Journal of Sustainable Development Issues, 2024, 2(2),

p. 115-128.

Journal homepage: https://journalsdi.com/index.php/jsdi/index; **ISSN: 3078-2546**

How Are Energy-Related R&D Investments Effective on Environment-Related Patents? Empirical Evidence from the USA and Canada

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ABSTRACT

All related economic actors have been interested in combating climate change as consistent with developing interest in environmental issues. In this context, R&D investment funds can be highly beneficial in developing environmental patents, which may have a key role in solving environmental problems. Accordingly, the study analyzes the marginal effect of sub-types of R&D investments on environment-related patents by focusing on the USA and Canada as the leading R&D investing countries, using data between 1990 and 2021, and adopting a kernel-based regularized least squares (KRLS) model. The results show that on the patents (i) R&D investments in cross-cutting technologies/research, nuclear, and renewable have a stimulating effect in the USA; (ii) R&D investments in renewable support the increase in Canada; (iii) in both USA and Canada, R&D investments in fossil fuels have a decreasing effect, whereas R&D investments in energy efficiency have no significant effect; (iv) Among all, R&D investments in cross-cutting technologies/research (renewable) have the highest increasing effect on the patents in USA (Canada); (v) marginal effect of the sub-types of R&D investments on the patents varies across factors, countries, and percentiles; (vi) the KRLS model has a high prediction performance, reaching ~97.1%. Overall, the study emphasizes the average and pointwise marginal effects of R&D investments on the patents, which imply that R&D investments should be re-distributed by considering their effects on the patents so that a successful policy on environmental patents can be designed by benefitting energy-related R&D investments.

Keywords: Environmental Patents; Energy-Related R&D Investments; USA; Canada; KRLS Model.

JEL Classification: C32, O30, O51

DOI: 10.62433/josdi.v2i2.36

Received: October, 2024 | 1st Revision: November, 2024 | Accepted: December, 2024

1. INTRODUCTION

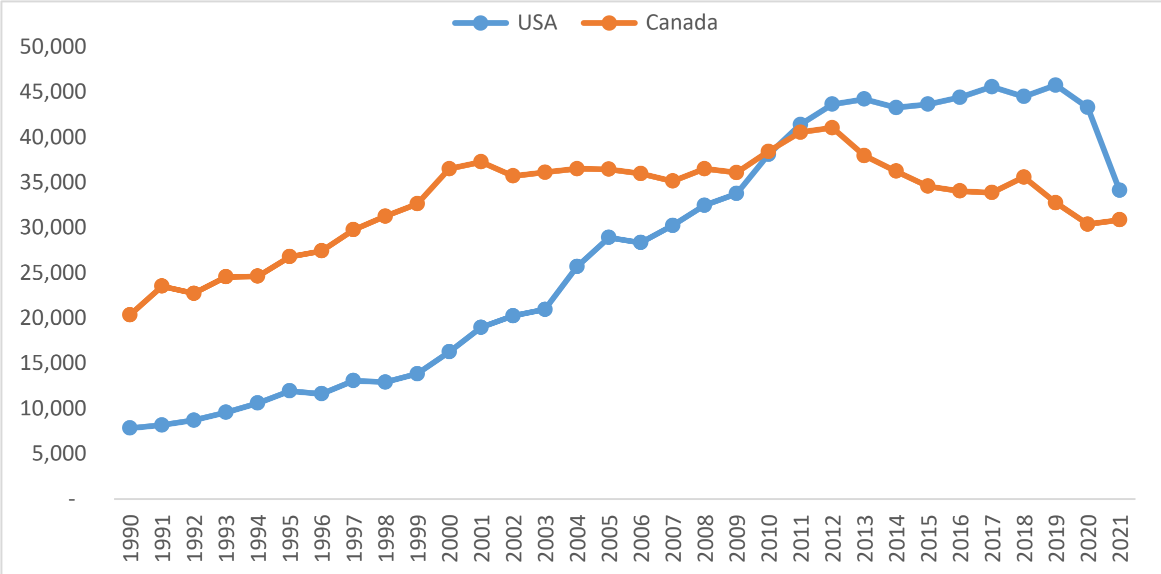
As environmental pollution has reached a level that threatens the world's future, measures have to be implemented at global and regional levels (Kartal & Pata, 2023). Governments implement strict environmental policies to achieve sustainable development, reduce pollution, and prevent environmental problems, where companies invent innovations to increase productivity (Jin et al., 2022). As the Porter hypothesis argues, companies invest in inventing innovations to control energy and waste management due to government regulatory pressures (Porter & Van Der Linde, 1995a-b). Recent studies have identified the effects of stringency environment policies. For example, Depren et al. (2023) examine the effect of environmental taxes on environmental quality in Nordic countries; Kartal et al. (2024a) investigate the mitigating effect of EPS on sectoral GHG in Finland and Sweden; Kartal et al. (2024b) examine the effectiveness of energy-related R&D expenditures and energy transition in reducing CO_2 emissions for Nordic countries. These studies have empirically proven that environmental policies and R&D investments are essential arguments for environmental improvement.

To curb the adverse effects of fossil fuel consumption on the environment, policymakers try to encourage the development of environmental technology and green patents to improve energy efficiency in most countries (Kwon et al., 2017). One of the most important sources of productivity growth is the increase in patent applications, a gauge of innovation. While the increase in the patent numbers is accepted as an innovation indicator, it significantly contributes to productivity growth and economic growth (Link et al., 2019). Countries leading in patents and innovation gain a severe advantage in global competition by creating and pioneering technology. Therefore, developing policies and incentive mechanisms to encourage patent production is essential. In this sense, increasing R&D expenditures provides a severe opportunity to patent output.

Increasing the number of patents is essential in increasing industrial production, encouraging technological development, and providing economic growth. As the rise in environmental pollution causes severe and irreversible problems in global dimensions, it necessitates the search for solutions to reduce and prevent environmental pollution. For this reason, increasing the number of patents developing green technology, which refers to technologies that encourage environmentally friendly production and make more efficient use of renewable energy sources, will also provide essential tools to reduce environmental pollution and achieve the net-zero target. Therefore, more R&D expenditures are needed to increase the environmental patent applications.

Based on Porter's hypothesis, the fact that EPS practices force firms to invent environment-related technology to avoid government sanctions and pay less environmental taxes raises the question of whether there is a relationship between patent applications and governments’ R&D expenditures. Because the USA and CAN are among the top countries producing environmental patents according to 2021 data (OECD, 2024) and also because these countries are the two countries with the highest R&D investment according to 2021 data (IEA, 2024), the USA and CAN are analyzed in the research.

Fig. 1 presents the progress of environmental pates in the USA and CAN.

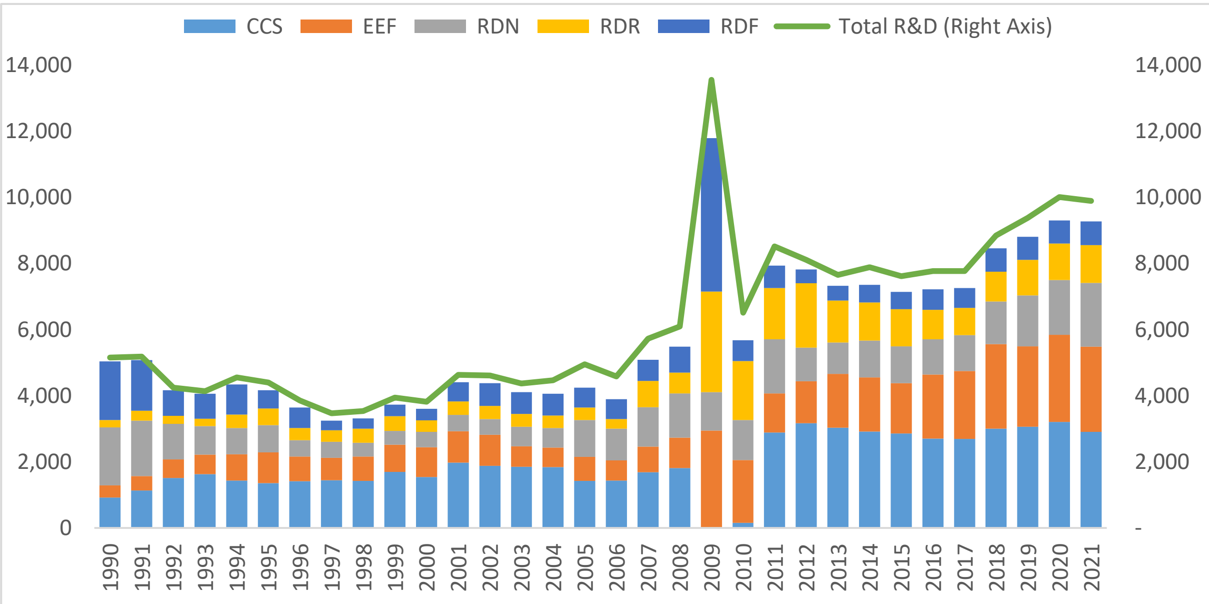


Notes: The unit is the number.

Fig. 1. The Progress of Environmental Patents in the USA and CAN

As shown in Fig. 1, the USA and CAN's environmental patents have been developing between 1990 and 2021, which are leaders on a global scale. In comparison, CAN had a clear superiority between 1990-2009. After 2010, the USA has produced more environmental patents than CAN. However, it is remarkable that both countries have had a slight downward trend in environmental patents in recent years.

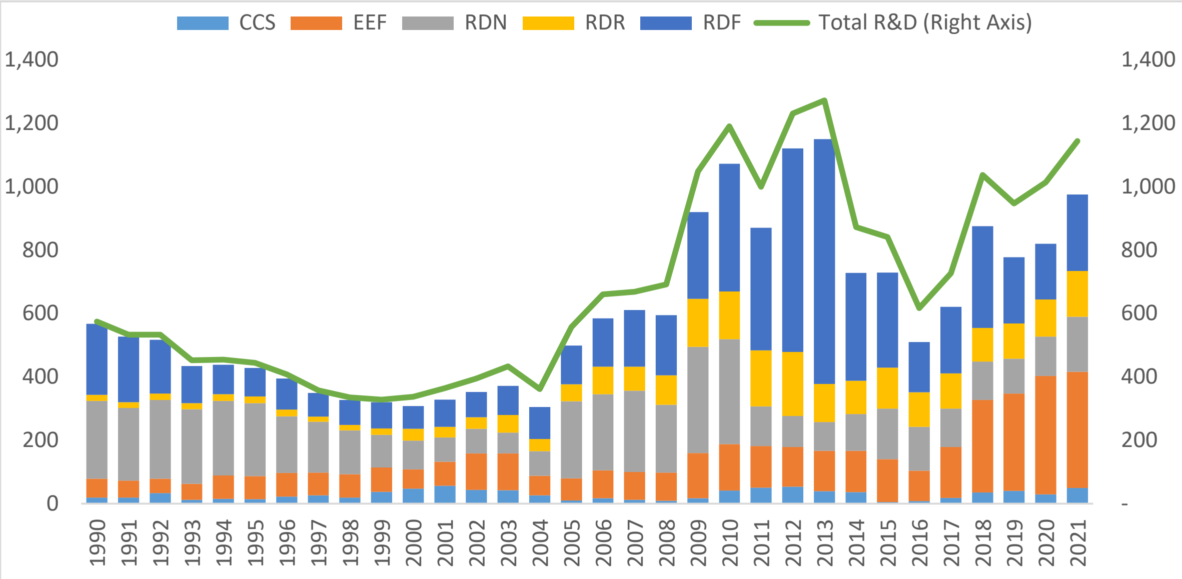
Fig. 2 shows the evolution of energy-related R&D investments in the USA over time.



Notes: The unit is a million USD.

Fig. 2. The Progress of Energy-Related R&D Investments in the USA

Fig. 2 shows that the share of CCS and EEF in the total has increased over time, while there was a significant jump in RDF in 2009. Also, Fig. 3 shows the evolution of energy-related R&D investments in the CAN across the years.



Notes: The unit is a million USD.

Fig. 3. The Progress of Energy-Related R&D Investments in CAN

Until 2010, the share of RDN was significant, but its share decreased in the following period. On the other hand, RDF has been increasing since 2008. As of 2017, EEF has been growing and has had the highest share in recent years

Considering the above-mentioned explanations, examination of the relationship between environmental patents and energy-related R&D investments is highly critical. Accordingly, the study aims to reveal the relationship between environmental patents and R&D investments. For this purpose, the KRLS method is used to investigate the USA and CAN, which make the highest R&D expenditures and are pioneers in producing environmental patents for 1990-2021. In this way, the study searches for the answers to the marginal effect of energy-related R&D investments on environmental patents. The study summarily defines that energy-related R&D investments have varying average and pointwise marginal effects on environmental patents, where energy-related R&D investment subtypes have various effects across the countries examined.

The second section reviews the literature; the third section explains the methods; the fourth section presents the empirical results; and the last section concludes

2. LITERATURE REVIEW

Unlike this study, if the literature is analyzed, no study directly probes the effect of energy-related R&D investments on environmental patents. For this purpose, a summary of the studies that explain environmental patents by using explanatory variables related to the environment and energy issues is presented.

Horbach (2008) proves that knowledge capital and environmental regulations, which he uses as an indicator of technological capability with firm-level data for Germany in support of the Porter hypothesis, increase environmental innovations. Johnstone et al. (2011) provide evidence that perceived EPS positively affects environmentally related technologies in 77 countries.

Cho and Sohn (2018) empirically prove that disaggregated green R&D expenditure is vital to increasing the number of patents in France, Germany, Italy, and the United Kingdom. Link et al. (2019) show that an improvement in R&D expenditures brings about a two-fold increase in new patent applications, according to their research results for the USA.

Roh et al. (2021) prove that firms' intellectual property rights and government incentives have a practical and positive influence on increasing process innovation and green products.

Recent firm-level studies on China have increased in related applied research. In these studies, it is noteworthy that different explanatory variables are used to improve green technology and innovation in Chinese firms. Chen and Chen (2021) draw attention to the fact that green patent share, R&D reaction, R&D efficiency, and economic scale have a significant and positive effect on increasing green patent applications with findings for China. Ren et al. (2021) investigate governmental support for corporations' environmental innovation capabilities in Chinese governmental manufacturing companies and find that government subsidies have no practical influence on environmental innovation. Cui et al. (2022) investigated the effect of the program implemented by the Chinese government on green patents in their research on Chinese firms. The research results show that the Chinese government's regulation increases green patents.

Similarly, Liu et al. (2022), again different from other studies for Chinese firms, prove that digital finance positively increases business green innovation by reducing financial limitations and incentivizing R&D expenditure. This effect is steadily higher in economically backward regions and highly polluting industries. Wang et al. (2023) show that ESG ratings for China bolster firm's green innovation. This positive effect is particularly reported for non-state-owned enterprises and firms with high financial constraints. Zhou et al. (2023) show that ESG ratings are vital for increasing the effectiveness of green technology innovation in Chinese companies. They explain that this positive effect alleviates financial constraints and encourages firms to be more risk-averse.

Xie et al. (2023) argue that green innovation and EPS are compelling arguments for reducing CO_2 emissions in OECD countries. In addition, it is seen that the level of benefits of green technologies is increased due to the enforcement of strict environmental rules and the widespread utilization of environmentally friendly technology.

Considering the literature on related empirical applied research, it is noteworthy that the number of studies investigating the effect of detailed and disaggregated Energy-Related R&D Investments on environmental patents is quite limited. The typical finding is that R&D expenditures on the environment increase environmental patents (Cho & Sohn, 2018; Link et al., 2019; Chen & Chen, 2021). This situation points to a critical research gap in the relevant literature. Thus, these research findings aim to contribute to the related literature.

3. METHODS

3.1 Data and Variables

This investigation analyzes the effect of R&D investment sub-types on the patents. In this context, the study focuses on the cases of the USA and CAN because they are the leading countries in terms of R&D investments and environment-related patents according to data for the 2021 year (IEA, 2024; OECD, 2024).

Compatible with the developing interest in environmental issues, the study focuses on environment-related patents. In line with the contemporary literature (e.g., Orlando et al., 2020; Xiong & Luo, 2023; Yin et al., 2023; Dahmani, 2024), the study considers R&D investments and includes sub-types for empirical analysis.

The study uses data from 1990 through 2021 as the most up-to-date data. Data on patents is collected from the OECD (2024), and data on sub-types of R&D investments is gathered from the IEA (2024).

Table 1 presents the details of the variables.

Table 1. Variables

Symbol	Definition	Unit	Data Source
PAT	Environment-Related Patents	Number	OECD (2024)
CCS	R&D investments in cross-cutting technologies/research	Million USD	IEA (2024)
EEF	R&D investments in energy efficiency		
RDN	R&D investments in nuclear		
RDR	R&D investments in renewable		
RDF	R&D investments in fossil fuels		

3.2. Empirical Procedure

Fig. 4 demonstrates the procedure followed in the empirical investigation.

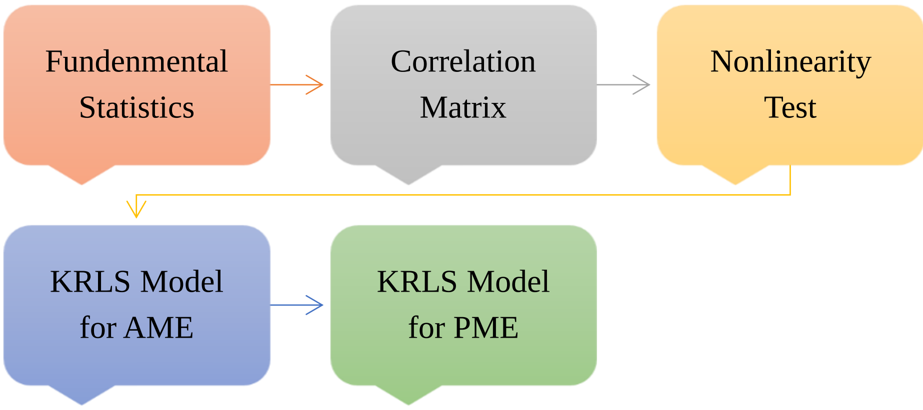


Fig. 4. Empirical Procedure

To make a comprehensive empirical investigation, the study applies 5 steps (i) examination of fundamental statistics; (ii) analysis of correlation matrix; (iii) testing the nonlinearity status of the variables using the BDS test (Broock et al., 1996); (iv) applying the KRLS model for AME (Hainmueller & Hazlett, 2014); and (v) performing the KRLS model for PME (Hainmueller & Hazlett, 2014). Hence, the effect of sub-types of R&D investments on the patents in the USA is examined across AME and PME by performing a machine learning-based KRLS model as compatible with the recent literature (Kartal et al., 2024c).

In the application of the machine learning-based KRLS model by following up the empirical procedure shown in Fig. 4, the study considers Eq. (1):

$$PAT = f\,(CCS, EEF, RDN, RDR, RDF) \tag{1}$$

In this way, the study tries to find answers to the research questions below:

- What types of effect do R&D sub-types have on the patents in the USA and CAN?
- How marginal effect do R&D sub-types have on the patents in the USA and CAN?
- Does the effect of R&D sub-types on the patents vary across average and marginal increases?

4. EMPIRICAL RESULTS

4.1 Preliminary Statistics

Table 2 shows the fundamental statistics of variables used in the study for both the USA and CAN.

Table 2. Fundamental Statistics

Country	Variable	Mean	Median	Max	Min	SD	JB	Prob.
USA	PAT	27,375.94	28,625.50	45,757.00	7,841.00	14,000.99	3.31	0.1910
	CCS	1,935.94	1,750.39	3,201.69	6.90	853.80	0.56	0.7554
	EEF	1,248.34	922.57	2,932.68	373.46	748.00	4.55	0.1029
	RDN	1,024.33	1,069.35	1,928.17	413.79	433.79	1.27	0.5297
	RDR	791.54	471.81	3,045.90	224.11	624.82	33.29	0.0000
	RDF	790.38	633.90	4,635.12	290.41	761.87	565.55	0.0000
CAN	PAT	32,882.69	34,861.50	41,051.00	20,350.00	5,375.72	3.35	0.1871
	CCS	28.43	25.97	56.88	4.94	15.04	2.25	0.3254
	EEF	123.40	88.47	374.41	45.71	87.96	25.60	0.0000
	RDN	168.56	149.04	335.79	66.10	75.56	2.18	0.3355
	RDR	76.11	65.80	202.09	16.13	55.00	2.43	0.2971
	RDF	210.85	172.53	772.74	71.97	161.75	39.75	0.0000

Notes: *SD and JB imply the Standard Deviation and Jarque-Bera, respectively.*

According to the results given in Table 2, PAT has a higher mean and median in CAN (Mean = 32,882.69, Median = 34,861.50) compared to the USA (Mean = 27,375.94, Median = 28,625.50), indicating more patent activity in CAN. Among the independent variables, CCS and EEF are substantially higher in the USA (1,935.94 and 1,248.34) than in CAN (28.43 and 123.40), suggesting a greater focus on CCS and EEF in the USA. This pattern is consistent across RDN, RDR, and RDF where the USA again shows higher average investments. According to the JB test results, it can be said that the distribution of RDR and RDF in the USA and EEF and RDF variables do not fit the normal distribution. These findings indicate a need for a robust and assumption-free statistical model like the KRLS to account for non-normality.

4.2 Correlation Matrix

The descriptive statistics are followed by the bi-variate correlations for each country, which are given in Table 3.

Table 3. Correlation Matrix

Country	Variable	PAT	CCS	EEF	RDN	RDR	RDF
USA	PAT	1.00					
	CCS	0.64	1.00				
	EEF	0.75	0.40	1.00			
	RDN	0.43	0.25	0.46	1.00		
	RDR	0.65	0.10	0.73	0.36	1.00	
	RDF	-0.03	-0.48	0.31	0.28	0.53	1.00
CAN	PAT	1.00					
	CCS	0.40	1.00				
	EEF	0.17	0.31	1.00			
	RDN	-0.37	-0.53	-0.20	1.00		
	RDR	0.64	0.27	0.56	-0.03	1.00	
	RDF	0.41	0.31	0.25	-0.05	0.73	1.00

Notes: *Values denote the correlation coefficients.*

According to Table 3, the bivariate correlations between PAT and EEF, RDR, and CCS are significantly high in the USA, while the correlation between PAT and RDN is moderate. Additionally, the correlation between PAT and RDF is not significant and is close to zero. In contrast, in CAN, the bi-variate correlations between PAT and RDR, RDF, CCS, and EEF are positive but not strong. Furthermore, there is a moderate negative correlation between PAT and RDN. Examining the bi-variate correlations among the independent variables reveals significant correlations in both countries. In the USA, significant correlations are observed between EEF and RDR (0.73), RDR and RDF (0.53), and CCS and RDF (-0.48). In CAN, significant correlations exist between RDR and RDF (0.73), EEF and RDR (0.56), and CCS and RDN (-0.53).

4.3 Nonlinearity Test

The BDS nonlinearity test is performed to understand the linear characteristics of variables used in the study in two countries. Table 4 shows the BDS nonlinearity test results.

Table 4. Nonlinearities of the Variables

Country	Variable	Dimensions					Decision
		2	3	4	5	6	
USA	PAT	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	CCS	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	EEF	0.0000	0.0000	0.0000	0.0663	0.5155	M
	RDN	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	RDR	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	RDF	0.0000	0.0000	0.0001	0.0004	0.0012	NL
CAN	PAT	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	CCS	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	EEF	0.0000	0.0263	0.8151	0.0000	0.0000	M
	RDN	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	RDR	0.0000	0.0000	0.0000	0.0000	0.0000	NL
	RDF	0.0000	0.0000	0.0001	0.0004	0.0012	NL

Notes: *Values show the p-values. M and NL represent mixed and nonlinear, respectively.*

In the results given in Table 4, it can be said that all variables except EEF in the USA have a nonlinear structure in different dimensions for both two countries. Thus, it is evaluated that the model that can handle the nonlinearity structure of the data should be used for the analysis. Since the KRLS model has no strict assumptions on the distribution of the data, it is decided to perform the model to measure the robust predictions.

4.4 AME Results by KRLS Model

In the fourth step of the empirical procedure, which is applying the KRLS model for each country, the results of the KRLS model for the USA and CAN are given in Table 5.

Table 5. AME Results for the USA and CAN

Country	Variable	AME	SE	t	P>t	P25	P50	P75	R^2
USA	CCS	6.34	1.66	3.82	0.00	0.76	9.21	10.71	92.8
	EEF	0.67	1.98	0.34	0.74	-2.26	1.18	2.66	
	RDN	5.85	1.94	3.02	0.01	5.15	7.72	11.22	
	RDR	4.65	2.27	2.05	0.05	2.35	4.40	7.40	
	RDF	-4.97	2.14	-2.32	0.03	-8.13	-3.25	-1.49	
CAN	CCS	-47.13	19.74	-2.39	0.02	-170.07	10.52	53.89	97.1
	EEF	-4.14	4.97	-0.83	0.41	-10.87	-2.06	4.26	
	RDN	-16.58	3.11	-5.33	0.00	-31.54	-18.01	5.11	
	RDR	64.50	5.61	11.49	0.00	-0.61	34.93	131.53	
	RDF	-6.75	2.44	-2.76	0.01	-18.03	-8.57	-0.19	

Notes: *SE is the standard error; P25, P50, and P75 represent the 25th, 50th, and 75th percentile.*

It is revealed that all independent variables have a significant effect on PAT for both countries, except EEF. Once the way and magnitude of the effect are analyzed for each independent variable, it is seen that CCS and RDN have a positive effect in the USA while their effects are negative in CAN. On the other hand, it is shown that RDR (RDF) has a positive (negative) effect on PAT in the USA (CAN) as well. In addition, the effect of independent variables in different quantiles is also evaluated for each country. The most important finding is that the effect of CCS, RDN, and RDR on PAT increases from the lower to upper quartiles while RDF's effect decreases from the lower to upper quartiles in the USA. Contrary to the USA, in CAN, the effect of CCS, EEF, RDN, and RDF decreases from lower to higher quantiles. However, similar to the USA, the effect of RDR increases from the lower to higher quantiles in CAN. Finally, the R^2 is above 90% for both countries. More specifically, in the USA, 92.8% of the variation in the dependent variable can be explained by the independent variables used in the model. This ratio is 97.1% in CAN.

4.5 PME Results by KRLS Model

The last step of the methodological procedure is to evaluate the PME results obtained by the KRLS model for each country. These results are visualized in Fig. 5 for the USA.

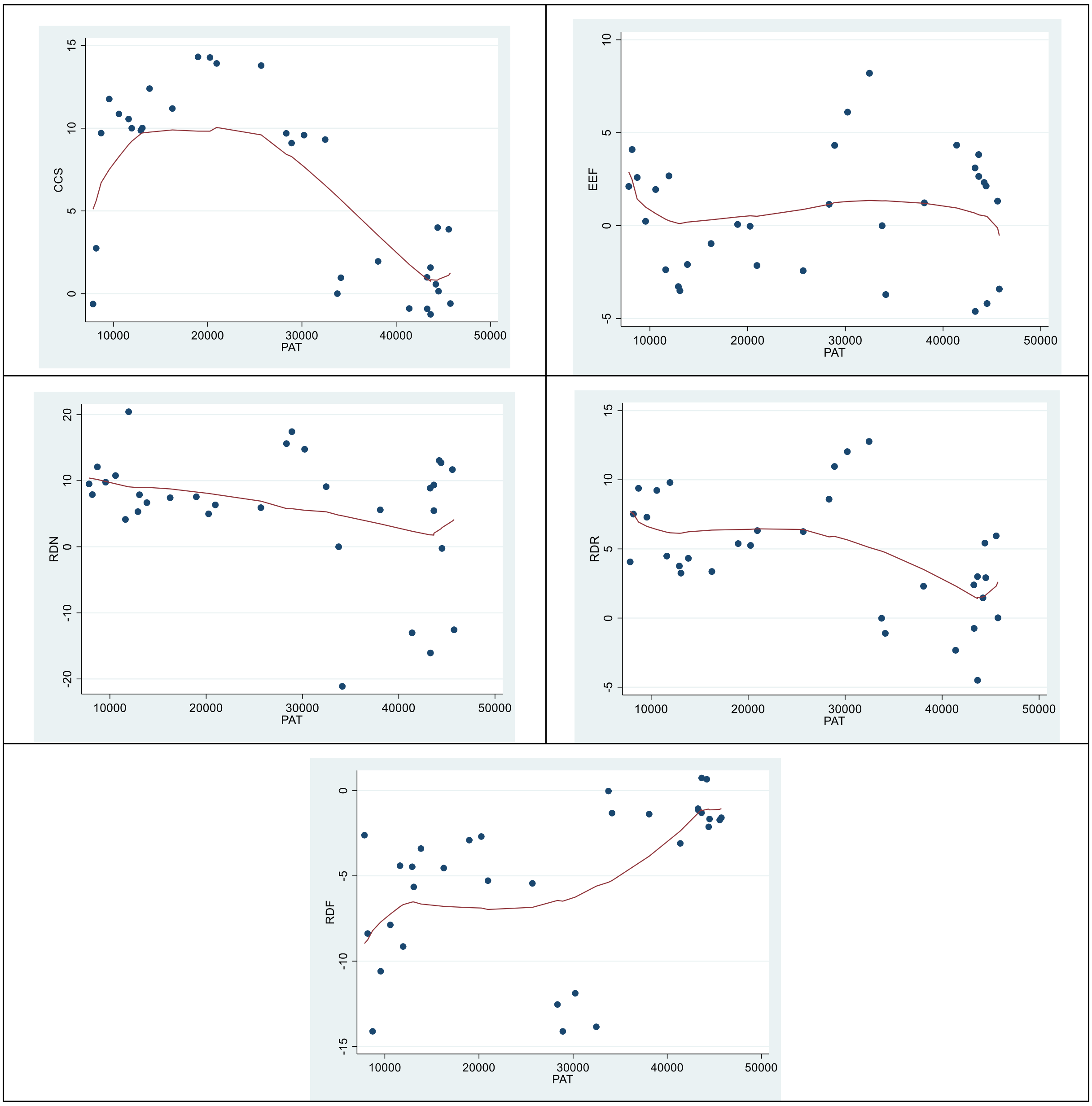


Fig. 5. PME Results for the USA

In Fig. 5, it is revealed that the effect of RDN, RDR, and RDF on PAT has a decreasing trend if PAT increases. On the other hand, the effect of EEF is almost stable around zero for each value of PAT. This result confirms the conclusion that the effect of EEF on PAT is not significant. Additionally, the effect of CCS on PAT has a complex structure. More specifically, its effect is around 10 up to 28.000 levels of PAT, beyond this threshold it starts to decrease to zero.

Also, the results are visualized in Fig. 6 for CAN.

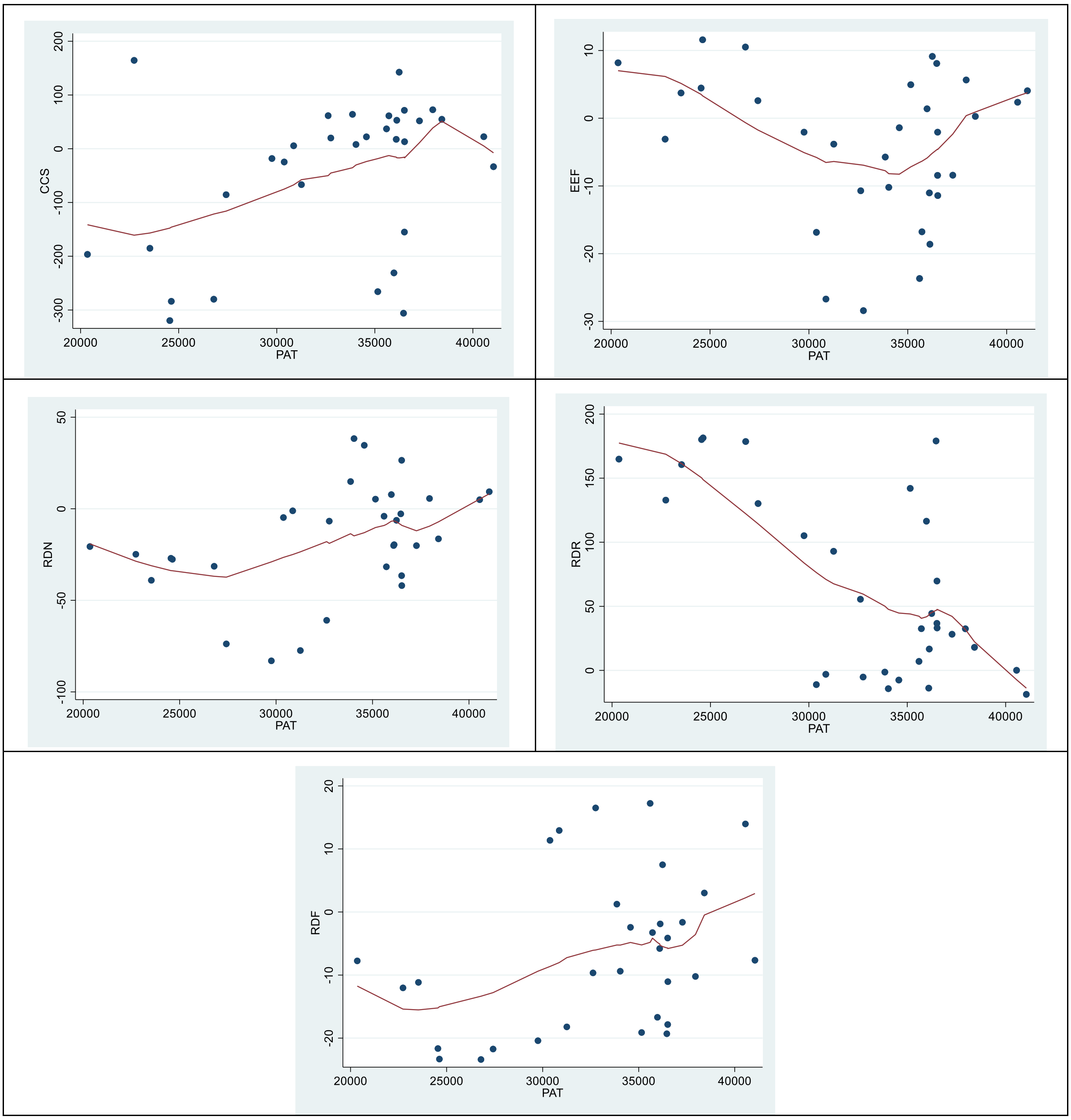
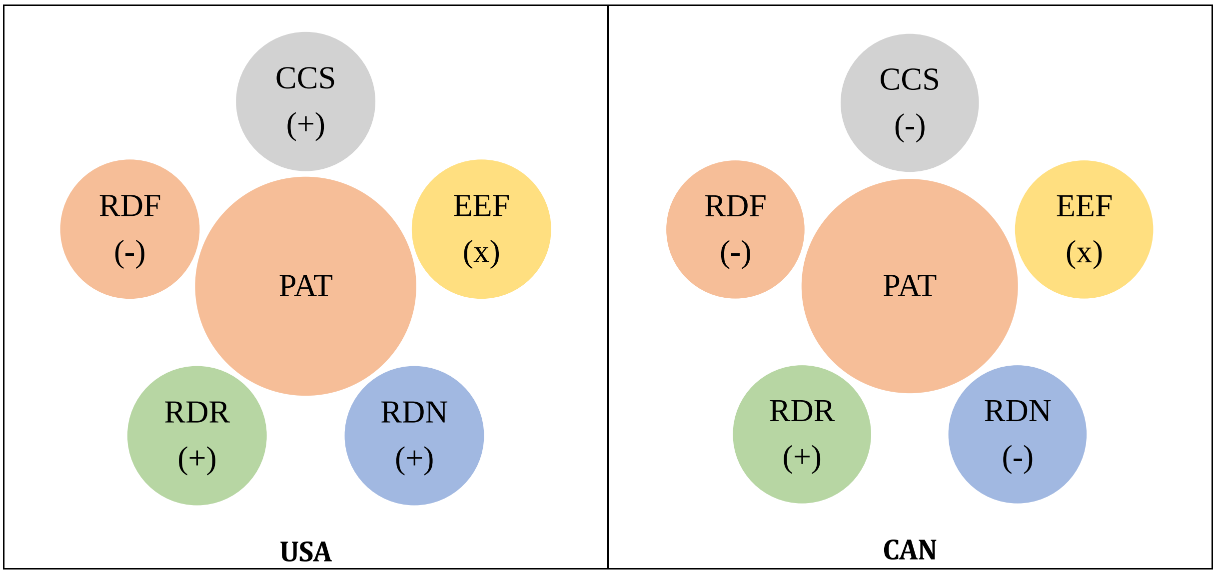


Fig. 6. PME Results for CAN

In CAN, it is shown that the effect of CCS, RDN, RDR, and RDF on PAT decreases when the values of PAT increase. Similar to the results obtained from the USA, the effect of EEF is almost stable around zero on average. Thus, it is revealed that its effect on PAT is not significant. However, two critical areas where the effect is significant: below 25.000 levels of PAT and the area where the PAT values are between 30.000 and 35.000 levels.

4.6 Empirical Summary

Based on the all aforementioned results, the summary of the analysis is visualized in Fig. 7.



Notes: x, +, and – denote insignificant, increasing, and decreasing effect.

Fig. 7. Summary of the Empirical Results

The effect of EEF on PAT is not statistically significant in both the USA and CAN. Additionally, the direction of the effect of RDR and RDF is consistent across both countries, with RDR having a positive effect while RDF has a negative effect. However, the effect signs for CCS and RDN vary between the two countries.

5. CONCLUSION

This study investigates the effect of sub-types of R&D investments on environment-related patents in the USA and CAN by adopting a KRLS model. The results show diverse effects of the R&D investments on patents. In the USA, CCS and RDR are found to significantly trigger environment-related patents. However, RDF has negative effects on PAT, while EEF is insignificant. In CAN, RDR positively affects PAT, whereas CCS and RDN exhibit negative effects, highlighting a divergence in the effectiveness of these investments.

The study further highlights dynamics regarding the difference of R&D investment types on quantiles. Both countries can be categorized with effects of CCS, RDR, and RDN increase in magnitude from lower to upper quantiles of PAT. These findings stress that these investments have stronger effects on firms with higher innovation capabilities. Conversely, RDF shows a decreasing effect across quantiles both in the USA and CAN, pointing to the fact that R&D investments in fossil fuels disrupt innovation in green technology. The investigation of the R&D investments by types also provides empirical insights that CCS investments stand as the most critical driver of environmental patents, while renewable energy-related R&D has the highest potential in CAN.

The findings suggest that the design of R&D investment policies should take country-specific dynamics into account. Country-specific dynamics can focus on the type of technology adopted and the marginal effects of each type of R&D investment on patents. In the USA, R&D investments in cross-cutting technologies and renewable energy should be prioritized, given their strong and consistent positive effect on PAT. The negative effect of fossil fuel R&D stresses the need to phase out investments in these areas and reallocate resources to cleaner technologies. The negative effect of

CCS and nuclear energy R&D investments in CAN indicates potential inefficiencies or a mismatch between investment areas and technological outcomes. Policymakers should reassess the allocation of R&D funds, focusing more on renewable energy, which shows the highest positive effect on environmental patents. The results further highlight the importance of tailoring energy R&D policies to the specific economic, technological, and institutional characteristics of each nation. So, it is imperative to design policies by taking these differences into account.

The KRLS results also convey that the effect of R&D investments varies across different levels of patenting activity. Accordingly, policymakers can target high-performing innovators (upper quantiles) with additional incentives in CCS, RDR, and RDN. Moreover, policymakers might provide support programs for low and mid-performing firms (lower quantiles) through capacity-building programs. Also, percentile-based funding strategies can be designed to ensure equitable distribution of resources.

Fossil fuel R&D investments are found to be negatively effective on PAT in both countries, thus both countries should consider gradually reallocating RDF funding toward cleaner technologies. Moreover, schemes should be designed to provide support for industries reliant on fossil fuels to minimize economic disruptions. Policymakers should incentivize R&D investments in green energy by providing tax benefits or using other means.

Future research might investigate the interactions between R&D investments and other external factors like government policies, market dynamics, and international collaborations. The results show the differing nature of the outcomes in different countries. Therefore, the analysis can be extended to other regions and emerging economies to expand the generalizability of the findings.

Author Contributions: Conceptualization, D.T., S.K.D., and F.A.; methodology, D.T., S.K.D., and F.A.; software, D.T., S.K.D., and F.A.; validation, D.T., S.K.D., and F.A.; formal analysis, D.T., S.K.D., and F.A.; investigation, D.T., S.K.D., and F.A.; resources, D.T., S.K.D., and F.A.; data curation, D.T., S.K.D., and F.A.; writing—original draft preparation, D.T., S.K.D., and F.A.; writing—review and editing, D.T., S.K.D., and F.A.; visualization, D.T., S.K.D., and F.A.; supervision, D.T., S.K.D., and F.A.; project administration, D.T., S.K.D., and F.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Acronyms	
AME	Average Marginal Effect
BDS	Broock, Scheinkman, Dechert, and LeBaron
EPS	Environmental Stringency Policy
ESG	Environmental, Social, Governance
GHG	Green House Gas
IEA	International Energy Agency
KRLS	Kernel-Based Least Squares
PME	Pointwise Marginal Effect
R&D	Research and Development
Dependent Variable	
PAT	Environment-related patents
Independent Variables	
CCS	R&D investments in cross-cutting technologies/research
EEF	R&D investments in energy efficiency
RDN	R&D investments in nuclear
RDR	R&D investments in renewable
RDF	R&D investments in fossil fuels
Analysis Scope	
CAN	Canada
USA	United States

REFERENCES

Broock, W. A., Scheinkman, J. A., Dechert, W. D., & LeBaron, B. (1996). A test for independence based on the correlation dimension. Econometric Reviews, 15(3), 197-235.

Chen, A., & Chen, H. (2021). Decomposition analysis of green technology innovation from green patents in China. Mathematical Problems in Engineering, 2021(1), 6672656.

Cho, J. H., & Sohn, S. Y. (2018). A novel decomposition analysis of green patent applications for the evaluation of R&D efforts to reduce CO2 emissions from fossil fuel energy consumption. Journal of Cleaner Production, 193, 290-299.

Cui, J., Dai, J., Wang, Z., & Zhao, X. (2022). Does environmental regulation induce green innovation? A panel study of Chinese listed firms. Technological Forecasting and Social Change, 176, 121492.

Dahmani, M. (2024). Environmental quality and sustainability: Exploring the role of environmental taxes, environment-related technologies, and R&D expenditure. Environmental Economics and Policy Studies, 26(2), 449-477.

Depren, Ö., Kartal, M. T., Ayhan, F., & Kılıç Depren, S. (2023). Heterogeneous impact of environmental taxes on environmental quality: tax domain-based evidence from the Nordic countries by nonparametric quantile approaches. Journal of Environmental Management, 329, 117031.

Hainmueller, J., & Hazlett, C. (2014). Kernel regularized least squares: Reducing misspecification bias with a flexible and interpretable machine learning approach. Political Analysis, 22(2), 143-168.

Horbach, J. (2008). Determinants of environmental innovation—New evidence from German panel data sources. Research Policy, 37(1), 163-173.

IEA. (2024). Data of R&D Investments. https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2, Accessed on 17 July 2024.

Jin, C., Tsai, F. S., Gu, Q., & Wu, B. (2022). Does the porter hypothesis work well in the emission trading schema pilot? Exploring moderating effects of institutional settings. Research in International Business and Finance, 62, 101732.

Johnstone, N., Haščič, I., Poirier, J., Hemar, M., & Michel, C. (2012). Environmental policy stringency and technological innovation: evidence from survey data and patent counts. Applied Economics, 44(17), 2157-2170.

Kartal, M. T., & Pata, U. K. (2023). The Function of Geopolitical Risk on Carbon Neutrality Under the Shadow of Russia-Ukraine Conflict: Evidence from Russia's Sectoral CO2 Emissions by High-Frequency Data and Quantile-Based Methods. Journal of Sustainable Development Issues, 1(1), 1-12.

Kartal, M. T., Ayhan, F., & Ulussever, T. (2024a). Impact of environmental policy stringency on sectoral GHG emissions: evidence from Finland and Sweden by nonlinear quantile- based methods. International Journal of Sustainable Development & World Ecology, 1-13.

Kartal, M. T., Shahbaz, M., Taşkın, D., Kılıç Depren, S., & Ayhan, F. (2024b). How are energy transition and energy-related R&D investments effective in enabling decarbonization? Evidence from Nordic Countries by novel WLMC model. Journal of Environmental Management, 365, 121664.

Kartal, M. T., Magazzino, C., & Pata, U. K. (2024c). Marginal effect of electricity generation on CO2 emissions: Disaggregated level evidence from China by KRLS method and high-frequency daily data. Energy Strategy Reviews, 53, 101382.

Kwon, D.S., Cho, J.H.,Sohn,S.Y.,2017. Comparison of technology efficiency for CO2emissions reduction among European countries based on DEA with decomposed factors. Journal of Cleaner Production, 151, 109e120.

Link, A. N., Morris, C. A., & van Hasselt, M. (2019). The impact of public R&D investments on patenting activity: technology transfer at the US Environmental Protection Agency. Economics of Innovation and New Technology, 28(5), 536-546.

Liu, J., Jiang, Y., Gan, S., He, L., & Zhang, Q. (2022). Can digital finance promote corporate green innovation? Environmental Science and Pollution Research, 29(24), 35828- 35840.

OECD. (2024). Data of Environment-Related Patents. https://data-explorer.oecd.org, Accessed on 17 July 2024.

Orlando, B., Ballestra, L. V., Scuotto, V., Pironti, M., & Del Giudice, M. (2020). The impact of R&D investments on eco-innovation: A cross-cultural perspective of green technology management. IEEE Transactions on Engineering Management, 69(5), 2275-2284.

Porter, M., & Van der Linde, C. (1995a). Green and competitive: ending the stalemate. The Dynamics of the eco-efficient economy: environmental regulation and competitive advantage, 33, 120-134.

Porter, M. E., & Linde, C. V. D. (1995b). Toward a new conception of the environment-competitiveness relationship. Journal of Economic Perspectives, 9(4), 97-118.

Ren, S., Sun, H., & Zhang, T. (2021). Do environmental subsidies spur environmental innovation? Empirical evidence from Chinese listed firms. Technological Forecasting and Social Change, 173, 121123.

Roh, T., Lee, K., & Yang, J. Y. (2021). How do intellectual property rights and government support drive a firm's green innovation? The mediating role of open innovation. Journal of Cleaner Production, 317, 128422.

Wang, J., Ma, M., Dong, T., & Zhang, Z. (2023). Do ESG ratings promote corporate green innovation? A quasi-natural experiment based on SynTao Green Finance's ESG ratings. International Review of Financial Analysis, 87, 102623.

Xie, P., Xu, Y., Tan, X., & Tan, Q. (2023). How does environmental policy stringency influence green innovation for environmental managements? Journal of Environmental Management, 338, 117766.

Xiong, S., & Luo, R. (2023). Investigating the relationship between digital trade, natural resources, energy transition, and green productivity: Moderating role of R&D investment. Resources Policy, 86, 104069.

Yin, X., Qi, L., Ji, J., & Zhou, J. (2023). How does innovation spirit affect R&D investment and innovation performance? The moderating role of business environment. Journal of Innovation & Knowledge, 8(3), 100398.

Zhou, Y., Huo, W., Bo, L., & Chen, X. (2023). Impact and mechanism analysis of ESG ratings on the efficiency of green technology innovation. Finance Research Letters, 58, 104591.