2023

Examining purity and green complexity score on wind and solar stock return

Kanokphorn Pongklang
Faculty of Commerce and Accountancy

Examining Purity and Green Complexity Score on Wind and Solar Stock Return

Miss Kanokphorn Pongklang

An Independent Study Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Finance
Department of Banking and Finance
Faculty Of Commerce And Accountancy
Chulalongkorn University
Academic Year 2023

-

น.ส.กนกภรณ์ พงษ์กลาง

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการเงิน ภาควิชาการธนาคารและการเงิน
คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2566

Independent Study Title	Examining Purity and Green Complexity Score on Wind and Solar Stock Return
By	Miss Kanokphorn Pongklang
Field of Study	Finance
Thesis Advisor	Associate Professor ANIRUT PISEDTASALASAI

Accepted by the FACULTY OF COMMERCE AND ACCOUNTANCY, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Science

INDEPENDENT STUDY COMMITTEE

.... Chairman

()

.... Advisor

(Associate Professor ANIRUT PISEDTASALASAI)

.... Examiner

(Assistant Professor Narapong Srivisal)

.... Examiner

(Assistant Professor JANANYA STHIENCHOAK)

กนกภรณ์ พงษ์กลาง : -. (Examining Purity and Green Complexity Score on Wind and Solar Stock Return) อ.ที่ปรึกษาหลัก : รศ.อนิรุต พิเสฏฐศลาศัย

สาขาวิชา	การเงิน	ลายมือชื่อนิสิต
		....
ปีการศึกษา	2566	ลายมือชื่อ อ.ที่ปรึกษาหลัก
		....

6484009526 : MAJOR FINANCE

KEYWORD:

Kanokphorn Pongklang : Examining Purity and Green Complexity Score on Wind and Solar Stock Return. Advisor: Assoc. Prof. ANIRUT PISEDTASALASAI

Field of Study:	Finance	Student's Signature ....
Academic Year:	2023	Advisor's Signature ....

ACKNOWLEDGEMENTS

Kanokphorn Pongklang

TABLE OF CONTENTS

Page

1. Introduction

In the era of climatic changes, capital allocation will decide not just humanity's development toward resolving the environmental changes, but also which industries and businesses will cope, grow, and become a part of the future industrial landscape. The transformation to a net-zero emissions economy is necessary to meet the Paris Agreement's climate targets by 2050, which would undoubtedly alter the global competitiveness landscape. As communities demand and embrace more environmentally friendly manufacturing methods due to legislation, political will, and the consequences of climate change, demand for zero-emission technology will increase even more. This path of technological changes is boosting automation, mechanization, electrification, and dynamic optimization[1], which are driving the renewable energy transition. The path to this new green economy will be filled with investment opportunities, as the long-term picture clearly shows. This study's goal is to guide investors in navigating this evolving environment by highlighting the megatrends and identifying the sectors that are best positioned to remain competitively green in the present and the future.

A lot of studies exploring the connection between the return, volatility, and other assets of investments in renewable energy have been sparked by the rising popularity of these investments. Technology and oil prices, for instance, have an impact on the stock values of renewable energy sources (Irene Henriques, 2008). Time-varying tail dependency was seen in relation to oil and renewable energy. (Reboredo, 2015) and their relationship is greater when there are bad markets (Ishaan Dawar, 2021). Depending on the geography, the state of the market, and the length of the investment horizon, different assets' dependency with renewable energy equity changes (Pham, 2021). To determine the appropriate hedging ratios between renewable energy and traditional assets, several studies also look at the relationship between clean energy and other assets. For example, (Saeed et al., 2020) examines the usage of clean energy[2] assets as a hedge against dirty energy[3] investments. (Shrimali, 2019) demonstrates that renewable energy equity does not improve the risk–return profile for investors compared to conventional alternatives. Portfolios that invest in renewable energy outperform those that invest in fossil fuels (Irene Henriques, 2018). Renewable energy equities have been shown to mitigate the downside risk of dirty energy stocks (Kuang, 2021a). The impact of shocks in equity and oil implied volatility on renewable energy stock realized volatility varies across renewable energy sub-sectors (Fuentes & Herrera, 2020). To this purpose, the

[1] Farmer and Lafond, 'How Predictable Is Technological Progress?', 2016, https://doi.org/10.1016/j.respol.2015.11.001.

[2] Renewable energy, often known as clean energy, is defined as energy produced from natural sources or processes. Renewable energy resources include wind, solar, hydro, geothermal, and bioenergy. **(Ellabban et al., 2014).**

[3] Dirty energy is defined fossil fuels-based energy

flow of adequate funds to finance renewable energy demands may be constrained by investor perceptions that investments in renewable energy do not offer attractive returns when compared to conventional options.

The recent study of (Kuang, 2021b) show that the risk and return on renewable energy stock sub-sectors vary significantly and renewable energy stocks generally underperform the overall equity market but outperform dirty stocks. In addition, the study provides new insights into effective diversification strategies and active portfolio management at the clean energy sub-sector[4] levels. How to construct a wind and solar stock portfolio as part of renewable energy portfolio and how it would perform in comparison to passively investing in renewable energy sector index. To fill this gap, our objective of this study is to examine the purity score and green complexity score on wind and solar stock return, which will be valuable in enhancing return, by test performance of different portfolios. We analyze the purity score and green complexity score as a new type of green/environmental rating. The purity score and green complexity score set specific metrics and magnitude for each firm's technology-dense, which consider as a winner in this shifting landscape. It dynamically reflects the actual status of a firm's business activity and provides a new way to measure the greenness/sustainability of firms from the perspective of output. To do so, we use the purity score and green complexity score as sorting factors to construct portfolios.

To the best of our knowledge, no similar study has ever been conducted. This study, in particular, contributes to the present literature in three dimensions. First, this is the first empirical study to examine the purity score and green complexity score on wind and solar stock return – by using them as factors sorting, whether high score portfolio that include higher technology-dense firms perform better than low score. Second, our study clarifies the risk-adjusted return relationship for investments in wind and solar stocks and provides empirical evidence of a relationship between those factors and returns, which may help reshape financial markets by facilitating fund to wind and solar businesses. Third, this research compares the performance of different factors sorting portfolios. As a result, it provides a more comprehensive view of wind and solar sub-sector. This considers that, rather than passively investing in the aggregated wind and/or solar energy index, investors can apply those sorting factors to construct their decarbonized portfolios. The results of high score portfolio compared to universal and/or low score portfolio would be useful not only to market participants who contribute funds to the energy transition, but also to policymakers in determining whether certain technologies' development can be primarily driven by the market.

[4] Sub-sector in clean energy which are

This paper is structured as follows. Section 2 summarizes some of existing literatures, section 3 introduces data, section 4 is our methodology, Section 5 is the results and discussion, and section 6 is about the conclusion.

2. Related literature

2.1) Green complexity measurement

(Penny Mealy, 2022) employ techniques from the literature on economic complexity to create two novel measures, the Green Complexity Index (GCI) and Green Complexity Potential (GCP), and show how they can capture specific environmental data about a country's present production capacity and potential for future green diversification. Given that the green transition is projected to change the global competitive environment in favor of nations that can presently generate green, high-tech products. Their methodology builds on existing work in the economic geography and economic complexity literature (Boschma et al., 2013; Hidalgo et al., 2018; Hidalgo et al., 2007; Neffke et al., 2011; Pari Patel, 1997; Weitzman, 1998) which has demonstrated that nations are more inclined to diversify into goods or businesses that call for comparable production capabilities to those they already have.

The GCP calculates the average relatedness of each nation to green complex items in which it lacks market share. Therefore, the GCP identifies which nations are best positioned to expand their green manufacturing capabilities into new green goods in the future, as opposed to the GCI, which allows countries to be evaluated using an assessment of their current green production capabilities. They demonstrate that the GCP can considerably predict increase in a country's GCI, green export share, and the number of green items in which a country is competitive after adjusting for each country's per capita GDP. A significant positive association between nations' GCP and GCI is also discovered. For instance, a high GCP score in the wind and solar sectors suggests that a nation is likely to improve its competitiveness in those technologies in the future, which may be taken as signaling a relatively appealing investment. Additionally, a high GCI is linked to strong indications of the strictness of environmental regulation.

Even after adjusting for per capita GDP, this study's findings show that nations with high GCI rankings also frequently have fewer emissions, greater rates of green patenting, and stricter environmental regulations. They also see a "greener" impact, which suggests that nations with superior green production skills may diversify into new green export prospects more easily. Given that they use the most particular green goods as building materials for facilities, wind and solar energy technology development makes one of the biggest contributions to a nation's green competitiveness. For instance, since its tenth five-year plan, which covered the years

2001 to 2005, China has made green energy technology a fundamental component of its industrial strategy. This plan set "promote new energy and renewable energy like solar PV and wind" as one of its main objectives[5].

2.2) Wind and solar industry

(Hepburn et al., 2020) suggests that governments exploring additional investments in energy infrastructure include those who are implementing "green recovery" programs or those that anticipate considerable future increase in energy consumption[6]. The International Energy Agency's (IEA, 2021) estimates that costs for solar and offshore wind are also projected to continue to decline, the cost of power produced from gas would increase globally in the next 10 to 30 years. It is without a doubt necessary to increase wind and solar capacity in order to achieve Net Zero by 2050. According to BNEF, until 2030, 505 gigawatts of additional wind power and 455 gigawatts of solar PV would need to be produced globally year, respectively[7].

(Perlin, 1999) states that the cost of solar PV has decreased by more than three orders of magnitude since its first commercial use in 1958. (Matthew Ives, 2021) also illustrate that Over the past ten years, the cost of wind and solar energy has decreased by 60% and 80%, respectively, due to larger, more efficient wind turbines and the automation of solar product manufacture. It is anticipated that these price drops will continue, which might have a significant negative impact on the world energy system. Additionally, they contend that as the world moves toward renewable energy and net zero, the share of global trade volumes held by renewable energy technologies—which include items like solar panels and wind turbines—has grown by about 1%. Furthermore, their examination of historical energy technology cost patterns reveals that the decades-long rise in the use of renewable energy technologies has repeatedly corresponded with sharp drops in those prices. For instance, during the past 50 years, the cost of solar photovoltaics has decreased by three orders of magnitude. Wind, energy storage, and electrolyzers (hydrogen-based energy) all exhibit comparable tendencies. These price drops are expected to continue and will bring some of these renewable technologies well below the cost basis for the current generation of electricity from fossil fuels. Additionally, their model indicates that a swift switch to an international energy system based on renewable energy sources with storage may save the globe trillions of dollars and

---

[5] IEA, 'The 10th Five-Year Plan for Economic and Social Development of the People's Republic of China (2001-2005)', IEA/IRENA Renewables Policies Database, 2021 https://www.iea.org/policies/1736-the-10th-five-year-plan-for-economic-and-socialdevelopment-of-the-peoples-republic-of-china-2001-2005?page=4&q=China.

[6] Ives, M.C., L. Righetti, J. Schiele, K. De Meyer, L. Hubble-Rose, F. Tieng, and others, A New Perspective on Decarbonising the Global Energy System, Oxford University Smith School of Enterprise and the Environment, 2021 www.energychallenge.info

[7] IEA, World Energy Outlook 2020, 2020, MML

result in significantly lower energy costs for everyone, producing a favorable dynamic that might spur quick change.

(Sharpe & Lenton, 2021) have also discovered compelling data that suggests energy storage and renewable technology will maintain their downward price trends. These trends have consistently been underestimated by the majority of the major climate mitigation models used to inform policymakers. Additionally, they have not seen any data that suggests renewables won't maintain their present downward price trends. Several tipping points have been passed as the cost of renewable energy has decreased (Sharpe & Lenton, 2021; Way et al., 2019), and the markets they compete in have steadily grown in size from specialty applications to mass market. The world's two most affordable methods of generating power from new construction are now solar and wind energy (IEA, 2020c)[8], while on a total-cost-of-ownership (TCO) basis, some electric cars (EVs) are approaching parity with their internal combustion engine vehicle (ICEV) equivalents (Hagman et al., 2016), with some even predicting their sticker prices will be cheaper within around 2-3 years[9]. Therefore, there is enough strong evidence to conclude that these long-term energy technology cost patterns are reliable and predictable (Farmer & Lafond, 2016; McNerney et al., 2011). For predicting technological advancement, several new techniques that are statistically supported and securely based in data have been created (Farmer et al., 2019; Wilson et al., 2013). The empirical evidence clearly supports the trends.

Additionally, (Way, 2021) estimates future energy system costs are examined, along with how, in three distinct scenarios, technological cost uncertainty affects system costs. Even without taking into consideration climatic damages or co-benefits of climate policy, a quick switch to green energy would result in total net savings of many trillions of dollars compared to maintaining a fossil fuel-based economy. If the current exponentially expanding deployment patterns for solar PV, wind, batteries, and hydrogen electrolyzers continue for another ten years, their models indicate that. Thus, as part of worldwide efforts to meet the Paris targets and attain net zero by 2050, wind and solar are two renewable energy sources that are essential to the climate transition and whose capacity might rise 10-fold in just 20 years.

2.3) Investing in renewable energy sector

In earlier research, volatility was frequently used as an objective function to lessen the risk associated with portfolios of clean energy and unclean assets. (Nasreen et al., 2020). However, the link between oil and the clean energy index is

[8] IEA, 2020c. World Energy Outlook 2020. Paris: International Energy Agency.
[9] Henze, V. 2020. https://about.bnef.com/blog/

nonlinear (Ishaan Dawar, 2021) and has an influence on how well clean energy risk reduction works with regard to assets with a range of volatile to extremely risky conditions (Kuang, 2021a). As a result, the current study incorporates volatility and tail risk into the appropriate optimization framework and performance evaluation, enabling investors to design an ideal portfolio to meet their investment goals.

(Kuang, 2021b) uses a relative risk ratio approach (Bredin et al., 2017; Conlon et al., 2020) to clearly demonstrate the effectiveness of risk reduction across several clean energy sub-sectors and risk metrics under varying degrees of decarbonization, as well as the adverse risk impact of diversifying into clean energy equities. Furthermore, the report contends that although renewable energy equities outperform filthy stocks, they lag the entire equity market. The minimum-tail risk approach is preferable to the minimum-variance strategy for investors who want to reduce the carbon footprint of their portfolios. For investors with a moderate level of risk tolerance, the index that monitors the owners and operators of renewable energy projects offers the best risk-adjusted returns and works well to reduce the volatility risk associated with filthy assets. However, the favored choices for lowering the tail risks of dirty assets are the wind and energy storage indexes. The most profitable category is renewable energy, followed by energy efficiency, bio/clean fuels, and innovative materials, which are in the middle. The top right corner of the efficient frontier graph represents the fuel cell index with the highest risk and reward.

3. Data

3.1) Sample

Our research sample comprises 150 large capitalization stocks from the global renewable energy sector, categorized according to the Bloomberg Industry Classification Systems (BICS). To construct our portfolio, we follow the methodology outlined in Rahat and Nguyen (2022), we first obtain monthly price data and market capitalization figures from DataStream. We collect data spanning from December 2017 to December 2022. With this data, we calculate monthly portfolio returns using an equal-weight approach, ensuring that each stock in the portfolio carries the same weight. We also acquire a benchmark index for our analysis, namely the NASDAQ Clean Edge Green Energy (CELS) index. This index is specially designed as a modified market capitalization-weighted benchmark. Its purpose is to track the performance of companies primarily engaged in the manufacturing, development, distribution, and installation of clean energy technologies. [10].

Table 1: Sample distribution by country and sub-sector

[10] Source: https://indexes.nasdaqomx.com/Index/Overview/CELS

This table provides a sample distribution by country and sub-sector. Our sample includes 111 solar and 39 wind stocks. China, the United States, and India are the top 3 countries in our sample, with 33,28, and 16 stocks, respectively.

Country	Solar	Wind	Total
Australia	3	0	3
Brazil	0	1	1
Canada	7	0	7
China	26	13	39
Denmark	1	1	2
France	1	0	1
Germany	2	3	5
Hong Kong	5	3	8
India	9	5	14
Israel	4	2	6
Italy	1	0	1
Monaco	0	1	1
Netherlands	1	1	2
Norway	2	0	2
Poland	8	1	9
South Korea	4	2	6
Spain	2	1	3
Sweden	5	2	7
Switzerland	1	0	1
Taiwan	12	0	12
Thailand	1	0	1
United Kingdom	0	1	1
United States	16	2	18
Total	**111**	**39**	**150**

Table 2: The median of purity score by sub-sector

This table provides the median of purity score by sub-sector and year. The wind consistently exhibits higher purity scores than the solar across all years, 2017-2021. The average median of purity score for solar is 0.6460, 0.7365 for wind, and 0.6844 for both solar and wind sector.

Sector	2017	2018	2019	2020	2021	Average
Solar	0.6400	0.6400	0.6500	0.6500	0.6500	0.6460
Wind	0.7331	0.7366	0.7552	0.7494	0.7082	0.7365
Solar and Wind	0.6800	0.6690	0.6892	0.6865	0.6971	0.6844

Table 3: The average purity score by country

This table provides the average purity score by country for 2017 to 2021. Denmark, Switzerland, and the United Kingdom have the highest purity score in our sample. Whereas the overall average purity score is 0.5704.

Country	2017	2018	2019	2020	2021	Average
Universe	0.5644	0.5629	0.5762	0.5703	0.5779	0.5704
Australia	0.3800	0.3800	0.3800	0.3800	0.3800	0.3800
Brazil	0.2668	0.2668	0.2668	0.2668	0.2668	0.2668
Canada	0.6429	0.6429	0.6429	0.6429	0.6429	0.6429
China	0.4978	0.4978	0.4978	0.4978	0.4978	0.4978
Denmark	0.8000	0.8000	0.8000	0.8000	0.8000	0.8000
France	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
Germany	0.6792	0.6792	0.6792	0.6792	0.6792	0.6792
Hong Kong	0.6744	0.6744	0.6744	0.6744	0.6744	0.6744
India	0.6754	0.6754	0.6754	0.6754	0.6754	0.6754
Israel	0.4650	0.4650	0.4650	0.4650	0.4650	0.4650
Italy	0.7100	0.7100	0.7100	0.7100	0.7100	0.7100
Monaco	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Netherlands	0.6866	0.6866	0.6866	0.6866	0.6866	0.6866
Norway	0.5250	0.5250	0.5250	0.5250	0.5250	0.5250
Poland	0.5456	0.5456	0.5456	0.5456	0.5456	0.5456
South Korea	0.6424	0.6424	0.6424	0.6424	0.6424	0.6424
Spain	0.7680	0.7680	0.7680	0.7680	0.7680	0.7680
Sweden	0.5021	0.5021	0.5021	0.5021	0.5021	0.5021
Switzerland	0.8000	0.8000	0.8000	0.8000	0.8000	0.8000
Taiwan	0.5563	0.5563	0.5563	0.5563	0.5563	0.5563
Thailand	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
United Kingdom	0.8000	0.8000	0.8000	0.8000	0.8000	0.8000
United States	0.5535	0.5535	0.5535	0.5535	0.5535	0.5535

Table 4: The average green complexity score by country

This table provides the average green complexity score by country for 2017 to 2021. In our sample, Norway, Australia, and Switzerland have the highest green complexity scores of 4.1994, 2.0324 and 1.9572, respectively. Whereas the average green complexity score during the time is 0.7707.

Country	2017	2018	2019	2020	2021	Average
Universe	0.6123	0.7585	0.8293	0.8595	0.7940	0.7707
Australia	2.2174	2.1818	2.0385	1.7037	2.0204	2.0324
Brazil	0.4400	0.3200	0.5652	0.8261	0.5313	0.5365
Canada	0.5376	0.6700	0.7212	0.8922	0.7093	0.7060
China	0.7995	0.8090	0.8015	0.7855	0.7989	0.7989
Denmark	1.6284	1.5789	1.5602	1.5156	1.5701	1.5707
France	0.9477	0.9689	0.8842	0.9120	0.9284	0.9282
Germany	1.7454	1.7575	1.7329	1.7428	1.7445	1.7446
Hong Kong	0.1014	0.2129	0.3195	0.3867	0.2572	0.2555
India	0.4592	0.5105	0.6017	0.6461	0.5554	0.5546
Israel	1.4521	1.3210	1.3176	1.1957	1.3142	1.3201
Italy	0.9845	0.9550	0.9398	0.9682	0.9619	0.9619
Monaco	0.9477	0.9689	0.8842	0.9120	0.9284	0.9282
Netherlands	0.4410	0.4511	0.4855	0.4650	0.4610	0.4607
Norway	4.4444	3.7000	3.2857	5.5000	4.0667	4.1994
Poland	0.9700	0.9672	0.9720	0.9644	0.9684	0.9684
South Korea	1.2843	1.3800	1.3400	1.3600	1.3408	1.3410
Spain	0.6416	0.6216	0.5982	0.6073	0.6172	0.6172
Sweden	1.5086	1.5322	1.4970	1.4940	1.5081	1.5080
Switzerland	1.9211	1.9737	1.8933	2.0411	1.9567	1.9572
Taiwan	0.7995	0.8090	0.8015	0.7855	0.7989	0.7989
Thailand	0.5946	0.6463	0.6370	0.5775	0.6141	0.6139
United Kingdom	1.2829	1.3005	1.2705	1.2406	1.2733	1.2736
United States	1.4372	1.4807	1.3941	1.3932	1.4263	1.4263

3.2) Asset pricing factors

From the Kenneth R. French data repository, international risk factors are obtained. The market returns are based on NASDAQ Clean Edge Green Energy (CELS), and we use the U.S. one-month T-bill rate as a proxy for the risk-free rate. The risk factors include the size factor (small minus big: SMB), which is calculated as the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios, the value factor (HML), which is calculated as the average return on the two value portfolios minus the average return on the two growth portfolios, and the momentum factor (WML) defined as the equal-weight average of the two winning portfolio returns for an area less the average of the two losing portfolio returns. Each factor is calculated as follows:

SMB(B/M) = 1/3 (Small Value + Small Neutral + Small Growth)

- 1/3 (Big Value + Big Neutral + Big Growth) (1)

SMB(OP) = 1/3 (Small Robust + Small Neutral + Small Weak)

- 1/3 (Big Robust + Big Neutral + Big Weak) (2)

SMB(INV) = 1/3 (Small Conservative + Small Neutral + Small Aggressive)

- 1/3 (Big Conservative + Big Neutral + Big Aggressive (3)

SMB = 1/3 (SMB(B/M) + SMB(OP) + SMB(INV) (4)

HML = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth) (5)

WML = 1/2 (Small High + Big High) - 1/2 (Small Low + Big Low) (6)

Asset pricing factors will be used for calculating risk-adjusted return in the next section.

3.3) Sorting factors for portfolio construction

(1) Green complexity score

The first factor is based on green complexity score, macro data as a country level, and a comparative analysis calculated by GCP/GCI by country where firm headquarter location is, to imply that a country has competitive strengths and capacity to maintain such advantages in the future. The score captures the technological sophistication of the green products that a country is currently and potentially exporting competitively. We collect green complexity index (GCI) and green complexity potential (GCP) of each country from Green Transition Navigator[11].

We calculate the green complexity score of each firm and divide all stocks into 2 groups based on their green complexity score of the previous year and update on an annual basis. The stocks with above-median scores are classified as high score, while those below the median are considered as low score.

(2) Purity score

The second factor is based on the purity score, micro data as a firm level, and is considered as a new type of green or environmental rating. The purity score captures magnitude for each firm’s technology-dense, which is considered a winner in this shifting landscape due to cost declines and rapid growth trend. We apply

[11] Data source: https://green-transition-navigator.org/

method from LO_SSEE, 2021[12] report to compute the purity score at firm level. The purity score indicates how much firm involved in midstream activities. We first analyze company descriptions to classify company sub-business then map onto the value chain activities to assign exposure score as table 2; approach placed less focus on upstream and downstream operations and gave midstream (core manufacturing) businesses with component production and installation better marks. Instead of focusing on services and inputs, midstream manufacturing operations aim to encompass the full spectrum of goods.

Table 5: Wind and solar value chain

Activity	Sub-business	Description
Upstream	Inputs	Metals and minerals Chemicals (Plastics, Polysilicon)
Midstream	Product manufacturing	Wind turbine components - Blades, towers, nacelle, bearings, castings Solar panel components - Wafer, cell, module Ancillary services - All non-module hardware - Monitoring and controls - PV manufacturing equipment
	Construction and installation	Windfarm, Solar power plant, and Mixed wind and solar developers
Downstream	Generation and distribution	Wind energy generation, Solar energy generation, and Mixed wind and solar generation

Source: LO_SSEE, 2021[13] report

Table 6: Exposure score of each sub-business

Exposure score is an average of each activity calculated by LO_SSEE, 2021 report which was calculated using two considerations – specialization and relevance, expert judgement, and engagement with industry professionals.

Activity	Sub-business	Description	Exposure Score (0-1)
Upstream	Inputs	Metals and minerals	0.33
		Chemicals	
Midstream	Product and manufacturing	Wind turbine components	0.80
		Solar Panel Components	

[12] LO_SSEE (Lombard Odier and the Smith School of Enterprise and the Environment ("SSEE") at the University of Oxford), 2021, "The predictors of success in a greening world".
[13] LO_SSEE (Lombard Odier and the Smith School of Enterprise and the Environment ("SSEE") at the University of Oxford), 2021, "The predictors of success in a greening world".

		Ancillary services	
	Construction and Installation	Wind farm	
		Solar power plant	
		Mixed wind and solar developers	
Downstream	Generation and distribution	Wind energy generation	0.50
		Solar energy generation	
		Mixed wind and solar generation	

Table 7: (Example) Purity score of each company

Company	**Sub-business**	**% Revenue**	**Exposure Score**	**Purity Score**
A	Wind turbine	100%	0.8	0.8
B	Wind turbine	20%	0.8	0.56
	Solar Power Generation	80%	0.5	

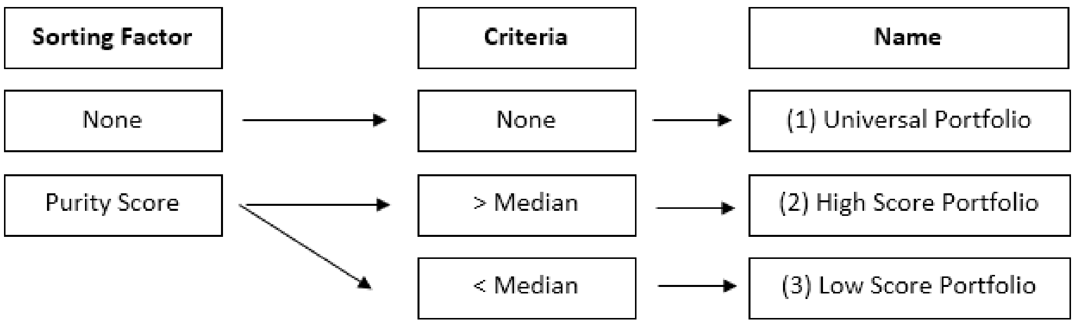
To minimize look-ahead bias, we divide all stocks into 2 groups based on their purity scores of the previous year and update on an annual basis. The stocks with above-median scores are classified as high score, while those below the median are considered as low score.

4. Methodology

4.1) Portfolio construction

We analyze portfolios using equal-weighted portfolio returns. Accordingly, we follow portfolio construct methodologies of (Rahat & Nguyen, 2022) based on sorting factors. Our sorting factors are purity score and green complexity score. The sorting factors are calculated annually, and consequently, the portfolios are rebalanced. Factor sorting portfolios are comprising high scores and low scores. Furthermore, to assess the comparative performance, we have three types of portfolios. The first one includes all firms, a universal portfolio, the second one comprises high scores of sorting factor, the final one includes low scores of sorting factor. Therefore, as figure 1, we have 5 portfolios which are 2 high score portfolios, (1) high score of purity (2) high score of green complexity score, 2 low score portfolios, (3) low score of purity (4) low score of green complexity score, and (5) a universal portfolio. Consequently, as figure 2, the comparison between high or low score and universal will reveal the impact of divestment. Meanwhile, the performance differences between high and low portfolios will reflect on technologically concentrated styles.

Figure 1: Portfolios Construction



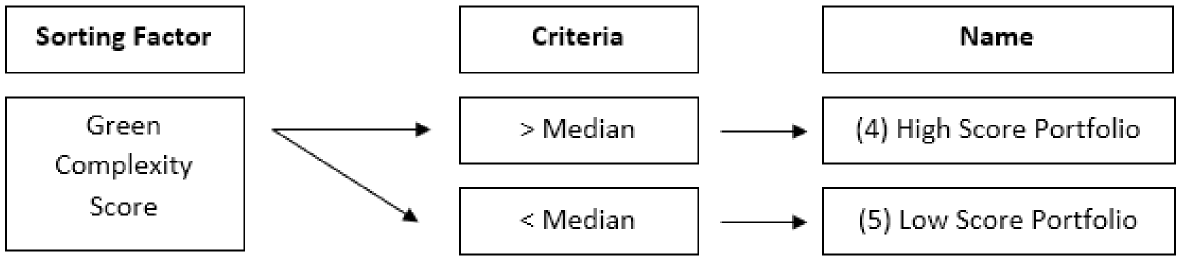
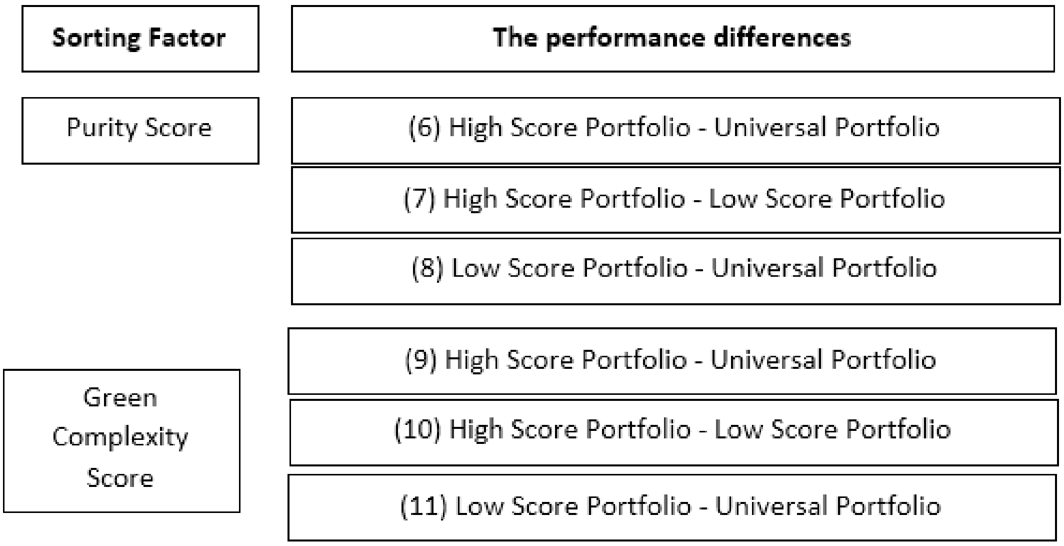


Figure 2: Portfolio comparison



4.2) Model

Our study includes a comparison of created portfolios' raw return and risk-adjusted performance. We employ the CAPM (capital asset pricing model), the raw return, the Sharpe ratio, the Sortino ratio, the Fama & French 3-factor model, and the Carhart 4-factor model. We calculate portfolio return as follow:

$$R_p = \Sigma_{i=1}^{n} w_i r_i \qquad (7)$$

Where

R_p the equal-weighted portfolio return at time t of each constructed portfolio,

w_i is the weight of each stock in the portfolio, and

r_i is the return of the stock

In addition, we follow (Markowitz, 1952) classical portfolio optimization approach to Determine the combination of assets that maximizes performance in a mean-variance scenario while examining both unconventional and traditional asset classes to see whether there are any benefits to diversification. By adding assets in a portfolio that are not perfectly connected, diversification is created. This lowers unsystematic risk and enables greater risk-adjusted returns. A typical investing approach is portfolio diversification, which has been employed with a variety of different asset classes, including gold, real estate, water, diamonds, and weather derivatives (Conover et al., 2009; Dempster & Artigas, 2010; Gilroy et al., 2013; Hung et al., 2008; Ratner & Klein, 2008; Small et al., 2012; Van Lennep et al., 2004). The Sharpe ratio *(SR)* represents the amount of excess return (return above the risk-free rate) per unit of risk (measured by standard deviation) and consequently compute the Sharpe ratio as follow:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{8}$$

Where

R_p is the equal-weighted portfolio return at time t of each constructed portfolio,

R_f is the U.S. one month T-bill rate[14], and

σ_p is the standard deviation of the portfolio.

To address downside risk, we also employ The Sortino ratio which is a variation of the Sharpe ratio that only factors in downside risk. Investors are only concerned about exposure to volatility that might result in negative returns, whereas Sharpe ratio handles all risk (including upside risk) equally, making the comparison with downside deviation feasible (Washer, 2013). Consequently, a common statistic for determining risk-adjusted performance across diverse asset classes is the Sortino ratio (Damianov & Elsayed, 2020; Sanford, 2022). We estimate the Sortino ratio (*ST*) as follow:

$$ST = \frac{R_p - R_f}{\sigma_d} \tag{9}$$

Where

R_p is the equal-weighted portfolio return at time t of each constructed portfolio,

R_f is the U.S. one month T-bill rate[15], and

σ_d is the standard deviation of negative asset returns.

To control other risk factors and estimate the marginal returns of portfolios over the risk-free rate, we use the capital asset pricing model (CAPM) to calculate

[14] Following Kenneth R. French's method
[15] Following Kenneth R. French's method

the risk-adjusted abnormal performance or Jensen's alpha, by (Jensen, 1968), of each equally weighted constructed portfolio as follow:

$$R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + \varepsilon_{pt} \qquad (10)$$

Where

R_{pt} is the equal-weighted portfolio return at time t of each constructed portfolio,

R_{ft} is the U.S. one month T-bill rate[16],

α_p represent the abnormal return of portfolio,

R_m is the return of NASDAQ Clean Edge Green Energy (CELS) which is a modified market capitalization weighted index designed to track the performance of companies that are primarily manufacturers, developers, distributors and/or installers of clean energy technologies[17],

$b_p$is factor loading of market premium $(R_{mt} - R_{ft})$, and

ε_{pt} is the idiosyncratic return component at time t

Moreover, we employ (Fama & French, 1993) three-factor model by adding two more risk factors which are size factor (Small minus Big: SMB) and value factor (High minus Low book to market: HML) to calculate the risk-adjusted abnormal performance of each equally weighted constructed portfolio as follow:

$$R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + \varepsilon_{pt} \qquad (11)$$

Where

R_{pt} is the equal-weighted portfolio return at time t of each constructed portfolio,

R_{ft} is the U.S. one month T-bill rate[18],

α_p represent the abnormal return of portfolio,

R_m is the return of NASDAQ Clean Edge Green Energy (CELS) which is a modified market capitalization weighted index designed to track the performance of companies that are primarily manufacturers, developers, distributors and/or installers of clean energy technologies[19],

SMB_t is the international size factor at time t,

---

[16] Following Kenneth R. French's method

[17] The NASDAQ Clean Edge Green Energy Index description: https://indexes.nasdaqomx.com/Index/Overview/CELS

[18] Following Kenneth R. French's method

[19] The NASDAQ Clean Edge Green Energy Index description: https://indexes.nasdaqomx.com/Index/Overview/CELS

$HML_t$is the international value factor at time t,

b_p, s_p and h_p are factor loadings of market premium $(R_{mt} - R_{ft})$, size factor (SMB_t), and value factor (HML_t) respectively

ε_{pt} is the idiosyncratic return component at time t

To examine the momentum effect in addition to Fama-French three-factor using the momentum factor (winners minus losers: WML), we use (Carhart, 1997) four-factor model to calculate the risk-adjusted abnormal performance of each equally weighted constructed portfolio as follow:

$$R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + w_p WML_t + \varepsilon_{pt} \quad (12)$$

Where

R_{pt} is the equal-weighted portfolio return at time t of each constructed portfolio,

R_{ft} is the U.S. one month T-bill rate[20],

α_p represent the abnormal return of portfolio,

R_m is the return of NASDAQ Clean Edge Green Energy (CELS) which is a modified market capitalization weighted index designed to track the performance of companies that are primarily manufacturers, developers, distributors and/or installers of clean energy technologies[21],

SMB_t is the international size factor at time t,

$HML_t$is the international value factor at time t,

WML_t is the international momentum factor at time t,

ε_{pt} is the idiosyncratic return component at time t, and

b_p, s_p, $h_p$and w_p are factor loadings of market premium $(R_{mt} - R_{ft})$, size factor (SMB_t), value factor (HML_t) and momentum factor (WML_t) respectively

We estimate the regression. The positive difference of returns, the Sharpe ratio, and Sortino ratio between the high score and a universal implies the divesting strategy of investment in across renewable energy sector and high technological-dense firm and/or country. Whereas the positive difference of returns, the Sharpe ratio, and Sortino ratio between the high score and the low score implies an investment style involving technologically concentrated firms provide necessary

[20] Following Kenneth R. French’s method
[21] The NASDAQ Clean Edge Green Energy Index description: https://indexes.nasdaqomx.com/Index/Overview/CELS

incentive to investors. A positive and significant α_p of the high score over a universal would signify the positive impact of divestment from across renewable energy sector to technological specialization firm and/or country. Likewise, a positive and significant α_p of the high score over the low score captures necessary incentive for investing in technological specialization firm and/or country. On the contrary, an insignificant α_p would imply that there are no return differentials between the two portfolios and vice versa.

According to previous study of (Way, 2021), The construction of wind and solar farms that are connected to the grid via specialized cabling and equipment, as well as midstream activities that manufacture solar panel and wind turbine components, function as the engines of growth for both industries, leading to cost reductions and remarkable growth as well as a source of increased market competitiveness. It may result in more anomalous results (In et al., 2019). While providing less pure play exposure to the topic of wind and solar items, downstream energy generation and material inputs do. Moreover, (Mealy, 2020) established two new metrics for measuring a nation's ability to produce green energy: the green complexity index (GCI) and the green complexity potential (GCP). Based on the quantity and Product Complexity Index (PCI) of green products in which each country is competitive, GCI assesses each nation's level of green competitiveness. According to the proximity and complexity of goods in which a nation is not currently competitive, GCP assesses the possibility for that nation to diversify into complex, green products in the future. Their further research indicates that nations with high GCI rankings also frequently have fewer emissions, greater rates of green patenting, and stricter environmental regulations. Additionally, they see a "green get greener effect," or the ease with which advanced green export options are accessible to nations with green production capabilities. With 75 unique items out of 295 in the category of renewable energy, the development of wind and solar products makes one of the biggest contributions to a nation's green competitiveness[22], 15 goods specifically for solar facilities, and 22 products devoted to the building of wind facilities [23]. The remaining nine goods are used in both wind and solar installations and have overlapped uses. Then again, (Reboredo, 2015) found that country's new energy policies drive stock investment. Therefore, we propose the testable hypothesis as follows:

[22] The list of products based on environmental goods lists compiled by the WTO, the OECD, and APEC using in Mealy and Teytelboym, 2020

[23] The remaining 29 green products, 15 are for biomass, 7 are for hydropower, 5 are for geothermal. The other additional 2 products that are not specific to any renewable energy industry.

Hypothesis 1a: The high portfolios outperform the low score portfolios and universal portfolios across various performance metrics, including raw return, risk-adjusted return, and asset pricing models that account for and control risks.

Conversely, the study of (Rezec & Scholtens, 2017) discovered that the risk-adjusted return on the renewable energy indexes is extremely low and that they are not currently a financially appealing portfolio investment. (Marti-Ballester, 2019) same results using a particular market benchmark, green energy mutual funds perform worse than their conventional equivalents. While the overall expenditure ratio has a detrimental impact on the financial performance of renewable energy. Furthermore, (Hemrit & Benlagha, 2021) identified economic and Pandemic-induced uncertainty having a negative impact on the renewable energy index. And (Reboredo et al., 2017) suggested that because renewable energy projects often give a low return owing to expensive manufacturing and creative technology expenses, they may be less appealing as investment opportunities. Therefore, we propose the testable hypothesis.

Hypothesis 1b: The high portfolios underperform the low score portfolios and universal portfolios across various performance metrics, including raw return, risk-adjusted return, and asset pricing models that account for and control risks.

5. Results and discussion

This research paper examines whether portfolios with high scores provide an appealing choice when compared to universal portfolios and low score portfolios in terms of risk-adjusted returns and Jensen's alpha. Furthermore, it investigates whether there is an adverse performance impact when investing in firms with high technological specialization in wind and solar industry. We assess the performance during 2018 to 2022. Table 8 illustrates portfolio performance, and it appears that portfolios with high scores outperform both universal and low score portfolios, regardless of the sorting factor. Based on green complexity score sorting, the high score portfolio has an average monthly return of 7.88%, a universal portfolio has a return of 4.45%, and a low score portfolio has a return of 1.93%. The return for differentials in the high score and universal portfolio and the high score and low score portfolio remains appealingly positive, while the return for the low score and universal portfolio is negative. When the portfolios are classified by purity score, the results remain consistent. Specifically, the high score portfolio has an average monthly return of 5.74%, while the low score portfolio has a monthly return of 3.16%.

Table 8: Portfolio performance

Portfolio	Return	Max Return	Max Loss	S.D.	Downside S.D.	Sharpe	Sortino
Sorting factor – None							
Universal	4.45%	78.64%	-15.66%	43.34%	10.12%	0.0507	0.4600
Sorting factor – Green complexity score							
High	7.88%	182.86%	-12.67%	59.14%	11.76%	0.0326	0.7007
Low	1.93%	19.13%	-17.88%	17.29%	7.80%	0.0407	0.3071
High – Universal	3.43%	104.23%	-9.16%	23.98%	4.75%	0.0056	1.0079
High – Low	5.95%	181.79%	-17.36%	58.37%	12.61%	0.0427	0.6552
Low – Universal	-2.52%	8.19%	-77.56%	37.53%	7.72%	(0.0517)	(0.3987)
Sorting factor – Purity score							
High	5.74%	149.70%	-14.19%	44.98%	9.84%	0.0610	0.5629
Low	3.16%	38.13%	-17.12%	30.56%	9.89%	0.0329	0.4045
High – Universal	1.29%	71.06%	-8.62%	18.66%	3.65%	0.0105	0.5065
High – Low	2.57%	142.13%	-17.24%	46.10%	8.23%	0.0243	0.2000
Low – Universal	-1.29%	8.62%	-71.06%	29.48%	4.91%	(0.0336)	(0.1294)
Rm	1.98%	33.82%	-23.43%				

The results of raw return and risk-adjusted return – Sharpe and Sortino ratios, are provided in Table 9. Our analysis reveals compelling insights into the performance of different portfolios based on two sorting factors, green complexity score and purity score. Portfolios created by sorting green complexity score indicate an interesting tendency. The high score portfolios raw returns outperform when compared to both universal and low score portfolio. Across the board, we consistently observe positive return indicators across high score, low score, and universal portfolios. Specifically, the high score portfolio stands out as a top performer, boasting a raw return of 0.0788. Conversely, the low score portfolio demonstrates relatively lower raw returns of 0.0193 while the return of universal portfolio stands at 0.0445. Interestingly, the raw return for differentials in the high score and universal portfolio stands at 0.0343, indicating signifies that a strategic shift from an all-stocks portfolio to companies situated in countries with high green complexity scores or specialized technologies can yield notably higher returns for investors. Moreover, the differential in high and low score are even larger positive at 0.0595, indicating that divesting the green complexity country benefits investors, and our findings indicate the presence of such advantages. Consequently, adopting an investment approach that involves divesting from assets with high green complexity holds immense for investors. On the contrary, the return for differentials in the low score and portfolio is negative. The negative return signifies that investors will have to pay a premium to continue investing in low green complexity score stocks, and they will be better off transitioning away from these stocks. The results are consistent for the Sortino ratio. However, in the case of the Sharpe ratio, the universal portfolio boasts a Sharpe ratio of 0.0507 which is higher both high score portfolio, 0.0326 and low score portfolio at 0.0407, indicating the high score portfolio has a higher level of risk, the standard deviation shown as Table 8, and does not efficiently using the level of risk it takes on to generate returns compared to universal and low score portfolio. The consistency across the raw return and Sortino ratios signifies that incentives persist regardless of the risk perception.

The portfolios created using purity score as sorting also reveal a similar story. We observe that the high score portfolio dominates their counterparts in terms of raw return, Sharpe ratio and Sortino ratio. To illustrate, the high score portfolio has a raw return of 0.0574, which is markedly higher than the low score portfolio's return of 0.0316. The high score portfolio outperforms the low score portfolio in terms of Sharpe and Sortino ratios, with values of 0.0610 and 0.5629, respectively, compared to 0.0329 and 0.4045 for the low score portfolio. Similarly, the differences in returns between the high score and universal portfolio, as well as the high score and low score portfolio, continue to show a positive trend, while the differences in returns between low score and universal portfolio show a negative trend. These results reaffirm the strategy of divesting from firms with lower technological density and shifting towards diversification across the wind and solar industry, particularly in favor of highly specialized technological firms.

Table 9: Return and Risk-adjusted return

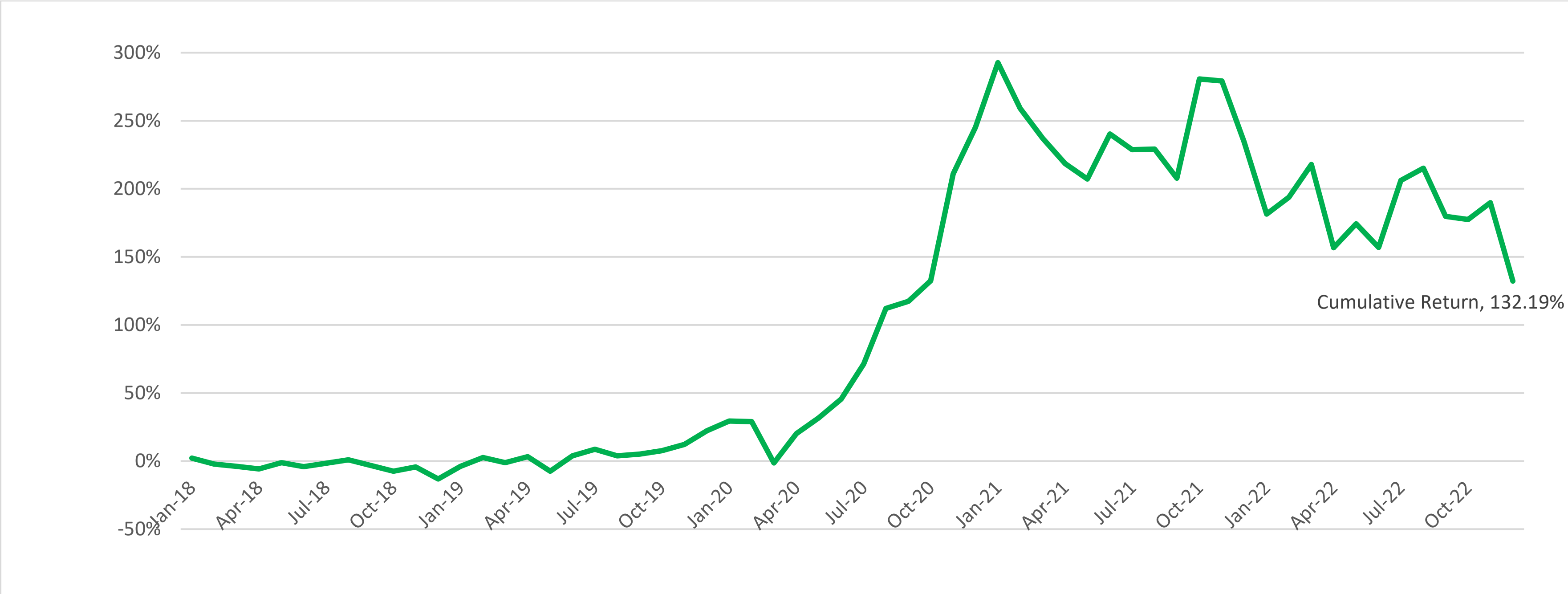
Return and Risk-adjusted Return

	Raw Return	**Sharpe Ratio**	**Sortino Ratio**
Sorting Factor - None			
Universal	4.45%***	0.0507	0.4560***
	(2.7023)	(1.5356)	(2.7651)
Sorting Factor - Green Complexity Score			
High	7.88%**	0.0326	0.7007**
	(2.3182)	(0.7986)	(2.4184)
Low	1.93%**	0.0407	0.3071**
	(2.1797)	(0.8168)	(2.5599)
High - Universal	3.43%*	0.0056	1.0080
	(1.8124)	(0.0984)	(1.5096)
High - Low	5.95%*	0.0427	0.6552**
	(1.7932)	(1.1074)	(2.4855)
Low - Universal	-2.52%*	-0.0517*	-0.3987***
	(-1.7671)	(-1.8267)	(-2.8688)
Sorting Factor - Purity Score			
High	5.74%**	0.0610	0.5629**
	(2.1336)	(1.4792)	(2.4699)
Low	3.16%***	0.0329	0.4045***
	(2.8583)	(0.9032)	(2.8998)
High - Universal	1.29%	0.0105	0.5065
	(1.0458)	(0.2792)	(0.9500)
High - Low	2.57%	0.0243	0.2000
	(1.0468)	(0.7735)	(0.8992)
Low - Universal	-1.29%	-0.0336	-0.1294
	(-1.0474)	(-1.0020)	(-0.7738)

*** represents significance at 1%, ** at 5%, * at 10%.

Figure 3: Market Return (CELS Index cumulative return)

This figure shows cumulative return of the NASDAQ Clean Edge Green Energy (CELS) index across the period, which is 132.19% with an annualized return of 26.44%.



Source: nasdaq.com/market-activity/index/cels

Table 9: Correlation between returns of sorted portfolios and market factors.

This table provides correlation between portfolio return and market factors. We observe that high score portfolios have lower correlation to the benchmark compared to universal and low score portfolios. Interestingly, divestment portfolios, low and universal, have negative correlation to benchmark, indicating that a diversification strategy where the portfolio aims to provide some protection against poor market conditions.

	Universal	HPS	LPS	HGS	LGS	HPS - U	HPS - LPS	LPS - U	HGS - U	HGS - LGS	LGS - U	Rm	SMB	HML	WML
Universal	1.0000	0.9517	0.6656	0.9545	0.5023	0.7414	0.7411	-0.7406	0.8443	0.8439	-0.8432	0.4940	-0.4218	-0.0841	0.1323
HPS	0.9517	1.0000	0.4046	0.9624	0.3300	0.9116	0.9114	-0.9109	0.9005	0.8980	-0.8945	0.3115	-0.3371	-0.0624	0.0576
LPS	0.6656	0.4046	1.0000	0.5024	0.6990	-0.0068	-0.0076	0.0085	0.3231	0.3280	-0.3344	0.7175	-0.4430	-0.1040	0.2489
HGS	0.9545	0.9624	0.5024	1.0000	0.2220	0.8257	0.8262	-0.8266	0.9657	0.9655	-0.9648	0.3419	-0.2988	-0.0812	0.0978
LGS	0.5023	0.3300	0.6990	0.2220	1.0000	0.0488	0.0462	-0.0437	-0.0385	-0.0397	0.0414	0.6119	-0.5170	-0.0401	0.1431
HPS - U	0.7414	0.9116	-0.0068	0.8257	0.0488	1.0000	0.9999	-0.9995	0.8380	0.8331	-0.8264	0.0194	-0.1722	-0.0238	-0.0513
HPS - LPS	0.7411	0.9114	-0.0076	0.8262	0.0462	0.9999	1.0000	-0.9999	0.8392	0.8343	-0.8276	0.0177	-0.1693	-0.0214	-0.0491
LPS - U	-0.7406	-0.9109	0.0085	-0.8266	-0.0437	-0.9995	-0.9999	1.0000	-0.8402	-0.8354	0.8286	-0.0159	0.1663	0.0190	0.0468
HGS - U	0.8443	0.9005	0.3231	0.9657	-0.0385	0.8380	0.8392	-0.8402	1.0000	0.9999	-0.9994	0.1843	-0.1696	-0.0726	0.0605
HGS - LGS	0.8439	0.8980	0.3280	0.9655	-0.0397	0.8331	0.8343	-0.8354	0.9999	1.0000	-0.9998	0.1869	-0.1681	-0.0725	0.0620
LGS - U	-0.8432	-0.8945	-0.3344	-0.9648	0.0414	-0.8264	-0.8276	0.8286	-0.9994	-0.9998	1.0000	-0.1903	0.1659	0.0722	-0.0639
Rm	0.4940	0.3115	0.7175	0.3419	0.6119	0.0194	0.0177	-0.0159	0.1843	0.1869	-0.1903	1.0000	-0.4940	-0.2206	0.3321
SMB	-0.4218	-0.3371	-0.4430	-0.2988	-0.5170	-0.1722	-0.1693	0.1663	-0.1696	-0.1681	0.1659	-0.4940	1.0000	0.2635	-0.0909
HML	-0.0841	-0.0624	-0.1040	-0.0812	-0.0401	-0.0238	-0.0214	0.0190	-0.0726	-0.0725	0.0722	-0.2206	0.2635	1.0000	-0.5103
WML	0.1323	0.0576	0.2489	0.0978	0.1431	-0.0513	-0.0491	0.0468	0.0605	0.0620	-0.0639	0.3321	-0.0909	-0.5103	1.0000

Remark: HPS = High purity score portfolio, LPS = Low purity score portfolio, HGS = High green complexity score portfolio, LGS = Low green complexity score portfolio, U = Universal portfolio, Rm = Market return, SMB = Size factor, HML = Value factor, WML = Momentum factor

The panel estimates for Jensen's alpha of portfolios sorted by green complexity score, as presented in Table 11, provide significant insights. Notably, a statistically significant and positive alpha is observed across all portfolios— high score, low score, or universal. This indicates that these investment portfolios generate returns surpassing the expected return for their corresponding risk levels. Furthermore, those portfolios exhibit well-diversified characteristics aimed at mitigating excess risk, which inevitably impacts investment performance. This alignment is consistent with the results of three different asset pricing models used in this study. According to the CAPM model, the alpha for the high score portfolio is 0.0623, 0.0328 for the universal portfolio, and 0.0114 for the low score portfolio. Even when the size factor and value factor are taken into account using the Fama&French 3-factor model, the alpha of the portfolios remains positive and significant: 0.0838 for the high score portfolio, 0.0497 for the universal portfolio, and 0.0251 for the low score portfolio. Similarly, when deploying the Carhart 4-factor model to account momentum factor, the alpha of the portfolios persists positive and significant: 0.0840 for the high score portfolio, 0.0499 for the universal portfolio, and 0.0253 for the low score portfolio. It suggests that those portfolios outperform the benchmark or a risk-adjusted expectation. The study of Kuang, 2021c also shows similar findings that wind and solar indices may be appealing to aggressive investors seeking higher returns with higher risk tolerance compared to other renewable energy indices. Moreover, in accordance with a prior study conducted by Way et al. (2021), within the wind and solar industry, midstream activities encompassing the production of components for solar panels and wind turbines, along with the construction of wind and solar farms integrated into the grid through specialized infrastructure, play a pivotal role in driving growth for both sectors. These activities have not only resulted in cost reductions and impressive industry expansion but have also enhanced market competitiveness. Thus, they have the potential to contribute to higher abnormal returns (In et al., 2019). Interestingly, the high score portfolio displays a notably higher alpha than both the universal and low score portfolios. Moreover, the differential portfolios—both high versus universal and high score versus low score—likewise manifest statistically significant and positive alphas. This suggests that an investment strategy involving divestment from countries with low green complexity scores holds appealing incentives for investors. Investment strategies that divest from nations with low levels of technology density or green complexity provide benefits for investors. On the other hand, the low score and portfolio differentials have a negative alpha. The portfolio's realized return was less than anticipated and out of line with the underlying risk, as indicated by the negative alpha. The portfolio may not have been sufficiently diversified to reduce the excess risk that influences investment performance, on the other hand. This suggests that investors would be better off moving away from low green complexity score equities because doing so would require them to pay a higher premium. Additionally, the coefficients associated with risk factors offer noteworthy insights. In the context of high and low score portfolios, only the size premium is deemed statistically significant. Conversely, for the universal portfolio, both the market premium and size premium exhibit significance. This implies that the universal portfolio carries a heightened risk exposure due to its sensitivity to market and size factors.

As shown in Table 12, the results for portfolios using purity sorting factors are similar. The high score portfolio shows a positive and significant alpha. However, the divestment alphas, although positive, but not statistical significance. This implies that the efficacy of divestment strategies is contingent on the proxy used to identify them, notably the green complexity score. Consequently, even if the realized returns of the low score portfolio align with the risk factors, investors are still paying a premium when compared to investing in firms with higher green complexity scores. Additionally, this study supports the finding of Cesar Hidalgo et al. (2007) that the green complexity score captures that countries that specialize in more technologically sophisticated products enjoy higher income and growth. Countries and regions are also significantly more likely to develop competitiveness in products and services that require capabilities similar to those they already have. Furthermore, Mealy et al. (2020) have demonstrated a correlation between high green complexity indexes and high indicators of environmental policy rigor. A nation may be viewed as having a relatively favorable investment climate if it receives a high complexity score in the wind and solar industries, which suggests that the country will likely expand its competitiveness in those technologies in the future. This implies that countries with well-developed green production capabilities find it more feasible to expand into new green export opportunities. These results also resonate with a study by IRENA (2019), which demonstrated that the costs of wind and solar energy have, for the most part, exceeded those of fossil fuel alternatives. Government support mechanisms like as feed-in tariffs, subsidies, and quotas have predominantly pushed deployment in the renewable energy sector, aligning with the previous research of (Reboredo, 2015) that the country's new energy policies encourage stock investment. This reinforces the notion that countries boasting high green complexity scores tend to be competitive and outperform their low-score counterparts in the renewable energy sector, owing to a combination of factors, including robust government incentives and policy support.

Table 11: Panel results Jensen's Alpha (Sorting factor – Green Complexity Score)

	Universal	**High**	**Low**	**High - Universal**	**High - Low**	**Low - Universal**
Sorting Factor - Green Complexity Score						
CAPM; $R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + \varepsilon_{pt}$						
αp	0.0328**	0.0623*	0.0114*	0.0290*	0.0505*	-0.0219*
	(2.236)	(1.904)	(1.851)	(1.862)	(1.854)	(-1.680)
bp	0.5810***	0.8286***	0.3883***	0.2489	0.4416	-0.1914
	(4.337)	(2.773)	(5.912)	(1.431)	(1.449)	(-1.461)
Fama&French 3-factor; $R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + \varepsilon_{pt}$						
αp	0.0497***	0.0838**	0.0251***	0.0336*	0.0582*	-0.0251*
	(2.745)	(2.04)	(2.935)	(1.720)	(1.678)	(-1.762)
bp	0.4543***	0.6297*	0.3116***	0.1768	0.3195	-0.1414
	(2.972)	(1.814)	(4.319)	(0.867)	(0.894)	(-0.92)
sp	-0.8387*	-1.2298	-0.5696***	-0.38963	-0.65872	0.27059
	(-1.886)	(-1.218)	(-2.714)	(-0.657)	(-0.634)	(0.605)
hp	0.1603	0.1123	0.1956	-0.0492	-0.0846	0.0341
	(0.565)	(0.174)	(1.46)	(-0.13)	(-0.127)	(0.119)
Carhart 4-factors; $R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + w_p WML_t + \varepsilon_{pt}$						
αp	0.0499***	0.0840**	0.0253***	0.0336*	0.0582*	-0.0251*
	(2.726)	(2.022)	(2.93)	(1.851)	(1.783)	(-1.833)
bp	0.4455***	0.6213*	0.3028***	0.1772	0.3198	-0.1413
	(2.734)	(1.679)	(3.941)	(0.815)	(0.839)	(-0.863)
sp	-0.8543*	-1.2446	-0.5851***	-0.3889	-0.6581	0.2707
	(-1.865)	(-1.196)	(-2.708)	(-0.636)	(-0.614)	(0.588)
hp	0.1882	0.1387	0.2232	-0.0506	-0.0856	0.0339
	(0.569)	(0.184)	(1.43)	(-0.115)	(-0.111)	(0.102)
wp	0.0521	0.0494	0.0516	-0.0025	-0.0019	-0.0003
	(0.168)	(0.07)	(0.353)	(-0.006)	(-0.003)	(-0.001)

*** represents significance at 1%, ** at 5%, * at 10%.

Table 12: Panel results Jensen's Alpha (Sorting factor – Purity Score)

	Universal	High	Low	High - Universal	High - Low	Low - Universal
Sorting Factor - Purity Score						
CAPM; $R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + \varepsilon_{pt}$						
αp	0.0328**	0.0453*	0.0202**	0.01207	0.02468	-0.01308
	(2.236)	(1.732)	(2.556)	(0.958)	(0.98)	(-1.038)
bp	0.5810***	0.5977**	0.5673***	0.0180	0.0317	-0.0124
	(4.337)	(2.501)	(7.864)	(0.157)	(0.138)	(-0.108)
Fama&French 3-factor; $R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + s_pSMB_t + h_pHML_t + \varepsilon_{pt}$						
αp	0.0497***	0.0712**	0.0281***	0.0210	0.0426	-0.02212
	(2.745)	(2.196)	(2.839)	(1.337)	(1.354)	(-1.405)
bp	0.4543***	0.37952	0.5294***	-0.0734	-0.1485	0.0765
	(2.972)	(1.385)	(6.339)	(-0.552)	(-0.558)	(0.575)
sp	-0.8387*	-1.3892*	-0.3007	-0.5490	-1.0870	0.53945
	(-1.886)	(-1.742)	(-1.237)	(-1.419)	(-1.404)	(1.393)
hp	0.16028	0.18708	0.127395	0.0256	0.0585	-0.0341
	(0.565)	(0.368)	(0.821)	(0.104)	(0.118)	(-0.138)
Carhart 4-factors; $R_{pt} - R_{ft} = \alpha_p + b_p(R_{mt} - R_{ft}) + s_pSMB_t + h_pHML_t + w_pWML_t + \varepsilon_{pt}$						
αp	0.0499***	0.0711**	0.0286***	0.0207	0.0419	-0.0218
	(2.726)	(2.166)	(2.873)	(1.298)	(1.318)	(-1.37)
bp	0.4455***	0.3857	0.5085***	-0.0585	-0.1215	0.0643
	(2.734)	(1.32)	(5.737)	(-0.413)	(-0.429)	(0.454)
sp	-0.8543*	-1.3783*	-0.3377	-0.5226	-1.0392	0.518
	(-1.865)	(-1.678)	(-1.355)	(-1.312)	(-1.304)	(1.299)
hp	0.1882	0.1677	0.1934	-0.0216	-0.0268	0.0042
	(0.569)	(0.283)	(1.074)	(-0.075)	(0.102)	(0.014)
wp	0.0521	0.0362	0.1234	-0.0881	-0.1593	0.0715
	(0.168)	(0.065)	(0.731)	(-0.326)	(-0.295)	(0.265)

*** represents significance at 1%, ** at 5%, * at 10%.

6. Conclusion

New investment opportunities have been made possible by the renewable energy sector's fast growth. The Paris Climate Agreement of 2015's worldwide commitment to a climate-resilient economy is predicted to have a positive impact on the renewable energy sector, attracting a wide spectrum of investors. This study investigates whether investment styles in wind and solar sector with technology-specific considerations incentivize portfolio investors. We use two criteria to create high and low score portfolios using 150 global large capitalization stocks in renewable energy and sector classified by Bloomberg Industry Classification Systems (BICS). The sorting factors include green complexity score and purity score. The assessment of comparative return and risk-adjusted performance demonstrates that high score portfolios dominate their low counterparts. Our results also indicate that divestment of low green complexity country enhances portfolio performance and has incentives for investors. The comparative green complexity score in wind and solar suggests leading producers of these renewable energy products in the future. The knowledge accessible to investors as they strategically build their portfolios in the renewable energy industry is augmented by knowing which nations are more specialized in the manufacturing and manufacture of wind and solar items than other kinds of eco-friendly goods.

Our results provide room for a more focused approach towards divesting from firms with lower technological density or specialized technologies in wind and solar industry. Considering the advantages of divestment and the generally improved risk-adjusted returns, Institutional investors from developed markets can legitimately explore international portfolio assets without going against their fiduciary obligations for responsible investing. These outcomes are also promising for fund managers who may allocate capital to technologically advanced and environmentally friendly investment vehicles to meet the financial objectives of investors who care about the environment. Finally, our findings ought to spur businesses to make investments in specialized technology for the renewable energy sector. We think that while investing in technologically advanced companies won't stop ecological degradation right away, it will undoubtedly help to preserve the health of the climate in the medium to long term. Overall, our study is important since it is one of few that examines the effects of divestiture in businesses with low technical density. The influence of a particular technology may be explored in more detail in future study, which can also take into account professionally managed portfolios

REFERENCES

VITA

NAME	KANOKPHORN PONGKLANG
DATE OF BIRTH	5 June 1995