, 2) in the first year, and then further increased by n times k% (n = 1, 2, ..., 11) in the subsequent years. Further, to better simulate real-world variations in growth ratios within renewables, three ratios (1:1, 3:1, and 1:3) are applied to wind and solar energy for each growth rate. The results indicate that increasing the use of renewables can significantly decrease electricity utility firms' exposure to systematic risk (Figure 4.5). Furthermore, this negative relationship remains consistent across all three ratios of wind-solar growth.

Notably, a more pronounced reduction in systematic risk occurs when the growth of wind energy outweighs that of solar energy. This is possibly due to wind energy's predominant role in the current US power generation landscape, boosting investor confidence in its expansion.

In contrast, different growth ratios of wind and solar energy exhibit diverse effects for idiosyncratic risk. When solar energy grows faster (slower) than wind energy, renewable energy positively (negatively) affects idiosyncratic risk (Figure 4.5). Importantly, this discovery offers a potential explanation for the previous inconsistent findings in studies investigating the impact of environmental factors on idiosyncratic risk (Bouslah et al., 2013; Sassen et al., 2016). When renewable energy data is integrated into more comprehensive environmental variables, disparities in wind-solar ratios among different samples may go unnoticed. This highlights the need for considering such differences in future research. In addition, as the total risk encompasses both systematic and idiosyncratic risks, it exhibits a similar trend to idiosyncratic risk, which has a more substantial impact compared to systematic risk. This leads to heightened (stable) risk as the proportion of solar (wind) energy increases (Figure 4.5). This may clarify discrepancies in studies examining the impact of corporate environmental responsibility (CER) on total risk (Cai et al., 2016; Trinks et al., 2020), as total risk's impact is a composite of the other two risk types.

Chapter 4 further investigates the separate effects of wind and solar energy on these risks while considering the varying growth rate. Both wind and solar negatively affect systematic risk. Conversely, solar (wind) demonstrates a positive (negative) relationship with both idiosyncratic and total risks (Figure 4.6). Wind and solar energy have both seen significant reductions in their levelised cost of electricity (LCOE) between 2010 and 2020. This reduction is expected to drive the increased adoption of both energy sources. This can enhance the diversity of the energy mix of electric utility firms, and consequently, reducing their systematic risk. Despite the reduction in LCOE, the LCOE of solar remains higher than that of wind. Consequently, single firms perceive higher risk associated with solar, leading to different effects of wind and solar on idiosyncratic risk. Meanwhile, the total risk still follows the trends of idiosyncratic risk, driven by its greater influence compared to systematic risk. In addition, the distinct effects of wind and solar reaffirm the potential for biased results when using a composite renewable energy variable. The effects of wind and solar over time are also examined. While both wind and solar negatively affect systematic risk over time, wind experiences a much faster rate of decline compared to solar. Meanwhile, solar (wind) energy significantly increases (decreases) idiosyncratic and total risks. Moreover, solar has a much larger impact compared to wind, indicating that an equivalent amount of wind is insufficient to offset the risks associated with solar. This suggests that electric utility firms may be more sensitive to higher costs than lower costs.

Concluding the findings from both Chapters 3 and 4, wind and solar energy have opposite risk perceptions in the debt and equity markets. Specifically, in the debt market, leverage has a positive (negative) relationship with solar (wind) energy. This implies that lenders are more willing to invest in solar energy rather than wind energy. Meanwhile, in the equity market, both the idiosyncratic and total risks are positively (negatively) correlated with the solar (wind) energy. Although both wind and solar energy have negative relationships with systematic risk, wind energy exhibits a stronger risk reduction ability compared to solar energy. Therefore, all three risks suggest that shareholders prefer wind energy because it decrease its idiosyncratic volatility, while they may decrease the use of solar energy to avoid the extra volatility.

To develop an effective business model for electricity retailers to utilise energy storage, Chapter 5 employs data from the PJM electricity market in the US to verify the feasibility of the proposed optimisation model for electricity retailers to maximise profits. Two sets of data are selected, one from December 2020 and the other from May 2021, to predict two kinds of load deviations. Winter data are intentionally chosen due to higher electricity demand for heating, leading to larger load and price fluctuations, which makes it an ideal choice for validating the proposed model. Meanwhile, the load curve remains relatively steady throughout the rest of the year (due to cooler summers in the sample area, resulting in stable electricity demand). Therefore, data from May 2021 are used to compare the feasibility of the proposed model in a scenario with lower fluctuations. The baseline model without cloud energy storage (CES) is used for comparison with ER-CES models that have different CES costs and electricity prices. The first scenario has a higher CES cost and lower electricity price, second has a lower CES cost and lower electricity price, and third has a lower CES cost and higher electricity price.

In December 2020, the baseline model cost \$45,231 for balancing on day n. In scenario 1, with an optimised discharging capacity of 66.5 MWh and charging capacity of 0 (Table 5.2), the total cost is \$44,864, saving \$367 ($C_{saving} = 0.8\%$) compared to the baseline model. These findings imply that energy storage investment is less cost-effective when CES costs are relatively higher than real-time electricity prices. In scenario 2, with reduced CES costs, optimised charging and discharging capacities rise to 189.9 MWh and 286.65 MWh, respectively (Table 5.2). The total cost decreases to \$37,651, yielding a savings of \$7,580 ($C_{saving} = 16.8\%$). Apparently, lower CES costs substantially increase energy storage capacities in the purchase strategy, further reducing total costs. In scenario 3, a higher electricity price is used to simulate the power shortage during crises, causing the cost of the baseline model rise to \$49,751. Optimized charging and discharging capacities increase further to 379.4 MWh and 415.5 MWh, respectively (Table 5.2). The total cost decreases to \$37,549, resulting in a \$12,202 saving ($C_{saving} = 24.5\%$). These results verify the efficiency of the ER-CES model, especially during market fluctuations with elevated electricity prices.

In May 2021, the cost of baseline model is \$36,292. In scenario 1, the optimisation model suggests no CES renting duo to lower electricity price. Scenarios 2 and 3 save

\$4,074 ($C_{saving} = 11.2\%$) and \$5,877 ($C_{saving} = 14.2\%$), respectively. A comparison suggests that the proposed optimisation model still achieves cost savings, even when fluctuations are relatively stable. Data from November 2022 in New South Wales (NSW), Australia, is randomly chosen for robustness testing. For simplicity, only scenario 1 with a higher CES cost is tested against the scenario without CES, showing a \$10,569 saving ($C_{saving} = 34.2\%$) with the ER-CES model.

By renting form the CES, electricity retailers can flexibly employ energy storage resources and the real-time electricity price mechanism to obtain a flexible equilibrium between power procurement and sale, thereby maximising profits. This choice eliminates upfront investments in fixed assets (energy storage devices) for electricity retailers, allowing flexible adjustments to rented energy storage based on changing customer electricity demand. The savings of the ER-CES model increase as CES costs decrease and electricity prices rise. This confirms the effectiveness of the ER-CES model in mitigating power grid fluctuations and reducing the risk of extreme scenarios.

6.2. Policy Implications

Considering the different preferences of debt and equity markets toward wind and solar energy, more diversified financing strategies can be developed at the firm level to facilitate the green transition. Wind energy projects have relatively lower risk in the equity market. Considering that equity costs are generally higher than debt costs, early-stage developments should be supported via internal capital and external equity capital should be introduced when the project reaches a certain stage. This approach can minimise capital costs and help in fully utilising market preferences. Meanwhile, given the higher risk perception of solar energy projects in the equity market but favourability in the debt market, firms can leverage debt financing more and explore varied financing avenues, such as green bonds and government incentive programs. Sustainable repayment schedules can be established to alleviate financial risks. Furthermore, since wind and solar energy have different impacts on systemic and idiosyncratic risks in terms of direction and magnitude, a thoughtful allocation between them should be considered to minimize the total risk exposure of the electric utility firms.

From the government's perspective, although current evidence suggests that market-driven measures can promote energy structure transition, there remains space for governments to implement policies and initiatives to further guide and accelerate the development of renewable energy. For instance, while formulating subsidy policies, governments should consider natural conditions in different regions and place an emphasis on available resources. This can contribute to the more efficient use of federal funds, mitigate risk exposure for electric utility firms, and enhance their overall financial performance. In addition, considering the potential impact of new Basel III norms on long-term liabilities for renewable energy, it may be necessary to explore alternative financing channels, such as government-guided special financing, to ensure the long-term feasibility of renewable projects. Furthermore, governments should actively promote private capital investment in renewable energy through measures like tax incentives. In summary, these targeted financing strategies can assist electric utility firms in optimising their capital structure, reducing financing costs, and mitigating risk exposures during the process of renewable energy development, thereby facilitating a faster green transition.

Regarding the deployment of energy storage, electricity retailers can explore more forms of collaboration with CES providers. For instance, they can consider signing long-term contracts to further reduce the cost of energy storage and increase the volume of renting. A win-win situation can be achieved by better controlling load deviation and flexibly adjusting supply-demand equilibrium. This can reduce electricity costs for consumers, improve power system stability, and, most importantly, reduce wind and solar energy wastage, thereby improving overall energy efficiency. Besides promoting the development of energy storage industry to further reduce battery prices and application costs, governments should also encourage and support innovative business models for improving energy storage utilization. This can be achieved by establishing dedicated funds or providing fiscal incentives to attract private capital investment into the energy storage sector. These measures can help accelerate the commercialisation of energy storage technologies, and consequently, advance the green transition.

6.3. Limitations and Potential Future Work

Due to data availability challenges, this study investigates how the energy structure transition influences firms' capital structure and risk exposure only in the US market, which exhibits a moderate development level of renewable energy. Future studies could be extended to regions with distinct characteristics, such as Germany and Northern European countries with high penetration of renewable energy, or China and India, whose renewable energy generation is increasing together with fossil fuels. Comparative research can yield more intriguing and valuable insights.

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Appendix

Appendix 1

R_{os}^2 of RF for Dataset 1 and Dataset 2

RF	Dataset 1				Dataset 2 with energy variables			
	LD/M	TD/M	LD/A	TD/A	LD/M	TD/M	LD/A	TD/A
2016	0.33	0.71	0.26	0.48	0.60	0.74	0.52	0.58
2017	0.48	0.50	0.51	0.35	0.71	0.59	0.73	0.56
2018	0.45	0.60	0.38	0.45	0.68	0.71	0.60	0.54
2019	0.40	0.59	0.24	0.48	0.68	0.68	0.48	0.51
2020	0.32	0.64	0.17	0.48	0.43	0.76	0.38	0.68

R_{os}^2 of ANN for Dataset 1 and Dataset 2

ANN	Dataset 1				Dataset 2 with energy variables			
	LD/M	TD/M	LD/A	TD/A	LD/M	TD/M	LD/A	TD/A
2016	0.35	0.75	0.38	0.49	0.60	0.80	0.61	0.61
2017	0.67	0.69	0.59	0.50	0.62	0.70	0.55	0.60
2018	0.58	0.72	0.50	0.58	0.63	0.73	0.56	0.63
2019	0.53	0.79	0.52	0.63	0.54	0.74	0.54	0.71
2020	0.62	0.85	0.55	0.63	0.51	0.91	0.56	0.80

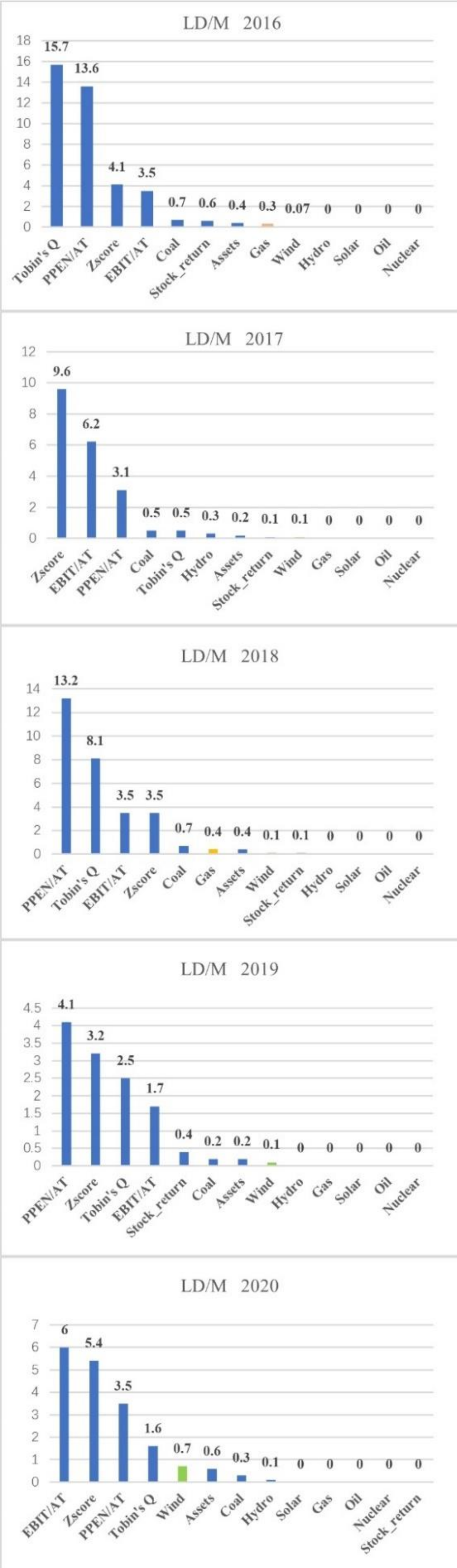
RMSE of RF for Dataset 1 and Dataset 2

RF	Dataset 1				Dataset 2 with energy variables			
	LD/M	TD/M	LD/A	TD/A	LD/M	TD/M	LD/A	TD/A
2016	0.07	0.05	0.08	0.05	0.05	0.05	0.06	0.05
2017	0.05	0.06	0.06	0.06	0.04	0.06	0.04	0.05
2018	0.05	0.05	0.07	0.06	0.04	0.04	0.06	0.05
2019	0.04	0.05	0.07	0.05	0.03	0.04	0.05	0.05
2020	0.05	0.05	0.07	0.05	0.05	0.04	0.06	0.04

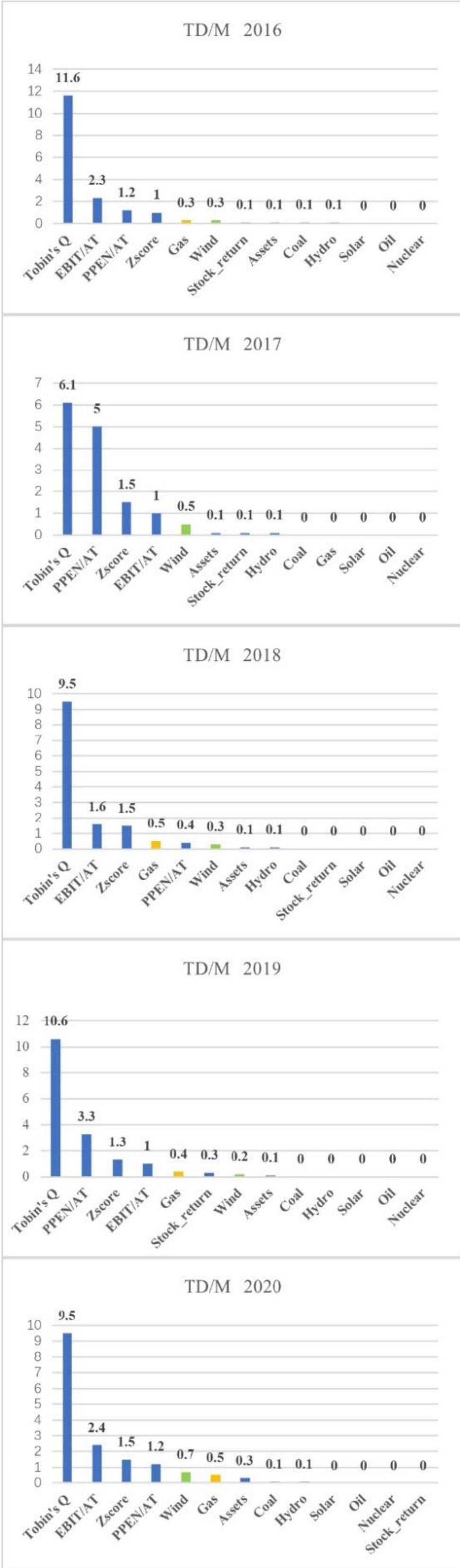
RMSE of ANN for Dataset 1 and Dataset 2

ANN	Dataset 1				Dataset 2 with energy variables			
	LD/M	TD/M	LD/A	TD/A	LD/M	TD/M	LD/A	TD/A
2016	0.07	0.05	0.07	0.05	0.04	0.03	0.05	0.04
2017	0.03	0.05	0.04	0.05	0.03	0.03	0.04	0.03
2018	0.04	0.04	0.05	0.04	0.03	0.03	0.04	0.03
2019	0.03	0.03	0.04	0.04	0.04	0.03	0.04	0.03
2020	0.04	0.03	0.05	0.04	0.04	0.02	0.05	0.03

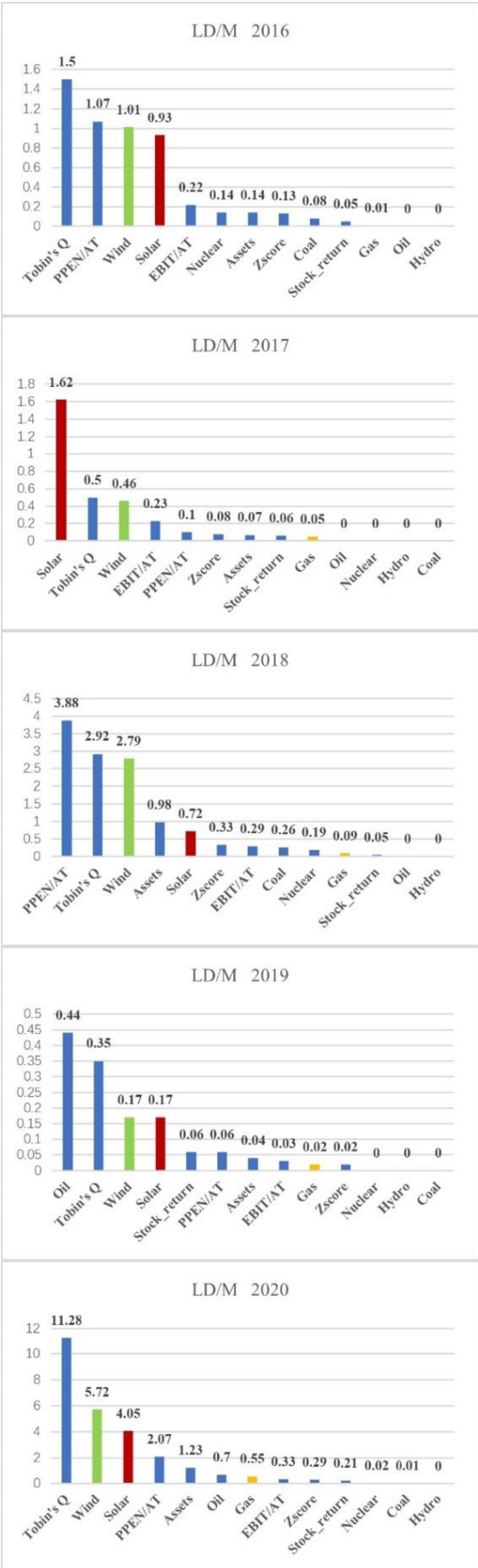
Appendix 2



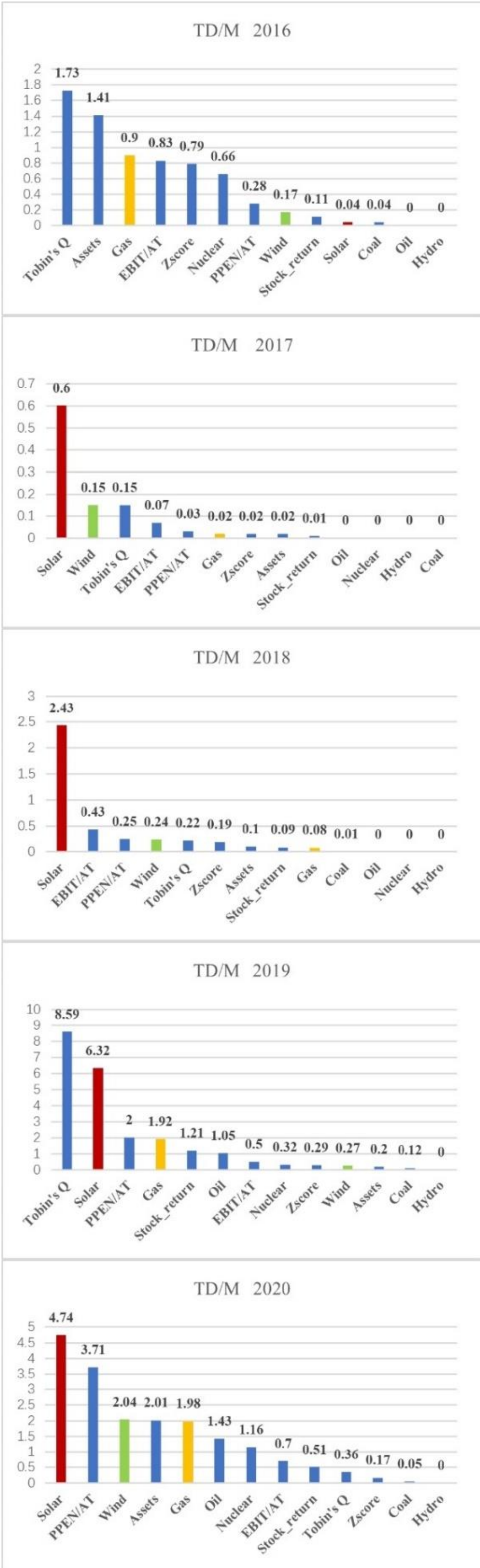
Factor importance for LD/M(L) from 2016–2020



Factor importance for TD/M(L) from 2016–2020



Factor importance for LD/M (H) from 2016–2020



Factor importance for TD/M(H) from 2016–2020