A Study of Innovation in the Clean Energy Sector: Patent Trend Analysis

A Thesis

Presented to the Faulty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

Delta Zhang

August 2022

ABSTRACT

Do most countries still stick to the guidelines to alleviate global warming since the Paris Agreement in 2008, and how well do domestic policies contribute to this global mutual goal? One avenue to answer these questions is to examine patenting trends in the clean energy sector, which serve as a proxy for the innovation of clean technologies. Prior research has documented the economic benefits of policies that buttress the scientific research and innovation process, including in the context of environmental regulation. There are also recent studies analyzing the effect of the stringency of environmental regulation on innovation in the clean energy sector. This paper extends the patenting trend analysis in clean sectors with multiple variables to study the effect of the stringency of environmental regulation on patenting. Empirical models explore the effects of regulatory stringency using different time lags, as well as accounting for other factors that vary over countries and time. Although the results are mixed, comparisons across models indicate that standardized variables perform better than non-standardized variables after a country-fixed effect is included in the model. Moreover, the result shows that the stimulative effect of regulation on innovation occurs over relatively short time horizons up to a few years.

BIOGRAPHICAL SKETCH

Delta Zhang is an MS student in Applied Economics and Management, concentrating in Environmental Energy & Resource Economics. He finished his bachelor's degree at University of Illinois at Urbana Champaign in 2020, majoring in Natural Resource and Environmental Sciences and minoring in Environmental Economics and Law. His email is: deltathegreat1114@gmail.com.

ACKNOWLEDGEMENTS

I cannot accomplish this milestone without the support and guidance from two of my advisors, Prof. Todd Gerarden and Prof. Ivan Rudik. What I learned from their courses became the essential ingredients of my thesis. With their patient instructions, I am enabled to season my thesis properly and eventually can present this qualified work to the academia.

Additionally, I want to give the most special and sincere thanks to Prof. Gerarden. He accompanied me during every step of my thesis. He was the beacon and provided myriad resources when I initially explored the topic for my thesis. He checked every detail to ensure that I was on the right track. He carefully reviewed and polished my draft that is beyond his obligation as an advisor. Undoubtedly, his support fueled me to overcome every obstacle during my thesis.

TABLE OF CONTENTS

Abstract i

Biographical Sketch ii

Acknowledgements iii

Table of Contents iv

1 Introduction 1

2 Patenting Trend in Recent Years 4

3 Data and Empirical Strategy 10

4 Results of Regressions and Key Findings 14

5 Analysis in Solar and Wind Sectors 18

6 Additional Analysis 20

7 Limitation and Concerns 23

8 Conclusion and Implications 24

Appendix A: Additional Tables 27

References 33

Introduction

Over the past 25 years, global events, like the Kyoto Protocol, financial crisis, Paris Agreement, and the COVID-19 pandemic have fueled or hampered innovation in clean energy technologies. Researchers have come to the consensus that patenting activities serve as one of the most potent metrics to tangibly reflect the innovation progress (Herman and Xiang, 2019; Schmoch, 2008). Popp et al. (2020) show that, since 2000, patent applications in the clean energy sector gradually climbed to the peak around 2010 but started to decline after that. In recent years, researchers have studied socioeconomic factors that contribute to this boom and bust of innovations in the clean energy sector. Based on plentiful relevant literature, from the perspective of firms, these factors can be classified into two primary categories: endogenous and exogenous. Endogenous factors include research and development (R&D) spending by businesses, economic conditions, and knowledge stocks. For exogenous factors, there is research focusing on foreign inducement, including the spillover effect of foreign environmental regulation and the tariff.

Among these factors, this study will focus on the inducement from the domestic environmental regulation because institutional or governmental intervention is of essence to environmental protection in recent years. For policymakers with environmental concerns, it would be ideal if their policies can reinforce the positive feedback loop of environmental protection. One revenue to achieve it is through clean energy innovation. Therefore, policymakers should be aware of the existence of the gap between the execution of policies and the occurrence of innovations, and the efficiency of the regulation. However, there is a lack of recent research quantitatively analyzing how regulations with different stringency levels would impact clean energy development. Wen et al. (2022) employed the instrumental variable fixed-effect method and showed that more renewable energy generation and higher energy efficiency can boost the innovation process. They indicated that the government has to focus more on research and innovation policies. Herman et al. (2019) and Li et al. (2022) pointed out that the geographic proximity of countries with differentiated environmental regulations could create the spillover effect which would spur the innovation of specific clean technology. Although Herman et al. (2019) included the regulation stringency level as a control variable in their model, they applied the uniformed lag to all other variables without any customization. The primary interest of their study is also not pinned on the effect of regulation stringency levels on patenting activities.

This paper, therefore, will fill this research gap and quantitatively analyze the correlation between the stringency of environmental regulation and the innovation in the clean energy sector. Referring to similar studies, this paper also adopts patenting activities as the proxy of the innovation progress. The analysis would address questions: how long and to what extent, would a more stringent regulation impact the innovation progress? To quantify the stringency level of the regulation, this paper relies on the Organization for Economic Co-operation and Development (OECD), which indexes the level of domestic environmental regulations. The following study selects other 4 explanatory variables frequently utilized in relevant literature to control confounding factors. Specifically, the study includes the availability of loans and venture capital. These two types of funds can effectively contribute to clean energy innovation by subsidizing the R&D (Olmos et al., 2012; Parris and Demirel, 2010). Moreover, to account for the effect of the economic condition and foreign inducement, the study selects GDP and high-tech exports respectively. Since clean energy technologies studied in this paper are classified into high-tech categories by OECD (2009), the high-tech export could function as a country-specific factor, and a higher percentage of this export serves as the indicator of a more stringent foreign environmental regulation encountered by the domestic country, because such regulation could subsequently incur a more stringent environmental-related import standard.

This paper will extend the analysis of the clean energy innovation trending to 2019 with the most updated data source and examine the ‘statistical soundness’ of these variables in patenting analysis compared with other studies. Although econometric models and the data source vary across studies, most variables included in relevant literature are in absolute-valued form. Different from existing literature, most explanatory variables in this paper are formatted to the standardized scale. This paper proposes that standardized variables can alleviate country-specific confounding factors that affect patenting activities. By comparing findings from other studies, this paper can also examine the validity of using scaled variables in the patenting analysis and consequently provide insight into the reliability of including these standardized variables in relevant studies for future researchers.

The remaining part will first introduce the recent patenting trend for selected clean energy technologies in 31 countries and compare trends with findings from other literature. Then, I will explain the data source and variables included in the model. After representing results, I will summarize findings and provide my interpretation of results across model specifications. The discussion section will also analyze both long-time and short-time effects of domestic environmental protection stringency on clean energy innovation. Finally, the paper will summarize key findings of the research and provide insight for future work for other researchers.

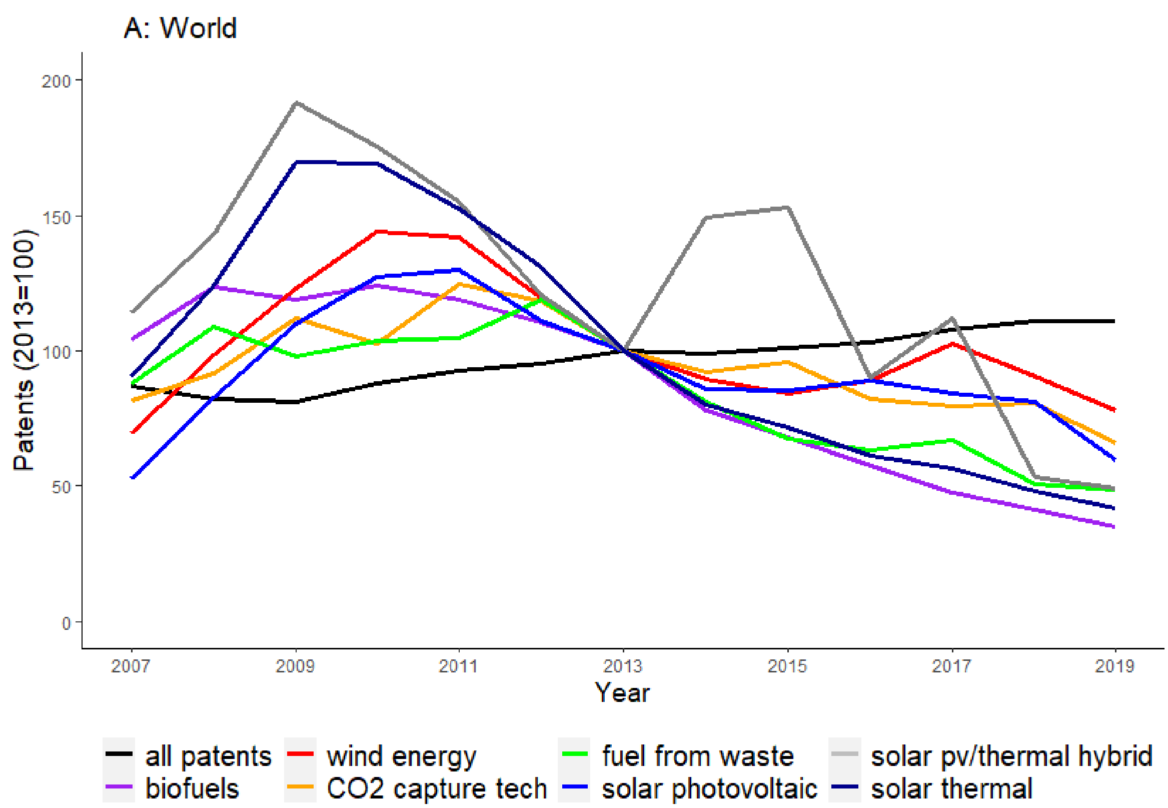
Patenting Trend in Recent Years

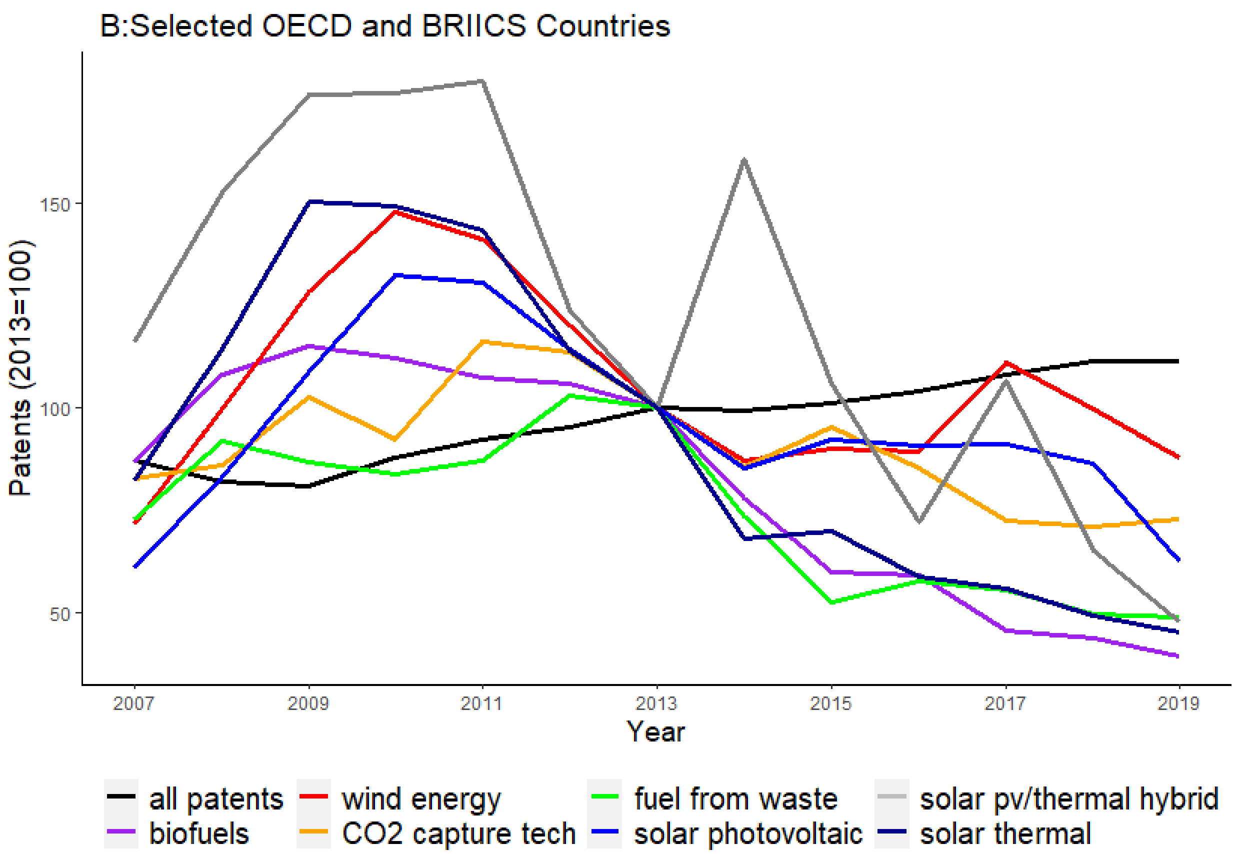
This analysis utilizes data from the OECD on patenting in seven different categories of clean energy technologies over the period 2007 to 2019. Appendix Table A lists the seven categories and their associated Cooperative Patent Classification symbols from the latest IEA's Patents and the Energy Transition 2021 report. More details on the data sources are provided in the next section.

Figure 1 summarizes trends in clean energy technology patents over time. Panel A displays the global number of patents in each technology over time, with the level of patents in each technology normalized to 100 in 2013. Panel B displays the same trend for 25 OECD and 6 BRIICS countries. The patent data are characterized by the priority date, which is the first filing date of the patent. Since several independent variables discussed in the data and empirical section are only available through 2007 to 2019, the model implemented in this study requires the patent data that start from 2007. Because this study is designed to provide the most updated analysis of patenting activities, and there are already plentiful studies focusing on the patenting trend around 2000, it is sufficient and more consistent for this study to represent the patenting trend starting from 2007. To better visualize the patenting trend across technologies, I normalize the patent number in 2013 equal to 100 for each sector. The similar patenting trend shared by both graphs implies that most patenting activities are contributed by more developed nations. In both graphs, most selected technologies started to decline around 2010 when the patent number reached its peak. The exception is the solar pv/thermal hybrid sector, which does not conspicuously follow the monotonic declining trend and has a sharp increase in 2014 and 2017. In contrast, the total patent number has been slowly increasing since 2009.

As expected, the patenting trend in figure 1 is inconsistent with it from IEA's latest report, which shows the stable level of patenting in green technologies after 2010. IEA's report relies on EPO's World Patent Statistical Database (PATSTAT), and patents are documented by the publication date rather than the priority date. Similarly, it's not surprising that these trends are similar to findings by Popp et al. (2020) that they extracted patent data from PATSTAT which documented patents by priority date. To avoid confusion, both application date and the first filing date are equivalent to the priority date, and these two terms are used interchangeably in patenting offices.

Figure 1: Clean Energy Patenting Trend





Notes: Patents are characterized by priority date. The patent count is normalized by making 2013=100. Data from the OECD website

Figure 2 represents world patenting trends of these technologies as the percentage of total innovations without normalization. Consistent with previous findings, patenting activities of these clean technologies declined after 2010. The percentage of all these technologies declines to a level close to or even lower than the percentage in 2007. Among these selected technologies, patenting of solar photovoltaics (solar pv) and wind are relatively more active. Innovations in biofuels, CO_2 capture, fuel from waste and solar thermal converge to a similar level in 2019 during the decline. One deviation from Figure 1 is the trend of solar pv/thermal hybrid. Not fluctuating dramatically like in previous graphs, the percentage of this technology remains stable graphically. The reason is that the number of patenting activities of this technology is negligible compared to the total patent number with the scale Figure 2 represents.

Figure 2: Clean Energy Patenting Trend Compared with Total Patenting

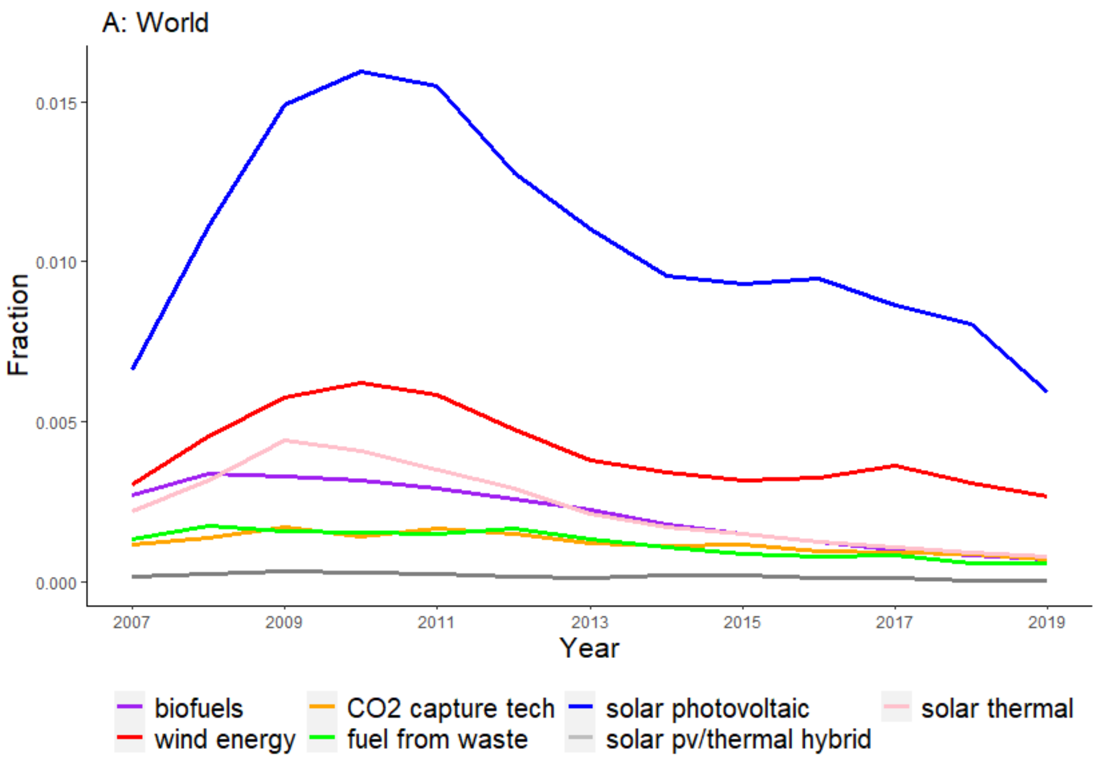
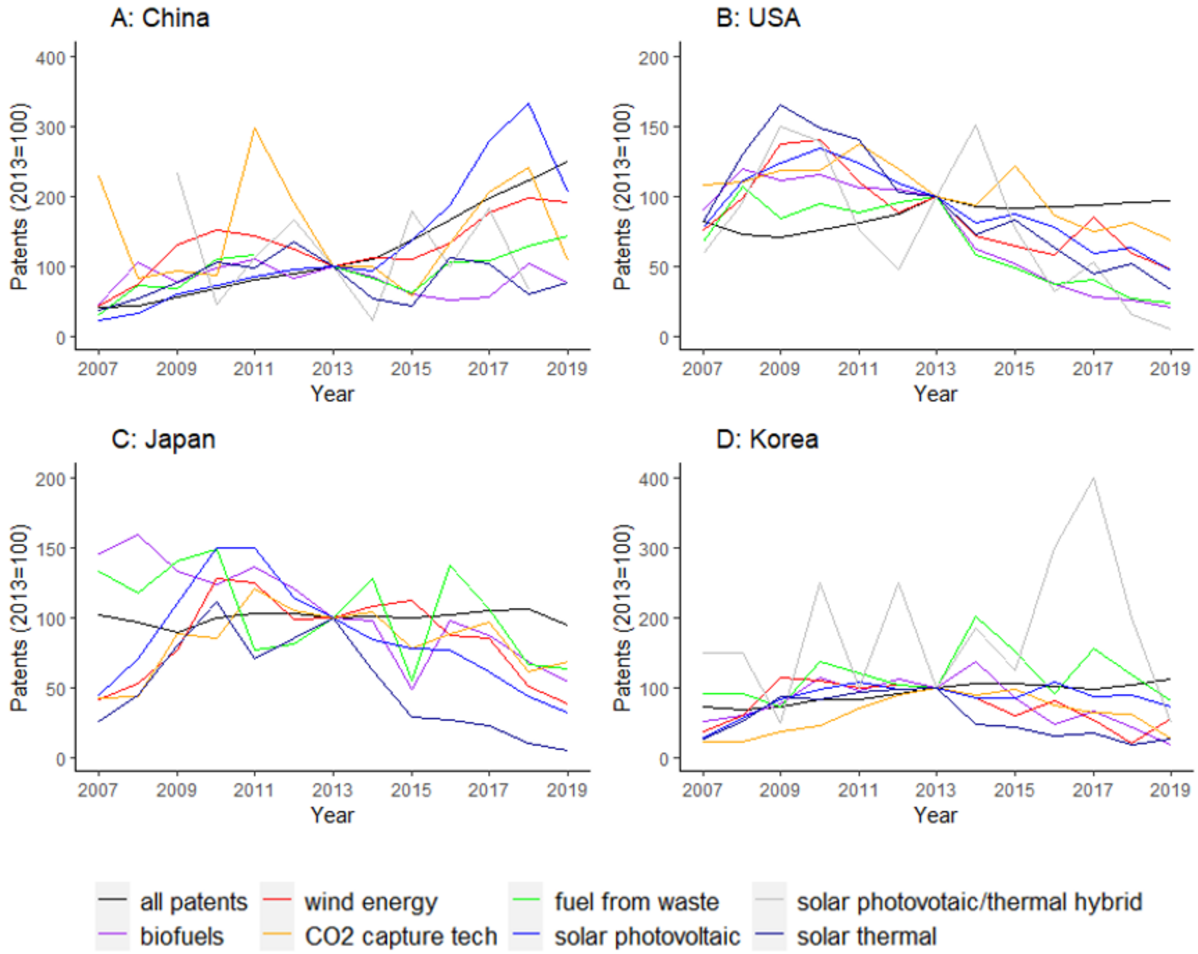


Figure 3 represents inventions from China, the USA, Japan, and Korea, countries with the most total patents in recent years. In the USA and Japan, more industrialized nations, patenting activities of most technologies share a similar declining trend with the global trend, consolidating the validity of the global patenting trend discussed earlier. China and Korea exhibit some abnormalities as some of their patenting activities are unstable. Specifically, in China, patenting related to CO2 capture technology and solar pv/thermal hybrid fluctuates dramatically throughout the chosen period. Furthermore, patents of solar pv had been increasing until a plummet during 2018-2019. In Korea, fuel from waste and solar pv/thermal also exhibit volatile trends.

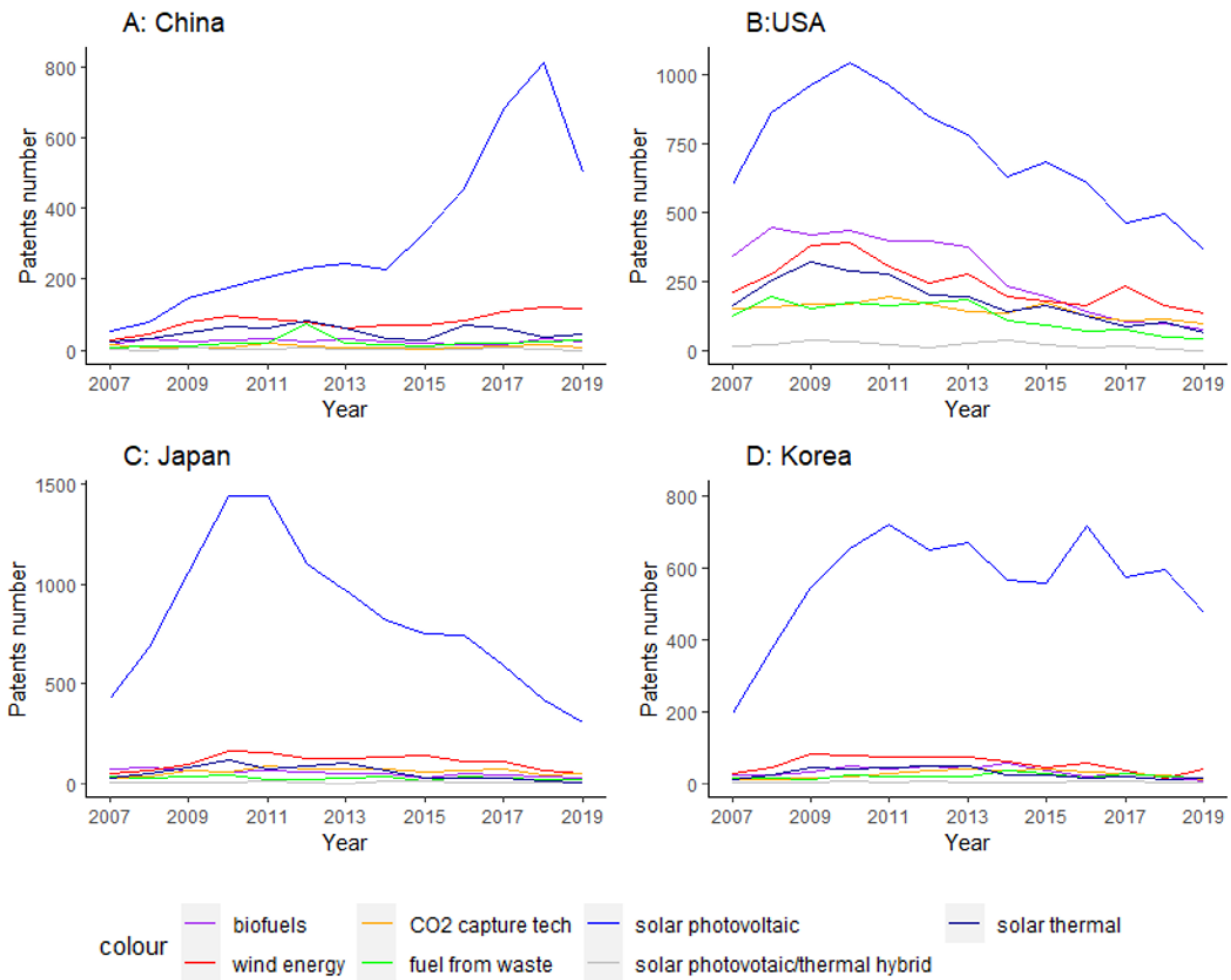
Figure 3: Normalized Clean Energy Patents by Countries



Notes: Figures show patenting activities by country. Patents are characterized by priority date. The patent count is normalized by making 2013=100. Data from the OECD website

Figure 4 represents patenting trends in these four countries without normalizations to compare their absolute and relative advantage more clearly for specific technologies. Firstly, except for solar pv, the USA has the dominating patenting number over all other six technologies across the years. Secondly, each of these four countries has the most patenting activities in solar pv, and wind tends to have the second most patents. Additionally, the gap between solar pv and wind is significantly larger than it is between any other technologies with consecutive patenting ranks. This pattern is consistent with the global patenting trend shown in figure 2, indicating solar and wind energy development tend to be prioritized by firms among all other clean energy due to their more tangible accessibility or more affluent knowledge stocks. Finally, the small or even negligible number of patents of other technologies explains the dramatic fluctuations exhibited in figure 3, especially for solar pv/thermal. For example, for solar pv/thermal, China has zero patents, and the USA, Japan, and Korea only have one patent in 2019; for carbon capture, they have 7, 96, 49, and 11 patents respectively. The smaller the patent number is, the more the percentage change of patents trend is.

Figure 4: Clean Energy Patents by Countries



Data and Empirical Strategy

Referring to the literature of related fields, this paper adopts patenting activities as a proxy of the innovation trending in the clean section and selects 5 key variables that have been widely considered "statistically sound" as explanatory variables in the model. One notable difference of this paper from the existing literature is that most independent variables (IVs) in this paper are originally standardized in uniformed scales across countries, can potentially alleviate country-specific bias which inherits in the absolute-valued variables. Comparing results across several model specifications, this paper can draw inferences of the correlation between the dependent variable (DV) and regulation stringency level with different lags. In addition, I can also examine the 'soundness' of the choice of other standardized IVs by revisiting the expectations of coefficients of these IVs within the model.

For DV, the patent data come from the OECD website, an open-source database that fully covers multiple prestigious databases, including the European Patent Office (EPO) and the US Patent and Trademark Office (USPTO). Specifically, EPS's Worldwide Patent Statistical Database (PATSTAT) was reviewed by van Zeebroeck et al. (2006) as the most reliable platform to examine technological specialization, guaranteeing the quality of patents of chosen fields. Referred to IEA's Patents and the Energy Transition report (2021), I selected patents from 7 domains to represent the development of the entire clean energy sector. Respectively, they are wind, solar PV, solar thermal, solar pv-thermal hybrid, biofuels, fuel from waste, and CO_2 capture technology.

Although patent numbers are currently considered as the most potent metric to measure the innovation activities (Schmoch, 2008), there are concerns like that the increase of innovations in a certain field could be the result of the unobserved exogenous factors, which could simultaneously increase the total innovation (Herman and Xiang, 2019). Therefore, referring to the methodology implemented by studies by Herman and Xiang (2020) and Popp (2002), I also adopt the revealed technological advantage (RTA) method, which takes the ratio of the number of patents in a selected domain to that of the total patent but times 100 to make the regression results clearer for readers. To further enhance the quality of patents, I only include patents that have an international family size larger than 1 since filing in multiple offices indicates the higher quality of the invention (Harhoff et al., 2003). Therefore, I extract patent data from the Technology Development section of the database, which is characterized by priority date, inventor countries, and family size. The priority date refers to the first filing date, which is considered nearest to the actual invention date (OECD, 2009). The family size option allows me to filter the patent data based on the number of international offices in which the patents are registered.

As mentioned, the model includes 5 IVs, which are ease of access to loans (EAL), venture capital availability (VC), GDP based on purchasing power parity (GDP(PPP)), high-tech export as the percentage of the total export (HTE), and environmental protection stringency (EPS). EAL and VC can effectively contribute to clean energy innovation by providing funds for R&D and loan subsidy as the incentive (Olmos et al., 2012; Parris and Demirel, 2010). These two variables are derived from the World Economic Forum Global Competitiveness Index from The World Bank. Based on the measurement of 12 aspects of competitiveness, including macroeconomic environment, financial market development, etc., these two variables are lagged 1 year in the model and are scaled from 1-7 where 7 represents extremely easy to obtain the resource. As mentioned in the description of the patenting trend, because EAL and VC are only available after 2006, the patent data collected for the model are from 2007 to 2019.

For GDP(PPP) and HTE, they are extracted from World Development Indicators (WDI) from The World Bank. WDI is composed of officially distinguished international sources and can precisely reflect the latest economic development across countries (WB, 2022). Since GDP in nominal terms is not considered as a qualified variable and tends to have an insignificant correlation with patent numbers (Aflaki et al., 2021; Li et al., 2022), I decided to utilize an alternative form and adjust it by purchasing power parity. The reason to include HTE is that the export can serve as an indicator of a country's reaction to foreign policies, especially the environmental regulations and the tariff. That is, this variable can account for changes in clean energy innovations that are caused by the induced effect from foreign inducement.

The last IV, EPS, is extracted from the OECD website. Weighted by 14 environmental policy instruments, the stringency level is indexed from 0 (least stringent) to 6 (most stringent) (OECD, 2009). This index is an indicator that reflects domestic firms' both explicit (e.g., cost of emission) and implicit (e.g., difficulties in raising funds) of developing the dirty sector across fields. Due to the availability of the environmental protection stringency data, there are 13 OECD countries excluded from this study.

The reduced form equation for no fixed effect model:

$$Y_{it} = \alpha EPS_{i(t-x)} + \beta EAL_{i(t-1)} + \gamma VC_{i(t-1)} + \delta \log(GDP_{i(t-1)}) + \theta HTE_{i(t-1)} + \epsilon_{it}$$

- Where i represents the individual country, 31 countries included in the model
- Where t represents the year corresponding to all other variables
- Where x is the year of lag
- Where Y is the sum of selected clean energy patents divided by total patents of a country time 100

- Where ϵ is the error term

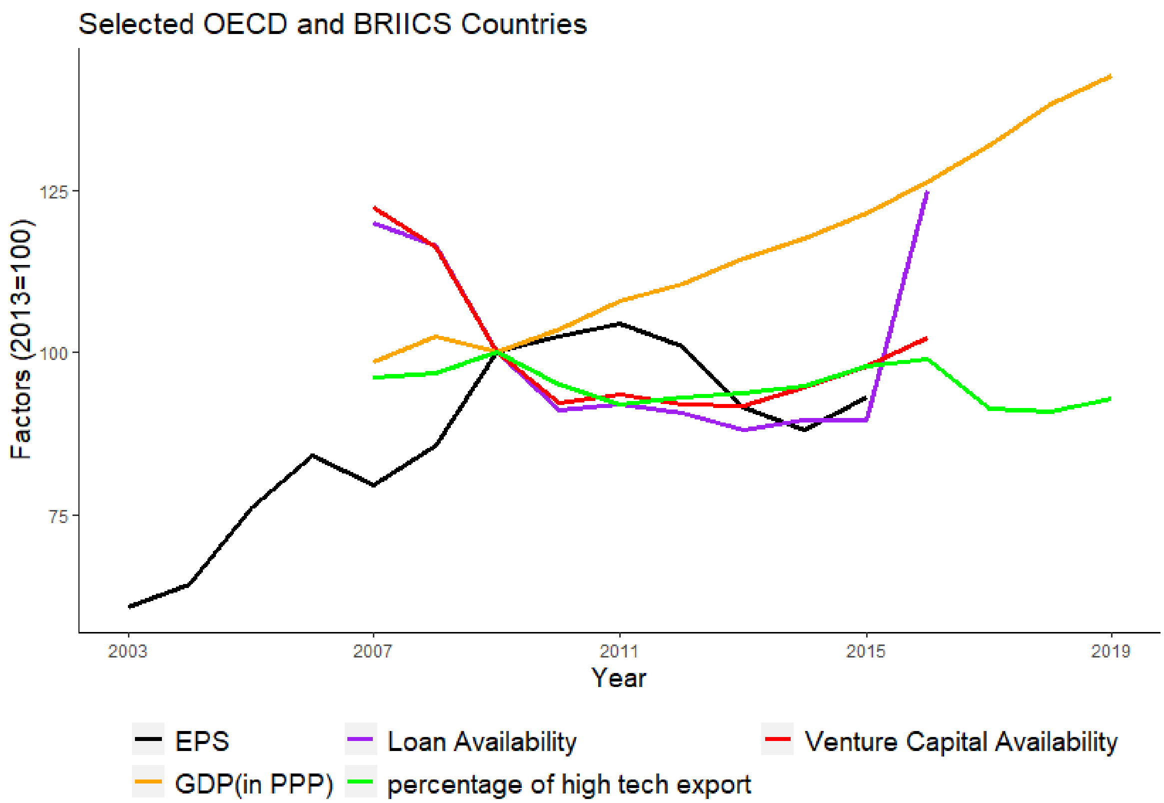
For IVs:

- EPS is environmental protection stringency index
- EAL is the index of ease of access to loan
- VC is the index of access to venture capital
- GDP is gross domestic production by purchasing power parity
- HTE is the percentage of high-tech export

This base model is subsequently specified into 3 other forms: with only year dummies, with only country fixed effects, with two-way fixed effects. The GDP is transformed into logarithmic form to analyze the effect of its percentage change on patenting. Additionally, it was assumed that the average lag the domestic-induced forces would have on the environmental-related technological innovation was 2 years (Lanjouw and Mody, 1996). I hypothesize that this lag will gradually shorten during the 21st century due to more developed and regulated economic conditions, so firms' reactions to inducement could become swifter. I set both EAL and VC a one-year lag in the model. The EPS is the primary variable of interest, and a different lag of EPS is applied separately in each model specification.

Due to the inconsistency among the data availability across variables, varied time ranges of each variable are chosen in order to fit the regression with specified lags. Specifically, patent data and GDP are extracted from 2007 to 2019. EPS is not available after 2015, so data from 2003 to 2015 are used for 1-4 years EPS lag analysis. VC and EAL cover 2007 to 2016. The normalized trending of these variables of all selected OECD and BRIICS countries is provided in figure 5. The normalization is achieved by averaging values of variables across countries in each year to accommodate for missing data.

Figure 5: Trend of explanatory variables



Note: the scale of all factors is normalized by making year 2009 = 100

Results of Regressions and Key Findings

This paper hypothesizes positive correlations existing between all IVs and patenting activities, so it is expected that all coefficients are positive in the model. For EAL, VC, and GDP, the rationale is based on the hypothesis of the environmental Kuznets curve. It is assumed that most selected OECD and BRIICS countries have already been in the stage in which more wealth or resources would alleviate the pollution emission. The higher values of these three variables indicate more availability of funds and better economic growth for firms, stimulating firms to adopt cleaner technologies by filing more applications of patents. For EPS, a more stringent regulation will conspicuously increase the firms' cost of emission either by taxation or permits and, therefore, make investment in clean energy technology more attractive for firms. As mentioned earlier, the HTE can capture the inducement effect from the foreign environmental regulation. That is, the pressure from more stringent environmental standards required by import countries could be alleviated by shifting to exporting more clean energy technologies which are classified to high-tech categories by OECD (2009).

The linear regression is conducted in R, and each table contains 4 models. Each table corresponds to a unique lagged EPS variable and is summarized through tables 1.1-1.4, which are listed in the List of Table section. Table 1.5 is a summary of coefficients of EPS with different lags across 4 models. Additionally, tables 1.6-1.7 summarize results of subsamples of table 1.2 that they correspond to BRIICS and select OECD countries respectively. The following discussion will focus on table 1.2 because 2-year lag is a bridge connecting the short-term and long-term effect and is also a reasonable scope of vision policymakers should be equipped with.

Table 1.2: EPS (2-year lag)

	No fixed effect	**Year dummy**	**Country fixed effect**	**Two-way fixed effect**
(Intercept)	0.205 (3.998)	4.094 (4.062)		
EPS(2 year lag)	0.423 (0.275)	0.696 * (0.276)	-0.099 (0.238)	0.177 (0.233)
GDP(PPP)(1 year lag)	0.201 (0.442)	-0.165 (0.436)	-3.120 ** (0.947)	2.431 (1.428)
Loan(1 year lag)	0.562 (0.447)	1.050 (0.540)	0.412 (0.268)	0.494 (0.377)

%High Tech Export(1 year lag)	-6.264 ** (2.378)	-4.688 * (2.358)	1.354 (4.585)	-3.389 (4.269)
Venture Capital(1 year lag)	-0.300 (0.504)	-0.973 (0.581)	-0.048 (0.341)	-0.365 (0.453)
Observations	235	235	235	235
R^2 / R^2 adjusted	0.073 /0.052	0.182 /0.130	0.117 / -0.023	0.313 / 0.167

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

With a specified 2-year lag of EPS across four models, the significance of all variables is lack of consistency across all models. The regulation stringency is only significant in the model with year dummies, but all signs are positive and consistent with the expectation. The GDP is significant at 1% level in the third model, but it is negative. After the year-fixed effect is added to the model, the coefficient of GDP in the fourth model turns to positive compared to it in the third model. This inconsistency, however, indicates the significant impact from certain years. For instance, in Figure 1, the overall patenting activities in the clean sector had been increasing constantly roughly during 2007-2010. However, the 2008 financial crisis dramatically hampered the economic growth during these years. The opposite trend of GDP growth and patenting activities would result in a negative coefficient. The poor performance of GDP, even adjusted by purchasing power parity, resonates with findings by Aflaki et al. (2021) and Li et al. (2022) that GDP again serves as a poor proxy of economic conditions in patenting analysis. Although coefficients of the ease to access loans are positive across all models, none of them are significant. The high-tech export is significant at 1% level in the no fixed-effect model and at 5% level in the second model. However, coefficients are negative in the first two models. This result contradicts findings by Herman and Xiang (2019) which shows the positive correlation between high-tech export and patenting activities. Surprisingly, all coefficients of venture capital are negative and not significant across all models.

Referring to figure 3, the possible reason for this abnormal result is that there is multicollinearity existing between the venture capital and ease of access to loans. Both R^2 and adjusted R^2 are highest in the second model among the first three models, inferring that confounding factors aligned with years affect the patenting activities systematically across countries. So, it is necessary to control the yearly fixed effect. One possible solution is to add dummy variables accounting for those relevant major events to alleviate omitted variable bias. Interestingly, both R^2 and adjusted R^2 are not reasonably large across all models and indicate the combination of these variables does not yield the reliable explanatory power under the linear regression model.

The following discussion focuses on EPS. The table 1.5 below summarizes coefficients of EPS across tables 1.1-1.4.

Table 1.5: Summary of coefficients of EPS variable

	No fixed effect	**Year dummy**	**Country fixed effect**	**Two-way fixed effect**
EPS(1 year lag)	0.612 * (0.286)	0.662 * (0.297)	0.243 (0.257)	0.050 (0.254)
EPS(2 year lag)	0.423 (0.275)	0.696 * (0.276)	-0.099 (0.238)	0.177 (0.233)
EPS(3 year lag)	0.358 (0.266)	0.708 ** (0.268)	-0.453 * (0.216)	-0.131 (0.211)
EPS(4 year lag)	0.306 (0.259)	0.757 ** (0.269)	-0.572 ** (0.198)	-0.223 (0.201)

Standard errors in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$

All EPS are significant in the second model, further confirming the existence of year-relevant confounding factors that systematically affect the patenting numbers in the model. Under the second model, the effect of stringency of regulation on patent tends to be consistent across years.

However, there is a decreasing trend of EPS coefficients as the lag increases across the other three models. Moreover, standardized variables in the model can only capture limited country-specific bias but eliminate such bias, and it is expected that standard errors of coefficients of all EPS are smallest in the third model.

Analysis in Solar and Wind Sectors

Table 2 and 3 summarize results of models with 2-year EPS lag that only include solar pv and wind as the DV respectively to examine how well these IVs perform in the individual technology level.

Table 2: Solar pv only

	No fixed effect	**Year dummy**	**Country fixed effect**	**Two-way fixed effect**
(Intercept)	0.307 (0.961)	1.005 (0.989)		
EPS(2 year lag)	0.027 (0.066)	0.094 (0.068)	1.005 (0.989)	0.134 (0.084)
GDP(PPP)(1 year lag)	0.081 (0.106)	0.018 (0.106)	0.094 (0.068)	1.467 ** (0.516)
Loan(1 year lag)	-0.063 (0.108)	-0.042 (0.131)	0.018 (0.106)	0.196 (0.137)
%High Tech Export(1 year lag)	0.442 (0.570)	0.621 (0.575)	-0.042 (0.131)	0.078 (1.548)
Venture Capital(1 year lag)	-0.016 (0.121)	-0.091 (0.141)	0.621 (0.575)	-0.241 (0.164)
Observations	235	235	235	235
R^2 / R^2 adjusted	0.022 /0.000	0.111 /0.054	0.033 / -0.122	0.256 / 0.096

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

Table 3: Wind only

	No fixed effect	Year dummy	Country fixed effect	Two-way fixed effect
(Intercept)	2.156 (3.383)	4.169 (3.585)		
EPS(2 year lag)	0.594 * (0.230)	0.743 ** (0.245)	-0.120 (0.126)	-0.202 (0.135)
GDP(PPP)(1 year lag)	-0.279 (0.373)	-0.498 (0.384)	-0.754 (0.505)	-0.937 (0.818)
Loan(1 year lag)	0.520 (0.374)	0.978 * (0.474)	0.048 (0.142)	-0.034 (0.216)
%High Tech Export(1 year lag)	-2.652 (1.986)	-1.574 (2.054)	2.769 (2.454)	2.043 (2.471)
Venture Capital(1 year lag)	-0.339 (0.423)	-0.856 (0.513)	0.021 (0.180)	0.411 (0.260)
Observations	235	235	235	235
R^2 / R^2 adjusted	0.062 /0.041	0.104 /0.044	0.046 / -0.113	0.137 / -0.056

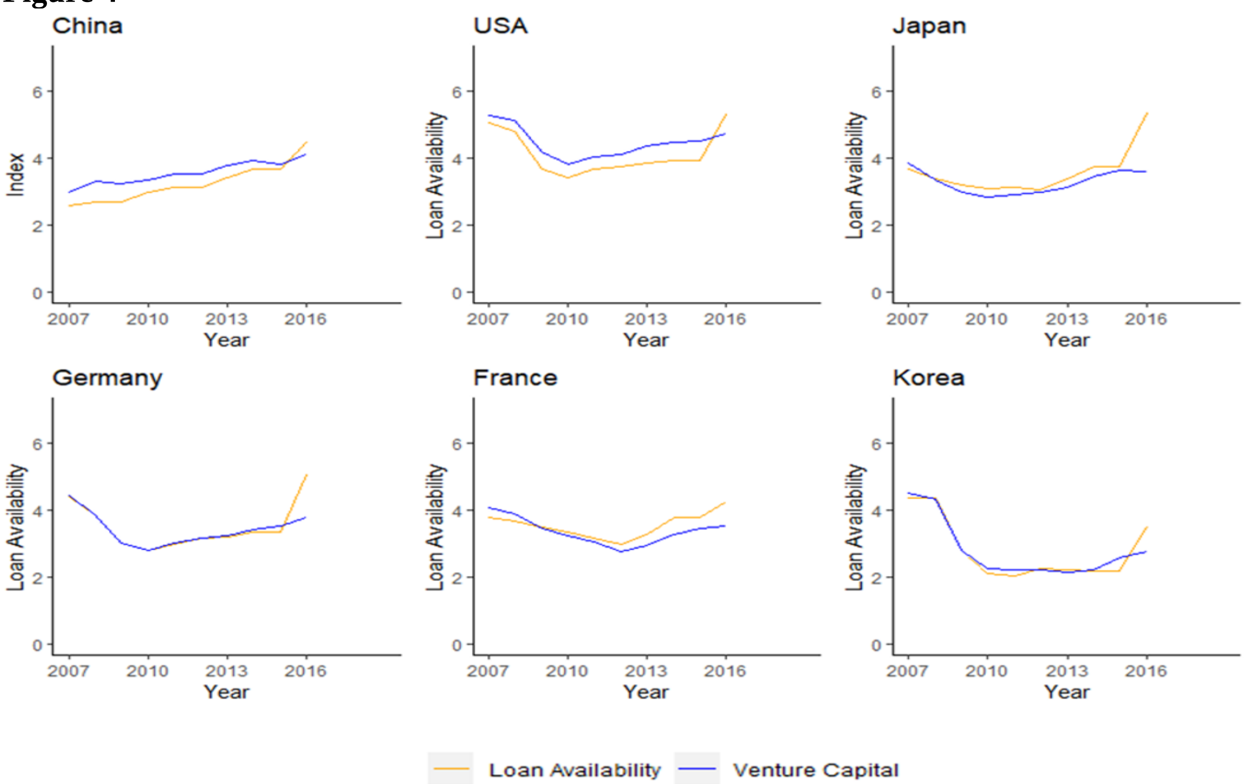
Standard errors in parentheses. * $p<0.05$ ** $p<0.01$ ***$p<0.001$

When focusing on the individual technology, models' predicting power is even more limited. For both solar pv and wind, coefficients tend to be less statistically significant across models, and both the R^2 and adjusted R^2 have even lower values than the results in Table 1.2. Especially for solar pv, only GDP is significant in the fourth model. However, there is one noticeable result that high-tech export shows positive signs across all models in the solar pv analysis that are consistent with the hypothesis. This result indicates that some factors would be more relevant to certain types of technology. Including this type of factor as the explanatory variable to describe the general trend of multiple technologies, the model might exhibit limited predicting power and abnormality in results. Similarly, it could be problematic to predict the trend of a single technology by using macro-scale variables because some of which could be less correlated with the specific technology.

Additional Analysis

To further examine the collinearity between EAL and VC, the paper compares the trend of EAL and VC of the top 6 countries with the most patents in Figure 4. By the comparison of these two trends, it is reasonable to claim that the collinearity between these two variables exists across chosen years at an individual country level. However, these two trends seem to deviate from each other after 2015, and the collinearity of these two variables weakens. Unfortunately, the availability of these two variables is only updated to 2016.

Figure 4



After reviewing the results discussed above, I decided to make several modifications in the model. This additional analysis will again focus on 2-year-lagged EPS only. The modified model drops GDP and VC to consolidate the explanatory power of IVs and address the issue of multicollinearity, respectively. Additionally, the choice of dropping of VC also addresses the concern of the potential correlation between regulation stringency and venture capital availability. The result is summarized in Table 3 below.

Table 4: Modified regression

	No fixed effect	**Year dummy**	**Country fixed effect**	**Two-way fixed effect**
(Intercept)	-0.419 (0.672)	-0.569 (0.956)		
EPS(2 year lag)	0.467 ** (0.162)	0.504 ** (0.172)	-0.223 * (0.107)	-0.191 (0.134)
%High Tech Export(1 year lag)	-3.384 (1.842)	-3.278 (1.860)	2.617 (2.448)	1.403 (2.457)
Loan(1 year lag)	0.231 (0.165)	0.241 (0.206)	0.045 (0.068)	0.187 (0.109)
Observations	225	225	225	225
R^2 / R^2 adjusted	0.057 /0.044	0.087 /0.035	0.034 / -0.115	0.121 / -0.065

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

Indeed, the modifications improve the model's predicting power to some extent. Besides the high-tech export remains negative in the first two models, there are more significant coefficients. Coefficients of venture capital do turn positive across all models, and one of them is significant at 5% level in the third model. However, the R^2 and adjusted R^2 remain low. One of reasons is that, even though most coefficients are significant in the first three models, patenting activities are driven by complex events and require more relevant explanatory variables in the model to properly predict the trend.

Autoregressive distributed lag model is also conducted. The reduced form of the equation is listed below. The result is summarized in Table 4.

$$Y_{it} = \alpha EPS_{i(t-1)} + \beta EPS_{i(t-2)} + \gamma EPS_{i(t-3)} + \delta EPS_{i(t-4)} + \epsilon_{it}$$

Table 5: Autoregressive distributed lag model

	No fixed effect	**Two-way fixed**
(Intercept)	2.091 *** (0.373)	
EPS(1 year lag)	0.402 (0.472)	0.075 (0.259)
EPS(2 year lag)	0.194 (0.615)	0.103 (0.288)
EPS(3 year lag)	-0.086 (0.616)	-0.240 (0.288)
EPS(4 year lag)	-0.036 (0.483)	0.190 (0.249)
Cumulative dynamic effect	0.474 (0.158)	0.128 (0.276)
Observations	268	268
R^2 / R^2 adjusted	0.039 / 0.024	0.266 / 0.125

Standard errors in parentheses * $p<0.05$ ** $p<0.01$ *** $p<0.001$

Although none of these lags are significant, in the first model, the decreasing magnitude across the table coincides with the previous findings that its effect on patenting is languishing. Referring to the second model, the EPS hardly exhibits a clear trend as the magnitude of EPS is inconsistent across different lags. The cumulative effect of EPS under both models are all positive, confirming the positive correlation between EPS and patenting activities shown in previous analysis. The standard error of the cumulative effect is calculated by the Delta Method. Moreover, referred to the second model, the cumulative effect indicates that, on average, holding all other factors unchanged, we can expect that the weight of patenting activities in the clean energy sector would eventually increase by 0.128% at some point after a country enacts an environmental regulation that is more stringent than the previous one by 1 stringency standard. Nonetheless, similar to other models already discussed, both ARDL models have the low value of R^2 and adjusted R^2.

Limitation and Concerns

Choosing patents as the proxy of technology innovation is not a flawless strategy. There is an unmeasurable mismatch between the technology innovation and patenting because some inventions are not patentable and never get patented (Perrons et al., 2021). In this case, inventors could choose alternatives to protect their intellectual property, including secrecy or lead time (OECD, 2009). Additionally, the changing patent law also hinders the consistency of patent trend analysis cross-sectionally over time (OECD, 2009). That is, the number of patents can only vaguely portray the landscape of the global innovation progress. Furthermore, the patenting trends are not consistent across different data sources. For example, contrary to findings by Popp et al. (2020), the IEA's 2020 report indicates that clean sector patenting by publication date remains relatively stable after 2010. This discrepancy indicates that there is a fissure forming between the patent application and the patent publication in recent years. Therefore, according to Parris and Demirel (2010), it is more rigorous to interpret the patenting activities as the 'signal' rather than a flawless 'indicator' of the innovation. In other words, more actively patenting activities of a country doesn't necessarily mean a more innovative environment. As a result, the internal validity of the correlation between the innovation and explanatory variables indicated by this paper could be undermined.

The other issue confronted in this study is the data availability. As discussed, the periods of venture capital and ease of access to loans provided by the OECD website only covers the years 2007-2016, and EPS is not available after 2015. Consequently, with these chosen variables, the analysis can only cover at most 10-year patenting activities. After lags of these variables are applied in the model, the range of patenting activities is further narrowed. Referring to recent relevant literature, the patenting analysis typically covers the broader scope of patenting activities. For example, despite the different research focus, Herman et al. (2019) cover 15 years, and both Aflaki et al. (2021) and Wen et al. (2022) cover 23 years. The limited data availability in the study could cause the issue of underfitting in models, partially accounting for low values of R^2 and a limited number of significant coefficients across models. As relevant organizations update more data in the future, the issue of underfitting could be alleviated, and models in this study would then have stronger explanatory powers.

Conclusion and Implications

This paper first extends the patenting trend of several representative clean energies with the updated data source. The updated trend revealed in the paper is consistent with findings by Popp et al. (2020) that, for most nations, the activity of patenting in most clean energy technologies has been languishing since 2010. As plentiful research indicates that recent patenting activities have been driven by policies instead of factors like energy pricing and competition (Herman et al.

(2019), Herman et al. (2020), Aflaki et al. (2021)), this paper then aims to address to what extent a more stringent environmental regulation would affect the activity of clean energy innovations. This paper then adopts the panel data model and relies on multivariate linear regressions to unravel this question.

With the standardized explanatory variables, empirical results from this paper can provide multiple general implications for policymakers and future researchers. Firstly, resonating with relevant literature, the empirical results show that affluent venture capital and loans can positively contribute to the innovation progress in the clean sector. Referring to the magnitude of coefficients, these two factors together could generate a more profound synergistic impact on innovations than policy does. This result indicates that the expansionary fiscal or monetary policy could be a reliable tool to increase the proportion of patenting activities in the clean energy sector. Consistent with other studies, the result shows that GDP, even adjusted by purchasing power parity, is not a qualified proxy of domestic economic conditions in the patenting analysis. Even for the analysis in other fields, as an explanatory variable, GDP should also be used with caution due to its increasing monotony across most years. In addition, the high-tech export, as an explanatory variable, should be better interpreted as a country-specific variable, as Herman et al. (2019) did.

Most importantly, this paper focuses on the macro-scale correlation between the regulation stringency and the innovation progress; therefore, the results are insightful references for nation-level environmental regulation designing. Results reveal that policymakers could refer to the standard imposed by the OECD and develop a customized metric to measure the regulation stringency level more tangibly. Therefore, they could quantify the effect of the regulation on innovations in the clean energy sector. With more foreseeable outcomes of policies, policymakers would be able to conduct a more comprehensive cost-benefit analysis for the policy design. This paper also reminds policymakers that the effect of the environmental regulation on innovations could fade significantly as time passes. Consequently, it is necessary for them to frequently update or release the new policy to “refresh” the stimulant to firms. However, policymakers should be cautious to avoid creating a volatile policy environment that could damper the development of clean energy development (Silvia et al. 2014).

Finally, supporting the innovation of clean energy technology is a solid revenue to consolidate the positive feedback loop of environmental protection. However, we should not merely rely on inducement brought by environmental policies. Innovations in the clean energy sector are volatile and affected by myriads of socio-economic factors. There is plenty of room left for future researchers to investigate. For example, as more data becomes available in the future, researchers could develop more complex models and explore why the gap between patents applications and publications has widened in recent years.

The phrase, ‘recycling is not enough’ is popularly quoted by academic and news journals. It is indeed one of the reasons we focus more on institutional changes to address environmental issues, like funding the clean energy sector. However, we should not undermine the impact of individual efforts in protecting the environment because if such endeavors could come from billions of people living on this planet, they would undoubtedly make a change.

Appendix A: Additional Tables

Table A

Wind		Y02E10/70/LOW
Solar	Solar PV	Y02E10/50/LOW
	Solar thermal	Y02E10/40/LOW
	Thermal-pv hybrid (other solar)	Y02E10/60
Others	Biofuels	Y02E50/10
	Fuel from waste	Y02E50/30
	Carbon capture	Y02C

1.1: EPS (1-year lag)

	No fixed effect	**Year dummy**	**Country fixed effect**	**Two-way fixed effect**
(Intercept)	1.143 (4.131)	2.510 (4.360)		
EPS(2 year lag)	0.612 * (0.286)	0.662 * (0.297)	0.243 (0.257)	0.050 (0.254)
GDP(PPP)(1 year lag)	0.006 (0.460)	-0.043 (0.462)	-2.705 ** (0.961)	3.454 * (1.546)
Loan(1 year lag)	1.907 ** (0.609)	1.349 * (0.622)	1.608 *** (0.459)	0.789 (0.457)
%High Tech Export(1 year lag)	-4.366 (2.572)	-4.534 (2.552)	1.339 (4.792)	-1.312 (4.472)
Venture Capital(1 year lag)	-1.556 * (0.664)	-1.165 (0.679)	-1.405 ** (0.513)	-0.949 (0.547)
Observations	207	207	207	207
R^2 / R^2 adjusted	0.062 /0.041	0.104 /0.044	0.046 / -0.113	0.137 / -0.056

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

1.2: EPS (2-year lag)

	No fixed effect	Year dummy	Country fixed effect	Two-way fixed effect
(Intercept)	0.205 (3.998)	4.094 (4.062)		
EPS(2 year lag)	0.423 (0.275)	0.696 * (0.276)	-0.099 (0.238)	0.177 (0.233)
GDP(PPP)(1 year lag)	0.201 (0.442)	-0.165 (0.436)	-3.120 ** (0.947)	2.431 (1.428)
Loan(1 year lag)	0.562 (0.447)	1.050 (0.540)	0.412 (0.268)	0.494 (0.377)
%High Tech Export(1 year lag)	-6.264 ** (2.378)	-4.688 * (2.358)	1.354 (4.585)	-3.389 (4.269)
Venture Capital(1 year lag)	-0.300 (0.504)	-0.973 (0.581)	-0.048 (0.341)	-0.365 (0.453)
Observations	235	235	235	235
R^2 / R^2 adjusted	0.073 /0.052	0.182 /0.130	0.117 / -0.023	0.313 / 0.167

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

1.3: EPS (3-year lag)

	No fixed effect	Year dummy	Country fixed effect	Two-way fixed effect
(Intercept)	-0.084 (3.936)	4.137 (3.980)		
EPS(2 year lag)	0.358 (0.266)	0.708 ** (0.268)	-0.453 * (0.216)	-0.131 (0.211)
GDP(PPP)(1 year lag)	0.260 (0.435)	-0.122 (0.425)	-2.548 ** (0.943)	2.812 * (1.383)

Loan(1 year lag)	0.605 (0.433)	0.952 (0.519)	0.504 (0.260)	0.450 (0.367)
%High Tech Export(1 year lag)	-6.052 * (2.332)	-4.760 * (2.302)	-0.724 (4.456)	-4.405 (4.127)
Venture Capital(1 year lag)	-0.401 (0.491)	-0.952 (0.559)	-0.097 (0.334)	-0.161 (0.433)
Observations	248	248	248	248
R^2 / R^2 adjusted	0.066 /0.047	0.176 /0.126	0.166 / 0.042	0.353 / 0.224

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

1.4: EPS (4-year lag)

	No fixed effect	Year dummy	Country fixed effect	Two-way fixed effect
(Intercept)	-0.423 (3.872)	4.400 (3.988)		
EPS(2 year lag)	0.306 (0.259)	0.757 ** (0.269)	-0.572 ** (0.198)	-0.223 (0.201)
GDP(PPP)(1 year lag)	0.322 (0.429)	-0.107 (0.423)	-2.204 * (0.866)	2.744 * (1.247)
Loan(1 year lag)	0.655 (0.422)	0.893 (0.508)	0.700 ** (0.243)	0.592 (0.349)
%High Tech Export(1 year lag)	-6.024 * (2.325)	-4.889 * (2.294)	-2.676 (4.277)	-6.443 (3.992)
Venture Capital(1 year lag)	-0.499 (0.485)	-0.953 (0.550)	-0.397 (0.328)	-0.303 (0.416)
Observations	261	261	261	261
R^2 / R^2 adjusted	0.061 /0.043	0.166 /0.119	0.196 / 0.083	0.375 / 0.258

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

1.5: Summary of coefficients of EPS variables

	No fixed effect	Year dummy	Country fixed effect	Two-way fixed effect
EPS(1 year lag)	0.612 * (0.286)	0.662 * (0.297)	0.243 (0.257)	0.050 (0.254)
EPS(2 year lag)	0.423 (0.275)	0.696 * (0.276)	-0.099 (0.238)	0.177 (0.233)
EPS(3 year lag)	0.358 (0.266)	0.708 ** (0.268)	-0.453 * (0.216)	-0.131 (0.211)
EPS(4 year lag)	0.306 (0.259)	0.757 ** (0.269)	-0.572 ** (0.198)	-0.223 (0.201)

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

1.6: BRIICS countries only (2 year lag EPS)

	No fixed effect	Year dummy	Country fixed effect	Two-way fixed effect
(Intercept)	-2.952 (5.426)	-3.342 (7.669)		
EPS(2 year lag)	-0.537 (0.571)	-0.507 (0.882)	- 0.422 (0.773)	-0.538 (0.965)
GDP(PPP)(1 year lag)	0.554 (0.561)	0.588 (0.884)	0.976 (1.934)	7.329 (4.657)
Loan(1 year lag)	0.487 (0.708)	0.813 (1.371)	0.896 (0.619)	-0.186 (1.249)
%High Tech Export(1 year lag)	-3.456 (2.934)	-3.361 (5.056)	-39.569 ** (12.031)	-44.821 ** (14.991)

Venture Capital(1 year lag)	-0.078 (0.851)	-0.197 (1.319)	-2.292 * (0.922)	-3.133 * (1.187)
Observations	35	35	35	35
R^2 / R^2 adjusted	0.293 /0.171	0.330 /-0.140	0.369 / 0.175	0.572 / 0.144

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

1.7: Selected OECD countries only (2 year lag EPS)

	No fixed effect	**Year dummy**	**Country fixed effect**	**Two-way fixed effect**
(Intercept)	5.224 (8.965)	-3.975 (8.832)		
EPS(2 year lag)	0.650 (0.351)	0.864 * (0.343)	-0.121 (0.252)	0.175 (0.246)
GDP(PPP)(1 year lag)	-0.374 (0.960)	0.692 (0.969)	-4.334 *** (1.161)	2.859 (1.679)
Loan(1 year lag)	0.523 (0.505)	1.076 (0.610)	0.427 (0.290)	0.515 (0.412)
%High Tech Export(1 year lag)	-6.551 * (2.953)	-5.067 (2.860)	5.211 (4.906)	-1.331 (4.449)
Venture Capital(1 year lag)	-0.128 (0.599)	-1.300 (0.717)	-0.135 (0.374)	-0.182 (0.507)
Observations	200	200	200	200
R^2 / R^2 adjusted	0.060 /0.036	0.197 /0.136	0.149 / 0.010	0.384 / 0.244

Standard errors in parentheses. * p<0.05 ** p<0.01 ***p<0.001

References

Aflaki, S., Basher, S. A., & Masini, A. (2021). Technology-push, demand-pull and endogenous drivers of innovation in the renewable energy industry. Clean Technologies and Environmental Policy: Focusing on Technology Research, Innovation, Demonstration, Insights and Policy Issues for Sustainable Technologies, 23(5), 1563–1580.

Harhoff, D., F. M. Scherer, and K. Vopel (2003), "Citations, Family Size, Opposition and the Value of Patent Rights", Research Policy, 32(8): 1343-1363.

Herman, K. S., & Xiang, J. 2019. Induced innovation in clean energy technologies from foreign environmental policy stringency? Technological Forecasting & Social Change, 147, 198–207.

Herman, K. S., & Xiang, J. (2020). Environmental Regulatory Spillovers, Institutions, and Clean Technology Innovation: A Panel of 32 Countries over 16 Years. Energy Research and Social Science, 62.

Li, D., Alkemade, F., Frenken, K., & Heimeriks, G. (2022). Catching up in clean energy technologies: a patent analysis. The Journal of Technology Transfer, 1–23.

Lanjouw and Mody, 1996 J.O. Lanjouw, A. Mody Innovation and the international diffusion of environmentally responsive technology Res. Policy, 25 (4) (1996), pp. 549-571.

OECD. (2009). *Oecd Patent Statistics Manual*. ISBN 978-92-64-05412-7.

Olmos, L., Ruester, S., & Liong, S.-J. (2012). On the selection of financing instruments to push the development of new technologies: Application to clean energy technologies. Energy Policy, 43, 252–266.

Perrons, R. K., Jaffe, A. B., & Le, T. (2021). Linking scientific research and energy innovation: A comparison of clean and dirty technologies. Energy Research & Social Science, 78.

Parris, S., & Demirel, P. (2010). Innovation in venture capital backed clean-technology firms in the UK. Strategic Change, 19(7/8), 343–357.

Popp, 2002 D. Popp Induced innovation and energy prices Am. Econ. Rev., 92 (1) (2002), pp. 160-180.

Popp, D., Pless, J., Haščič, I., & Johnstone, N. (2020). Innovation and entrepreneurship in the energy sector. NBER Working Paper No. w27145

The World Bank, 2022, retrieved from https://databank.worldbank.org/source/world-development-indicators# on Feb 2021

Silvia Albrizio, Enrico Botta, Tomasz Koźluk, & Vera Zipperer. (2014). Do Environmental Policies Matter for Productivity Growth? OECD Economics Department Working Papers.

Schmoch, 2008 U. Schmoch Concept of a technology classification for country comparisons Final report to the world intellectual property organisation (wipo), WIPO (2008)

Wen, J., Okolo, C. V., Ugwuoke, I. C., & Kolani, K. (2022). Research on influencing factors of renewable energy, energy efficiency, on technological innovation. Does trade, investment and human capital development matter? Energy Policy, 160.

van Zeebroeck et al., 2006 N. van Zeebroeck, B. van Pottelsberghe de la Potterie, W. Han Issues in measuring the degree of technological specialization with patent data Scientometrics, 66 (3) (2006), pp. 481-492.