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Contact to corresponding author: Chun-Ping Chang, cpchang@g2.usc.edu.tw

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Hua-Tang Yin
Xi'an Jiaotong Univeristy, China
orcid.org/0000-0002-2834-9867

Jun Wen
Xi'an Jiaotong Univeristy, China
orcid.org/0000-0002-7544-1076

Chun-Ping Chang
Shih Chien University, Taiwan
orcid.org/0000-0003-1782-4551

Going green with artificial intelligence: The path of technological change towards the renewable energy transition

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Abstract

Research background: The twin pressures of economic downturn and climate change faced by countries around the world have become more pronounced over the past decade. A renewable energy transition is believed to play a central role in mitigating the economic-climate paradox. While the architectural and computational power of artificial intelligence is particularly well suited to address the challenges of massive data processing and demand forecasting during a renewable energy transition, there is very scant empirical assessment that takes a social science perspective and explores the effects of AI development on the energy transition.

Purpose of the article: This paper aims to answer two key questions: One is, how does AI software development promote or inhibit the shift of energy consumption towards renewables? The other is, under what policy interventions does AI software development have a more positive effect on promoting renewable energy consumption?

Methods: We employ a dataset of 62 economies covering the period 2011–2020 to analyze the impact of AI software development on the energy transition, where possible confounders, including political and economic characteristics and time-invariant elements, are controlled using fixed-effects estimation along with specified covariates.

Findings & value added: AI software development can promote the energy transition towards renewables. There is suggestive evidence that the core mechanism linking such a positive relationship tends to lie in improving innovation performance in environmental monitoring rather than in green computing. Government support for R&D in renewable energy technologies is found to be significantly beneficial for harnessing the positive impact of AI software development on the energy transition. Compared to non-market-based environmental policies, market-based environmental policies have a more significant positive moderating effect on the relationship between AI software development and energy transition.

Introduction

The twin pressures of economic downturn and climate change have become more pronounced over the past decade (Geels, 2013; Mildenberger & Leiserowitz, 2017; Scruggs & Benegal, 2012). While countries around the world are looking to take active measures to revitalize their economies, they face the risk of further climate degradation from the increased consumption of conventional energy sources that accompanies economic expansion (York, 2012). Economic decarbonization, or more specifically, a transition towards renewable energy, is believed to play a central role in mitigating the economic-climate paradox (Bergh, 2009; Inglesi-Lotz, 2016). The architectural and computational power of artificial intelligence is particularly well suited to address the challenges of massive data processing and forecasting during a renewable energy transition. Neural networks, machine learning, and cognitive computing can contribute to empowering the planning and management of energy use, reducing the carbon intensity of economic systems, and mitigating climate change.

Notably, only 4% of the existing literature on the AI-climate change relation involves energy transition (Leal Filho *et al.*, 2022). Moreover, these studies mainly analyze the feasibility of AI for renewable energy transition within the technical domain in the form of case study and literature review (Antonopoulos *et al*., 2020; Cheng & Yu, 2019), and there are rare empirical assessments regarding the causal effects of AI development on energy transition based on observational data. Besides technical feasibility, the realization of the energy transition is also heavily dependent on the incentives of economic entities (Gao *et al*., 2020; Piselli *et al*., 2021; Yazdanpanah *et al*., 2015) and the constraints of policy conditions (Huang & Zou, 2020; Zou & Wang, 2024). Therefore, it is important to take a social science, or more specifically, an economic perspective, to complement an investigation about the impact of AI development on the energy transition and provide more inspiration for policy designers struggling to shift the growth path towards a green one in a governmental sense. In consideration of data accessibility and the clarity of the empirical results' policy implications, this paper concentrates on examining the impact from AI software development. Concretely, we seek to answer the following questions: One is whether, on average, AI software development promotes or inhibits the shift of energy consumption toward renewable energy; the other is under what conditions, or rather, under what policy interventions, AI software development has a more positive effect on promoting renewable energy consumption.

To shed light on the above concerns, we collected a dataset of 62 economies over the period 2011–2020 to conduct a relevant cross-country panel investigation. Our baseline model employing fixed-effects estimation shows that, conditional on a given set of characteristics related to an economy' s economic status, foreign linkages, and politics, the better performance of AI software development is positively and significantly associated with the preference for renewable energy use. Moreover, one of our robust checks, a dynamic estimation cross-validated by different types of GMM techniques, reveals that the positive effect of AI software development on the energy transition in the following year can still be maintained at 90% of its current effect. Furthermore, our channel analysis suggests that AI software development is more likely to support the energy transition to renewable energy by inducing technological advances that improve environmental quality detection, rather than by promoting that of green computing. Additionally, we conduct a bunch of heterogeneity examinations, which reveals that environment policy stringency can play a positive moderating role in the relationship between AI software development and the energy transition towards renewables. Relative to non-market-based environment policy stringency, market-based environment policy has a more significant moderating effect.

Our research can contribute in several ways. First, our work investigates the effect of AI development on an economy's share of renewable energy consumption by panel data econometric approaches that control country-specific political and economic characteristics. It fills the gap in the empirical assessment of the AI-energy transition nexus at the aggregate level, which complements previous literature focusing on some specific technology issues of AI for renewable energy use in the technical domain, and jointly provides environmental policy designers with more comprehensive and integrated information for decision-making. Second, in contrast to the static examination perspective adopted by the empirical literature on similar topics, this paper explores the persistence and dynamism of the positive effects of AI software development on the energy transition in a set of extended investigations, which may serve as a methodological reference for subsequent studies to assess the consequences of AI development in a more complete way. Finally, we uncover the importance of considering environmental policy conditions when probing the AI-energy transition nexus, thus offering inspiration for peer scholars in the related field to build their empirical frameworks on the relationship between AI and sustainable development.

The remainder of this paper is organized as follows. Next section reviews the existing literature. Then, the methodology and data applied in the empirical work is introduced. Subsequent part illustrates the results, and final two sections offer discussions, and conclusions.

Literature review

The prevailing consensus is that the development of AI will be a catalyst for disruptive socioeconomic change, but its impact in specific areas remains controversial and incompletely explored (Obschonka & Audretsch, 2020). For instance, in terms of the aggregate level of economic activity, one may argue that by improving information flows and allocation efficiency, AI can boost productivity, innovation, and then economic expansion (Acemoglu & Restrepo, 2018), but others voice concerns that the gains may accrue disproportionately to skilled labor and capital holders (Berg *et al*., 2018; Korinek & Stiglitz, 2017), thereby depressing growth by reducing aggregate demand. The role of AI in such a conventional economic field has yet to be explored, and even more so in the realm of sustainable development.

AI and sustainable development

Since the introduction of deep learning algorithms in 2006, AI technology has made breakthroughs with broad applications (Zhao *et al*., 2017). The data explosion after 2012 has provided ample "fuel" for AI, enabling deep learning algorithms to make breakthroughs in speech and image recognition, and facilitating the commercialization and industrialization of AI applications (Zhuang *et al*., 2017).[1] Politicians and decision-making bodies around the world are increasingly interested in the potential of AI to reshape the pattern of development.

Initial studies have begun to investigate the relationship between AI and sustainable development from various perspectives. At the micro level, some look into corporate sustainability activities within or across firms. Di Vaio *et al*. (2020) apply a systematic literature review (SLR) approach to study how AI and machine learning are changing sustainable business models (SBMs). Dauvergne (2022) analyzes, through a political economy lens, the ways in which AI is driving the greening of supply chains globally. Rusch *et al*. (2022) survey applications of AI in recycling during product management processes. On a macro and governmental scale, others have turned their attention to how AI supports the synergy between public governance and sustainable development. For example, Truby (2020) and Wilson and van der Velden (2022) consider the integration of sustainable-development principles into AI governance frameworks. Galaz *et al.* (2021) assess the possible systemic risks of applying AI in economic sectors critical to sustainable development. In addition, there are also researchers interested in addressing social-good issues along with AI development (Cowls *et al.*, 2021; Hermann, 2022; Sartori & Theodorou, 2022).

[1] Big data plays a critical role in the advancement of deep learning in recent years. Deep learning models are data hungry, requiring large amounts of training data to learn meaningful representations and achieve good performance. The availability of large datasets from various sources such as social media, e-commerce, scientific experiments, etc., has fueled the application of deep learning in various domains.

The possible channels of AI's effect on energy transition

Vinuesa *et al.* (2020) comprehensively discuss the role of AI in sustainable development across economic, social, and environmental dimensions, outlining the research landscape on the environmental consequences of AI development and categorizing them into climate change, underwater life, and on-road life. To further build on this work, Leal Filho *et al.* (2022) provide a detailed review of AI research specifically related to climate change. We here concentrate on the impacts of the software development of AI.

Inspired by the existing literature, the development of AI software may have an impact on the energy transition towards renewables via two mechanisms, the first of which lands on the cost of environmental monitoring. The preference for renewable energy consumption in an economy is closely associated with the incentives for firms and consumers to internalize the social costs of environmental degradation caused by their conventional energy consumption (Bielecki *et al*., 2020; Owen, 2006; Xia *et al*., 2022). If the use of conventional energy that leads to environmental degradation can directly or indirectly impose more costs or penalties on users, then economic entities will be more inclined to consume renewable energy. Effectively penalizing environmentally harmful behavior depends on timely and precise environmental monitoring (Roach & Walker, 2017). Although some environmental metrics can be recorded automatically, accurate assessment of changes in environmental quality at a given location often still requires manual or semi-automated information collection, leading to persistently high costs of environmental regulation (Biber, 2013; Wehn & Uta Almomani, 2019). The development of AI software can help alleviate this problem. The information directly needed for in-depth assessment of environmental degradation risks (such as relevant images, sounds, videos, etc. of the monitored site) tends to correlate strongly with some relatively easily obtainable, frequently collected, unstructured, first-hand data with lower acquisition costs (Hajjaji *et al*., 2021). In an economy with a high level of AI software performance, it is easier to use mature deep learning software (or projects) to clean and organize unstructured data related to environmental quality (Goh *et al*., 2021; Paschen *et al*., 2020), extract massive numerical features, and estimate the correspondence between these numerical features and various environmental degradation risks. In this way, based on these correspondences, environmental regulators can comprehensively and timely inspect the environmental degradation risks of a monitored site with inexpensively collected unstructured data, thereby improving the effectiveness of environmental regulation. Therefore, the development of AI software can reduce the dynamic environmental monitoring costs of regulators by enhancing the processing capabilities of environmental unstructured data, thereby increasing the willingness of economic entities to internalize the environmental costs of their energy consumption, and thus promoting the shift of energy consumption to renewable ones.

Another possible mechanism linking AI software development and the renewable energy transition lies in green computing. Under current technological constraints, the renewable energy transition faces an inherent challenge: the intermittent nature of renewable energy production (and storage) often makes it difficult to flexibly meet fluctuating energy demand (Baranes *et al.*, 2017). This is mainly because, unlike the controllable supply of traditional energy sources, the production of most types of renewable energy is affected by the uncertainties of geology, hydrology, and climate, while consumer energy demand can also fluctuate due to some exogenous shocks. There are two complementary measures to address this issue: one is to have breakthroughs in renewable energy storage technologies (Olabi, 2017); the other is to better predict, regulate, and match the supply of renewable energy with the energy demand of economic entities. The development of AI software can at least play a positive role in the latter, the green computing. In an economy with a high level of AI software development, people can more conveniently apply deep learning techniques based on more unstructured data regarding changes in the natural environment and consumption behavior to predict factors influencing renewable energy supply and demand (Al-Othman *et al.*, 2022; Ebert-Uphoff & Hilburn, 2023), thereby improving their ability to match renewable energy supply with demand and thus facilitating the energy transition. However, innovation in green computing can involve attempts to deeply integrate AI software with energy systems. Since the improvement in green computing brought about by AI software development can only play an auxiliary role in effectively matching renewable energy supply and demand, in the absence of significant breakthroughs in renewable energy storage and delivery, the trial-and-error costs of green computing innovation are high, while the expected benefits of its success are relatively small. Therefore, the stimulus provided by the development of AI software for economic entities' incentives to engage in green computing innovation activities may be rather small or even insignificant, and thus not bring notable benefits to renewable energy consumption.

If the development of AI software promotes the transition to renewable energy mainly by improving the ability to monitor environmental quality and increasing people's willingness to internalize the social costs of environmental degradation, then this effect will exhibit heterogeneity across economies with different degrees of environmental policy stringency. In countries with more stringent environmental policies, the development of AI software reduces the monitoring costs regarding the risks of environmental quality degradation of environmental protection authorities. Faced with more effective environmental regulation, people have stronger incentives to adopt renewable energy. In contrast, in countries with more relaxed environmental policies, the reduction in environmental quality detection costs can hardly improve the incentives of economic entities to internalize the social costs of their polluting behavior. Therefore, the positive impact of AI software development on energy transition is relatively insignificant. Moreover, the main channel for AI software development to facilitate energy transition is essentially to reduce the information costs required for environmental regulation. Compared to environmental policies that require a higher amount of information collection (non-market-based environmental policies), the implementation efficiency-enhancing effect of AI software development is more significant for environmental policies that require a lower amount of information collection, i.e., market-based environmental policies (Stavins, 2010). Thus, we expect that, all else being equal, the stringency of market-oriented environmental policies will play a stronger positive moderating role than that of non-market-oriented environmental policies with regard to the facilitating effect of AI software development on energy transition.

Gaps left by existing AI-energy transition literature

Nearly 70% of AI-climate change studies focus on areas such as water, agriculture, land, and wildfires, while only about 4% focus on energy transition, which is at the core of economic decarbonization to address climate change. Most of these 4% studies on the interactions between AI and energy transition are carried out in the form of a literature review (Al-Othman *et al.*, 2022; Hernandez-Matheus *et al.*, 2022; Jha *et al.*, 2017) or a case study (Donti & Kolter, 2021; Mason *et al.*, 2018) to explore the technical feasibility of applying AI to support energy transition. There is little work that empirically evaluates the casual impact of AI on the energy transition, taking into consideration the incentives of economic entities and environmental policy conditions.

To our knowledge, the work by Kopka and Grashof (2022) is the only study that comes close to this regard. Using a sample of German regions at the NUTS–3 level over the period 2005–2015, they test the effect of AI development on the level of energy consumption and discuss the heterogeneity of this effect with respect to the regional environment and the regional industrial structure. However, there is room to complement their study in at least the following four areas: (1) The proxy for the dependent variable. The dependent variable adopted in this study is the level of energy consumption, which is insufficient for direct testing on the response of the energy consumption structure to AI development, i.e., up and down movements in the level of energy consumption do not capture the complete information on the change of energy consumption towards renewables. (2) Data and empirical strategy. Since all the samples are from Germany, the empirical conclusions obtained may only hold under the specific economic and political conditions of Germany, and there is a risk of extrapolation when applying them to other countries. In addition, the development of well-performing AI relies on training with massive amounts of data. 2012 was a watershed year in terms of the ease of access to large datasets, and since then, the availability of data has increased dramatically, allowing the full impact of AI development on the economy's real sector to be unleashed. For most of the time span of their sample (2005–2015), the potential for AI to affect the state of energy consumption was limited by data availability, which likely weakened the statistical power of the estimates. (3) Dynamic behavior. The development of AI is a technological change with far-reaching effects for the future, and it is likely to have lagged impacts on energy consumption in addition to the current one (Jha *et al*., 2017; Kopka & Grashof, 2022). However, their study does not provide a further quantitative examination of the long-term effects of AI. (4) Environmental policy conditions. Typically, in the absence of policy intervention, people do not spontaneously undertake additional costs to switch to renewable energy use. The willingness of most economic entities to adopt renewable energy tends to vary with the stringency of environmental policy, but we note that the environmental policy conditions for the impact of AI development on energy consumption were not covered in their empirical work.

To fill these gaps, we collected a cross-country panel dataset of 62 economies covering the period 2011–2020, with the share of renewable energy consumption containing information on the energy structure transition as the key explanatory variable, and control for differences in country-specific economic and political characteristics by using panel data econometric techniques to directly investigate the casual effect of AI software development on the energy transition. Next section presents the variable measures and model specification for the baseline estimation in the study. The extended investigations of the dynamic behavior of AI software development — energy transition and the moderating effects of environmental policies are presented in Results subsections.

Methods and data

To empirically examine the effect of AI software development on the energy transition towards renewables, we take the advantage of panel dataset and set the baseline specification as follow:

$$REC_{it} = \alpha\ AIsoftware_{it} + \beta' Control_{it} + \mu_i + \varepsilon_{it} \qquad (1)$$

REC is the share of renewables in total energy consumption (obtained in WDI Dataset), which measures the preference of renewables in energy consumption; *AIsoftware* denotes the AI software development of an economy measured by the natural logarithm of (1 + the number of AI projects), where the number of AI projects is calculated as the fractional count (based on the share of contributions) of AI-related repositories released in GitHub. Specifically, all AI projects are categorized into four types by their impact: very high impact projects (with more than 100 forks), high impact projects (with number of forks in the range of 6 to 100), medium impact projects (with number of forks in the range of 1–5), and low impact projects (with 0 fork).[2] The fractional number of AI projects in the four types are counted as

[2] On GitHub, a fork is developed when a user makes a copy of someone else's codebase under her own account. When a user forks a project, she (or he) has a complete copy of the project. She can modify, update, and commit to it under her own account without affecting the original project. In addition, she can also submit her pull requests to the original project, so that the maintainer of the original project can review them and decide whether to merge her changes into the original project. With a fork, a user can quickly build her own project on the basis of other projects, and contribute to other projects as well. The more forks a project has,

AI_veryhigh, *AI_ high*, *AI_medium* and *AI_low*, which are left for robustness checks.[3] Then the two core explanatory variable (*AIsoftware_1* and *AIsoftware_2*) for baseline estimations are constructed to be *ln*(1+ *AI_veryhigh* + *AI_ high*) and *ln*(1+ *AI_veryhigh* + *AI_ high* + *AI_medium* + *AI_low*), respectively. Their raw data were collected from the OECD Artificial Intelligence Policy Observatory.[4]

Simply regressing *REC* on *AIsoftware* may not truly reveal their relationship, as there are possibly omitted elements that could increase the volatility of the estimate or contaminate the estimate by imposing simultaneous impacts on both variables. A set of economic characteristics, including the development stage, industrial structure, urbanization rate, potential for economies of scale, and accessibility of basic education, can have effects on both *AIsoftware* and *REC*, thereby confounding the estimate. We hence include their proxies-GDP per capita (*GDP*), manufacturing value added as a percentage of GDP (*Industry*), the annual growth rate of the urban population (*Urban*), the natural logarithm of the total population (*Pop*) and the gross secondary school enrollment (*Edu*) rate-to mitigate the bias sourced from the differences of economic conditions. Moreover, net FDI inflows as a share of GDP (*FDI*) and the ratio of international trade to GDP (*Trade*) are added to account for the spillovers originating from the foreign linkages of trade and investment. We also incorporate the extent of democracy (*Democracy*) to take into consideration the institutional quality varying across different countries.[5] Other regional-specific features like hydrogeology, religion, customs, etc. that do not vary significantly in the time period that our sample covers can be captured by the terms of country-fixed effects (μ_i).[6] Table 1 shows the summary statistics for the variables mentioned

the more influence it has.

[3] Some countries in our sample have no observations for the AI software development indicator in certain years. Most likely because there were no new AI-related projects in that year, the OECD Artificial Intelligence Policy Observatory did not document these data, so the missing values are set to zero.

[4] The raw data provided by the OECD Artificial Intelligence Policy Observatory is updated in near real time. The observations we collected are a snapshot taken on September 6, 2023, between 20:00 and 20:35 UTC+8.

[5] *Democracy* is the electoral component index derived from the Variety to Democracy dataset; other control variables are taken from the WDI dataset.

[6] During some of the time periods covered by our sample, the difference in the growth rate of the number of AI-related projects posted on GitHub between AI-leading countries is not very large, and thus introducing time-fixed effects probably over-absorbs the marginal effect of AI software development on the energy transition and weakens the statistical power

above, and to save space, we do not describe them in details.

Given the set of selected control variables and a series of country-specific fixed effects, it is reasonable to argue that the conditional correlation α can better approach to the causal effect of AI software development on the energy transition.

Results

Baseline estimations

Employing the fixed-effect specification introduced in literature review, we perform baseline estimations whose results are displayed in Table 2. The explanatory variable measuring the AI software development is *AIsoftware_1* for models in columns (1) – (3) and *AIsoftware_2* in columns (4) – (6), and the regressand in all six columns is *REC*. The models in columns (1) and (3) show that, after ruling out time-invariant characteristics captured by a series of country-specific fixed effects, *REC* is positively and significantly associated with AI software development (measured by *AIsoftware_1* or *AIsoftware_2*). The controls for *GDP*, *Industry* and *Urban* are added to the models listed in columns (2) and (4). Columns (3) and (6) further incorporate other control variables, i.e. *Pop*, *Edu*, *FDI*, *Trade* and *Democracy*. We observe that as the control variables successively enter the model, the coefficient sizes for *AIsoftware_1* and *AIsoftware_2* do not considerably change and remain significantly positive at the 1% level. The positive conditional correlation does not appear to be sensitive to additional feature balancing, implying that the AI software development could have a positive effect on the energy transition towards renewables.

Robustness checks

To alleviate the concern of arbitrariness in measuring AI software development, in columns (1) – (4) of Table 3, we replace the explanatory variables with each of the four basic elements used to construct the core indicator of AI software development in the baseline (*AI_veryhigh*, *AI_ high*,

of our estimates. Hence, we do not include the time-fixed effects in our baseline model, but intend to perform additional tests that can alleviate the concern of possibly omitted confounders.

AI_medium, and *AI_low*), respectively, and then re-estimate the model.[7] The coefficients for these four measurements of replacement are positively significant at least at the 10% level, suggesting that the baseline conclusion is robust to adopting alternative indicators. Moreover, with the exception of the coefficient for the proxy built on the number of AI-related projects with very high impact (*AI_veryhigh*), all three other proxies are highly significant at the 1% level, which may be attributed to the fact that, compared to AI-related projects that are more focused on the implementation of specific functionalities, the development of AI software projects that play a fundamental role and have a broad and far-reaching impact on other projects does not have a particularly significant positive influence on technological changes that can be applied on the ground in the environmental field in the short term.

Moreover, given the covariates we have controlled and the timing-invariant country-specific characteristics absorbed by the terms of fixed effects, shocks on the different countries' energy transition towards renewables may be correlated if the inclusion of *Trade* and *FDI* is not adequate to account for the foreign linkages affecting the preference to adopt renewable energy. The possible existence of cross-sectional dependence (CD) may invalidate the inference by giving rise to an inconsistent-estimated variance-covariance matrix. To take into consideration the CD issue, we employ the robust standard errors clustered at each year to re-conduct the statistical inferences in the baseline. Columns (5) and (6) of Table 3 report the results, where *AIsoftware_1* and *AIsoftware_2* still be positively significant at the 5% level. While the employment of year-clustered stand error can address the issue of contemporary cross-sectional correlation, it does not consider the case that error terms of different countries in different years are dependent. We then deploy the Driscoll-Kraay approach that allows for the non-contemporary cross-sectional correlation to estimate the stand errors. Columns (7) and (8) of Table 3 show the results, the coefficients for *AIsoftware_1* and *AIsoftware_2* are positively significant at 1% level, indicating that the baseline conclusion is robust to the possible existence of CD as well.

One might be tempted to question whether there are omitted characteristics other than the control variables included in the baseline regression that would substantially confound the relationship between the energy

[7] Each of the 4 measurements on the replacement has undergone a transformation, i.e. taking the logarithm after adding one.

transition and AI software development. Estimations with more controls may help mitigate this concern. In terms of a country's economic status, we add the gross tertiary enrollment rate (*Human capital*) and the level of financial development (*Finance_develop*) to factor in the extent of advanced human capital and the availability of financial services. Regarding the aspect of foreign linkage, we additional include the proxy for the performance of political interactions with other economies (measured KOF Political Global Index). The index of high court dependence (from V-Dem Dataset) is further incorporated to control the difference in judiciary quality that might confuse the true relationship. Table 4 presents the re-estimated results where the four newly-considered control variables are brought into the model successively. We observe that neither the magnitude nor the statistical significance of the estimated coefficient decreases considerably with more controls, for either *AIsoftware_1* or *AIsoftware_2*. Besides, we conduct a sensitivity test to examine how many times the explanatory power of a potential omitted variable (for the energy transition) would have to be equal to that of a key control variable for the baseline conclusion to be qualitatively overturned. Figure 1 reports the results of the test. The closer the red dots corresponding to the estimated result are to the red curve of each subfigure, the less significant the impact of AI software development on energy transition is when there is a confounding effect from potentially omitted variables. We find that when the omitted variables explain three times as much variation in *REC* as *GDP* or *Urban*, the red dots of the estimation results are still in a position far from the lower left of the red curve. This suggests that even if a variable with three times the explanatory power of *GDP* or *Urban* is not included in the model, the confounding bias it introduces cannot disprove the highly significant positive effect of AI software development on the energy transition.

Although the possibility that the omitted variable issue could invert the baseline conclusions has been ruled out, there are still concerns about other endogenous biases as reverse causality. In consideration of the difficulty in finding consensual instrumental variables to deal with endogeneity and the interest in examining dynamic effects, we apply the GMM approach to estimate a dynamic version of our baseline model. Table 5 reports the results of the dynamic model estimated using three GMM techniques, respectively. That listed in Columns (1) and (2) are difference GMM (DIF-GMM) estimators, which take benefit of first-order difference transformation to eliminate country-specific fixed effects and relies on relatively loose assumptions about the moment conditions. Columns (3) and (4) present system GMM estimators that additionally exploit the information from the level equations to improve estimation efficiency, but use more moment conditions and thus correspond to stricter orthogonality assumptions. Both of the aforementioned GMM techniques are two-step GMM, but some literature has argued that while one-step GMM lacks consideration of heteroskedasticity, the improvement in estimation efficiency gained from two-step GMM (even in the presence of heteroskedasticity) is not significant, and that one-step technique is still superior to the two-step. We thus also perform estimations for the dynamic model using the one-step system GMM, whose results are shown in columns (5) and (6). The Hansen and AR(2) statistics for all six models are well above 0.1, indicating that there is no sufficient evidence to reject the correctness of the employed orthogonality conditions. *AIsoftware_1*'s and *AIsoftware_2*'s coefficients are positively significant at the 5% level at least, which are qualitatively consistent with that of the baseline, therefore alleviating the concern of the endogeneity bias. The coefficients for the lagged term of *REC* in all six columns are also positively significant at the 1% level and their size are around 0.9. This suggest that the effect of AI software development is not merely a static stimulus, but a dynamic promoting force that can sustain over three years.

Additionally, since the dependent variable *REC* is naturally bounded between 0 and 100, some may be concerned that a linear model is no longer appropriate for estimating the effect imposed on *REC*. More specifically, due to the possibility that the marginal effects of observations where *REC* hits a bound are likely to be much lower (or higher) than those that do not hit a bound, the average partial effect (APE) derived from a linear model may not be adequate to account for these marginal effects of observations at the corners (Papke & Wooldridge, 1996). To address this concern, we check whether the APE of the corner observations is substantially different from that of the non-corner observations. Note that the values of *REC* in the samples of our baseline estimation are distributed from 0 to 82.790, the upper bound (100) is far from being hit, and we only need to consider the lower bound (0). We set up a dummy variable (*Bound_dum*) that takes the value 1 if *REC* equals zero and 0 otherwise, and then introduce it and its interacted term with *AIsoftware_1* (or *AIsoftware_2*) into the baseline model. The estimated results are presented in columns (1) and (2) of Table 6, where the coefficients for the interacted terms are not statistically significant, implying that there is little difference between the APE of the bounded observations and that of the unbounded observations, thus alleviating the zero-bound concern.[8] To further increase the robustness to this issue, we employ the panel fractional response model (FRM), (a type of general linear model (GLM) specifically proposed to allow for the marginal effect differences associated with bounded dependent variables (Papke & Wooldridge, 2008),) and rerun the estimation. Columns (3) and (4) of Table 6 show the results. The significant coefficients of *AIsoftware_1* and *AIsoftware_2* remain positive, but they only indicate the consistency of sign. The size-comparable figure for the coefficient of *AIsoftware_1* (or *AIsoftware_2*) in the baseline is the APE calculated by averaging the marginal effects over all observations for the FRM estimation, which is listed in the second last row of Table 6.[9] It can be seen that the size of the APE for FRM is quite close to that of the baseline, again confirming the robustness of our baseline conclusion to the bounded value issue.

Possible channels of green technology change induction

Thus far, we have robustly verified the facilitating impact of AI software development on energy transition. In the theoretical analysis of the introduction, we have argued that the positive impact of AI software development on energy transition could potentially be achieved through two channels. First, AI software development leads to technological changes in environmental monitoring, which lowers the cost of detecting environmental quality and thereby promotes the adoption of renewable energy. Second, AI software development can strengthen green computing and improve the ability to predict energy demand and renewable energy supply, thereby enabling intermittent and volatile renewable energy supply to better match fluctuating energy demand, thus facilitating the use of renewable energy. However, compared to the former, the latter plays a less dominant, even insignificant role in linking AI software development with energy transi-

[8] Using a similar approach, we also test whether the APE of observations close to the lower bound (0), rather than just at the lower bound, is significantly different from the APE of observations far from the lower bound. In this test, observations whose REC takes values below the 10% quantile are considered to be close to the lower bound and cannot reject the hypothesis that there is no difference between the APEs of the two types of samples.

[9] Following the common practice in FRM estimation, the naturally bounded dependent variable, in our case *REC*, is divided by 100 and transformed into a fractional variable ranging from 0 to 1. Therefore, the exact figure used to compare with the coefficient of the baseline model should be, and is, the APE calculated based on the FRM model multiplied by 100.

tion. Because although it helps improve the prediction of energy demand and renewable energy supply, AI software development can only take a supplementary position in matching the two.

To verify the mediating role of these two possible channels, we examine the effects that AI software development has on innovation performance in environmental monitoring (*Environ_mon*) and green computing (*ICE_EE*).[10] Panel A of Table 7 presents the results, which show that, at the 5% significance level, the AI software development has a significant positive impact on *Environ_mon*, while not influencing *ICE_EE* significantly. To enhance the robustness of these results, we also estimate the effects of each of the four types of AI software development on innovation performance in these two fields. The models in Panel B show the effect examination on *Environ_mon*, and Panel C shows that on *ICE_EE*. The coefficients for AI-related proxies of *Environ_mon*'s regressions are reported to be significantly positive in Panel B, and those of *ICE_EE*'s regressions are insignificant. These works serve as suggestive evidence in line with the theoretical arguments in 2.2 of the channels bridging AI software development — the energy transition relationship. They imply that the improvement in the innovation performance of environmental monitoring, rather than that of green computing, mediates the positive influence running from AI software development to the energy transition towards renewables.

Heterogeneity in environmental regulations and in R&D support for renewables

Having confirmed the mechanisms that connect AI software development and energy transition, we seek to explore under which types of policy interventions the positive effects of AI software development on energy transition could be stronger. Reviewing the above mechanism analysis, we suggest that AI software development can induce technological changes in

[10] The total number of patent applications is the most frequently used indicator to informatively measure technological advance or innovation performance in a given field (Zheng *et al*., 2023; Long *et al*., 2023; Yin *et al*., 2022). Following this practice, *Environ_mon* is set as the natural logarithm of (1 + the number of patents in the field of environmental monitoring), and *ICE_EE* is calculated similarly, but based on the number of patents in the field of green computing. The statistic for the number of patents in a specific green field can be obtained from the OECD Statistics Dataset, where the fields that a patent belongs to are identified according to its alphanumeric symbols of the IPC or CPC systems. For more details on the search strategy for identifying green patents and the algorithm to categorize them adopted by the OECD statistics Dataset, see (Haščiči & Migottoi, 2015).

environmental quality monitoring, thus reducing the information collection costs of environmental quality regulations to encourage people to internalize the social costs of environmental pollution caused by their economic activities, and thereby promote energy transition towards renewables. In the absence of environmental regulation incentives, people and governments have no incentive to consider the environmental externalities of their behavior when engaging in economic activities. The convenience and productivity that AI software development brings to scientific research and new technology development may not improve environmental quality monitoring technologies. Therefore, we expect the positive effects of AI software development on energy transition to be stronger in countries with more stringent environmental policies. To check whether this is the case, we include the interaction terms of environmental policy stringency (*EPS*) with *AIsoftware_1* (and *AIsoftware_2*), along with *EPS* itself, and re-estimate the model. Columns (1) and (3) of Table 8 report the results, which show that the coefficients for the interaction terms of *EPS* with *AIsoftware_1* and *AIsoftware_2* are significantly positive at the 1% level. These heterogeneous effects of AI software development on energy transition under different levels of environmental policy stringency are also shown in the right subplot of Figure 2(a), indicating that stricter environmental policies can contribute to strengthening the promoting effect of AI software development on energy transition.

The central rationale for why environmental policy can positively dampen the impact of AI software development on energy transition is that AI software development can reduce the cost of acquiring environmental quality information for regulation. Environmental regulations that require less information collection can have their information acquisition constraints alleviated more easily by AI software development. It can be expected that, compared to other types of environmental policies, stricter market-based environmental policies can more effectively unblock the positive impact mechanism of AI software development on energy transition. We examine the moderating effects of market-based environmental regulations, non-market-based environmental regulations, and renewable energy support policies on the energy transition-promoting effect of AI software development. Columns (2) to (4) and (6) to (8) of Table 8 present the results, where the models in columns (2) to (4) are also visualized in the left subplot of Figure 2(a) and the two subplots of Figure 2(b). It can be observed that among the three types of environmental policies, market-based environmental regulations have the largest positive moderating effect.

One may be interested in the moderating effects of specific policies on the relationship between AI software development and energy transition. Thus, we additionally conduct a suite of interaction analyses of specific environmental policies. The models listed in Table 9 examine the moderating effects of a range of specific market-based environmental regulations, including carbon trading schemes (*TRADESCH_CO2*), renewable energy trading schemes (*ITRADESCH_RENEW*), carbon taxes (*TAXCO2*), diesel taxes (*TAXDIESEL*), nitrogen oxide taxes (*TAXNOX*), and sulfur oxide taxes (*TAYSOX*). The results show that carbon trading schemes, carbon taxes and diesel taxes have significant positive moderating effects, while this is not the case for sulphur oxide taxes. Aside from that, the models in Table 10 test the moderating effects of specific non-market-based environmental policies, like diesel emission limits (*ELV_DIESEL*), nitrogen oxide emission limits (*ELV_NOX*), particulate matter emission limits (*ELV_PM*), and sulfur oxide emission limits (*ELV_SOX*), and Table 11 inspects the moderating effects of direct renewable energy support policies, namely solar feed-in tariffs (*FIT_SOLAR*), wind feed-in tariffs (*FIT_WIND*), and public spending on renewable energy technologies (*RD_SUB*). It is found that diesel emission limits, particulate matter emission limits, and public spending on renewable energy technologies can play a more significant positive moderating role in the relationship between AI software development and energy transition.

Discussion

Our study explores and verifies the positive impact of AI software development on the energy transition, and elaborates on the energy-sector discussions of Vinuesa *et al.* (2020) and Goralski and Tan (2020) on AI's environmental outcomes. Based on a regional sample within Germany, Leal Filho *et al*. (2022) identifies the role of AI as a catalyst in the energy transition. Compared to their work, our work better examines the benefits of AI on the progress of the energy structure towards renewables rather than on the decline of total energy consumption. Moreover, our estimation controls for differences in the characteristics of economic development stages, political arrangements, and other institutional qualities across countries or regions, thereby mitigating the extrapolation risk of the derived conclusions when they are applied to out-of-sample countries.

In addition, we formally account for the time-lag characteristics of technology diffusion stressed by Grubler (1996) and Luttmer (2012) in our empirical work. Specifically, we draw on the methodology built to inspect the innovation consequences by Lokshin *et al*. (2008) in our extended investigation, and demonstrate the strong persistence of the facilitating effect of AI software development on the energy transition by a dynamic panel model estimated using GMM techniques. This complements the static assessment framework for the impact of AI on sustainable development employed by Yi and Xiao-li (2018), Kopka and Grashof (2022), and Luo *et al.* (2023), and may serve as a methodology reference for subsequent studies to examine the impact of AI more comprehensively.

We also reveal that technological advances in the field of environmental monitoring as an important mechanism linking AI software development and the energy transition, which provides testimony for the advocation of Hino *et al*. (2018) that environmental monitoring is a key factor in the shift towards a green economy. Moreover, since the existing literature has found that state governance factors such as corruption control (Wen *et al*., 2023; Zhou *et al*., 2022), judicial efficiency (Donis *et al*., 2023; Huang *et al*., 2022), and government effectiveness (Huang *et al*., 2019) significantly favor environmental technological advances, a governor may need to evaluate whether the institutional quality of the economy helps smooth the environmental monitoring mechanism detected by our work when assessing the possibility of harnessing AI software development to facilitate the renewable energy transition.

Aside from the above, we discuss the environmental policy conditions under which AI software development can act as a stimulus for the energy transition. These works, which essentially concern the role of AI in sustainable development from the lens of external constraints and economic entities' incentives, are highly complementary to existing research within the AI-energy transition field that analyzes how AI can be integrated in some specific technologies to promote a green transition in energy use, either within the engineering or the natural science domain (like the studies conducted by Kumari *et al.* (2020), Shin *et al.* (2021), Jha *et al.* (2017), etc.). Hence, our work, together with their research, can jointly provide a more comprehensive and holistic picture of AI's interactions with changes in energy consumption.

Conclusions

Based on a cross-country panel dataset, this paper first performs a range of examinations to robustly investigate the effect that AI software development has on the energy transition towards renewables, among which the issues of possible confounders and other endogeneity concerns have been addressed. It then explores and verifies the channel through which AI software development imposes an impact on the course of the energy transition. In addition, it further analyzes the heterogeneity of AI software development's effect across different types of environmental policy interventions. According to these empirical works, we can draw the following policy implications:

As AI software development promotes the adoption of renewable energy by inducing more technological improvements in the field of environmental quality monitoring, countries hoping to ride the AI wave to promote energy transition could consider incentivizing AI software projects while providing reasonable subsidies or financial support for innovative products relevant to environmental quality monitoring, and enhancing government efficiency in intellectual property services related to environmental quality monitoring, thereby smoothing the mechanism through which AI software development facilitates the transition of energy use to renewables. In line with the results of our heterogeneity analysis, environmental policy stringency plays a significant positive moderating role in the relationship between AI software development and the renewable energy transition. This implies that governments aiming to exploit the opportunities of AI software development to promote energy transition can only achieve their goal if the environmental policies enacted are sufficiently strict, since under strict environmental policies, the reductions in environmental monitoring costs brought about by AI software development increase people's willingness to internalize the costs of environmental degradation caused by economic activities, thus favoring the adoption of renewable energy. Moreover, because policies requiring less information collection are more likely to have their monitoring costs mitigated by AI technologies, compared to strengthening non-marketed environmental policies, increasing the stringency of marketed environmental policies enables AI software development to have greater facilitating effects on energy transition.

While enlightening, our work has the following limitations: First, the explanatory variable adopted in this paper is the share of renewable energy in total energy consumption, which broadly reflects the energy transition of an economy. Comparatively, the models proposed by Brodny *et al*. (2020), Xiao and Li (2023) and Wang *et al.* (2023) are more detailed and well-rounded in capturing the structural changes in energy consumption, and if the input variables and computational power necessary to estimate their models are available, future studies concerning the evolvement of the energy transition can draw on their algorithms to develop more precise and informative indicators for energy consumption structure.

Second, following the practice adopted by a considerable number of economic studies, we examine the first half of the "AI software development — enhanced environmental monitoring — energy transition" mechanism in the empirical work of channel exploration, while skipping the latter half, since the positive effect of improved environmental monitoring on the energy transition has been empirically widely confirmed by existing research (Zou & Wang, 2024; Zhou *et al*., 2022; Huang & Zou, 2020; Biber, 2013). However, when the analysis based on this mechanism is applied to a particular country, especially a developing country, the effect of environmental monitoring on the energy transition might be conditioned on some region-specific institutional factors. In such cases, before deriving further conclusions, studies in the future can consider taking measures to exclude the possible confounders and re-verify the local causal effect of environmental monitoring on the energy transition of this economy once again. Finally, cloud computing services have experienced rapid growth in some economies in recent years with the continuous advancement of hypervisors and software-defined network (SDN). The creation, training, and application of an AI often rely on data processing capabilities beyond those of an ordinary personal computer. The accessibility of cloud computing services to economic entities and the competition pattern in the cloud computing service market may have appreciable impacts on the dynamic response of various economic variables to AI software development. Given the insufficiency of observational data at the aggregate level, we do not include this aspect in our empirical framework. Peer scholars may consider a case study to explore the role that government support for cloud computing infrastructure or cloud computing service market structure plays in the evolution of the economic and environmental outcomes led by AI software development.

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Annex

Table 1. Summary statistics

Variables	N	Mean	SD	Min	Median	Max
REC	568	20.516	16.838	0.000	16.645	82.790
AIsoftware_1	568	2.143	1.803	0.000	1.802	7.757
AIsoftware_2	568	4.319	2.473	0.000	4.366	11.019
GDP	568	2.991	2.367	0.143	2.301	12.368
Industry	568	13.534	5.753	0.954	12.564	34.651
Urban	568	1.076	1.321	-2.282	0.862	12.035
Pop	568	16.310	1.740	12.673	16.082	21.057
Edu	568	106.638	15.697	66.251	103.759	163.935
FDI	568	0.071	0.239	-1.041	0.026	2.794
Trade	568	106.683	74.010	22.486	86.337	442.620
Democracy	568	0.762	0.229	0.003	0.879	0.940

Table 2. Baseline regressions

	(1) REC	(2) REC	(3) REC	(4) REC	(5) REC	(6) REC
AIsoftware_1	0.552***	0.560***	0.529***			
	(3.42)	(3.52)	(3.18)			
AIsoftware_2				0.421***	0.434***	0.481***
				(3.41)	(3.52)	(3.57)
GDP		-0.037	0.070		-0.024	-0.025
		(-0.15)	(0.25)		(-0.11)	(-0.10)
Industry		0.036	-0.126		0.057	-0.070
		(0.32)	(-1.06)		(0.61)	(-0.69)
Urban		0.100	0.221		0.152*	0.194
		(1.13)	(1.64)		(1.84)	(1.42)
Pop			7.556			3.624
			(0.97)			(0.48)
Edu			0.054*			0.041
			(1.88)			(1.42)
FDI			-0.369			-0.311
			(-0.69)			(-0.64)
Trade			0.038			0.037
			(1.55)			(1.61)
Democracy			6.058**			6.982**
			(2.12)			(2.27)
N	693	684	568	693	684	568
Adj-R^2	0.077	0.074	0.157	0.107	0.106	0.188

Notes: Robust t-statistics are shown in brackets. The number of asterisks indicates the significant level of a coefficient. (* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$).

Table 3. Robustness checks: alternative explanatory variables & std

	(1) REC	(2) REC	(3) REC	(4) REC	(5) REC	(6) REC	(7) REC	(8) REC
AIsoftware_veryhigh	0.358*							
	(1.68)							
AIsoftware_high		0.551***						
		(3.41)						
AIsoftware_medium			0.578***					
			(3.72)					
AIsoftware_low				0.491***				
				(3.79)				
AIsoftware_1					0.529**		0.529**	
					(3.07)		(3.16)	
AIsoftware_2						0.481***		0.481***
						(3.85)		(4.16)
N	568	568	568	568	568	568	568	568

Notes: Similar as Table 2.

Table 4. Robustness checks: additional controls

	(1) REC	(2) REC	(3) REC	(4) REC	(5) REC	(6) REC	(7) REC	(8) REC
AIsoftware_1	0.509***	0.497***	0.520***	0.519***				
	(3.11)	(3.09)	(3.12)	(3.06)				
AIsoftware_2					0.439***	0.431***	0.468***	0.467***
					(3.30)	(3.26)	(3.34)	(3.30)
Original CVs	√	√	√	√	√	√	√	√
Human capital	√	√	√	√	√	√	√	√
Finance_develop		√	√	√		√	√	√
Global_polictics			√	√			√	√
Court_dep				√				√
N	545	540	530	530	545	540	530	530

Notes: Similar as Table 2.

Table 5. Robustness checks: dynamic investigation &endogeneity concern

	(1) DIF-GMM	(2) DIF-GMM	(3) SYS-GMM	(4) SYS-GMM	(5) One-step SYS-GMM	(6) One-step SYS-GMM
	REC	**REC**	**REC**	**REC**	**REC**	**REC**
L.REC	0.899***	0.861***	0.987***	0.994***	0.993***	0.994***
	(7.10)	(6.64)	(22.91)	(32.88)	(31.29)	(32.63)
AIsoftware_1	0.284**		0.230***		0.283***	
	(2.02)		(3.04)		(2.85)	
AIsoftware_2		0.272***		0.133**		0.166**
		(2.99)		(2.00)		(2.30)
Hansen	0.861	0.828	0.151	0.118	0.191	0.129
AR(2)	0.105	0.110	0.106	0.128	0.110	0.122
N	498	498	568	568	568	568

Notes: Similar as Table 2.

Table 6. Robustness checks: bounded-value consideration

	(1)	(2)	(3)	(4)
	REC	**REC**	**REC**	**REC**
AIsoftware_1	0.530***		0.022**	
	(3.10)		(2.36)	
*AIsoftware_1*Bound_dum*	6.133			
	(0.07)			
AIsoftware_2		0.482***		0.020***
		(3.50)		(3.17)
*AIsoftware_2*Bound_dum*		-0.122		
		(-0.12)		
APE			0.005**	0.005***
			(2.36)	(3.18)
N	568	568	568	568

Notes: Similar as Table 2.

Table 7. Possible channels

Panel A	**(1)** **Environ_mon**	**(2)** **Environ_mon**	**(3)** **ICT_EE**	**(4)** **ICT_EE**
AIsoftware_1	0.047**		-0.007	
	(2.41)		(-0.38)	
AIsoftware_2		0.032**		0.005
		(2.17)		(0.36)
N	453	453	453	453
Panel B	**(1)** **Environ_mon**	**(2)** **Environ_mon**	**(3)** **Environ_mon**	**(4)** **Environ_mon**
AIsoftware_veryhigh	0.089**			
	(2.59)			
AIsoftware_high		0.044**		
		(2.24)		
AIsoftware_medium			0.051**	
			(2.65)	
AIsoftware_low				0.032**
				(2.27)
N	453	453	453	453
Panel C	**(1)** **ICT_EE**	**(2)** **ICT_EE**	**(3)** **ICT_EE**	**(4)** **ICT_EE**
AIsoftware_veryhigh	-0.015			
	(-0.51)			
AIsoftware_high		-0.011		
		(-0.59)		
AIsoftware_medium			0.002	
			(0.09)	
AIsoftware_low				0.005
				(0.35)
N	453	453	453	453

Notes: Similar as Table 2.

Table 8. Moderating effects of environment policies

	(1) REC	(2) REC	(3) REC	(4) REC	(5) REC	(6) REC	(7) REC	(8) REC
AIsoftware_1	-1.489***	-0.529*	-1.187*	-0.473*				
	(-2.80)	(-1.82)	(-1.82)	(-1.88)				
AIsoftware_2					-1.009***	-0.345	-0.786*	-0.234
					(-2.99)	(-1.39)	(-1.80)	(-1.19)
*AIsoftware_1*EPS*	0.662***							
	(3.81)							
*AIsoftware_1*EPS_MKT*		0.594***						
		(3.30)						
*AIsoftware_1*EPS_NMKT*			0.320**					
			(2.58)					
*AIsoftware_1*TECHSUP*				0.442***				
				(4.93)				
*AIsoftware_2*EPS*					0.518***			
					(4.45)			
*AIsoftware_2*EPS_MKT*						0.551***		
						(4.23)		
*AIsoftware_2*EPS_NMKT*							0.257***	
							(2.98)	
*AIsoftware_2*TECHSUP*								0.347***
								(5.41)
N	342	342	342	342	342	342	342	342

Notes: Similar as Table 2.

Table 9. Moderating effects of market-based environment policies

Panel A						
	(1) **REC**	**(2)** **REC**	**(3)** **REC**	**(4)** **REC**	**(5)** **REC**	**(6)** **REC**
AIsoftware_1	-0.413**	0.364*	0.267	-0.635**	0.225	0.142
	(-2.03)	(1.74)	(1.42)	(-2.52)	(1.20)	(0.54)
*AIsoftware_1*TRADESCH_CO2*	0.477***					
	(5.38)					
*AIsoftware_1*TRADESCH_RENEW*		0.097				
		(1.01)				
AIsoftware_1.TAXCO2*			0.312***			
			(3.40)			
*AIsoftware_1*TAXDIESEL*				0.328***		
				(4.40)		
*AIsoftware_1*TAXNOX*					0.246**	
					(2.49)	
*AIsoftware_1*TAXSOX*						0.147
						(1.29)
N	342	342	342	342	342	342
Panel B						
	(1) **REC**	**(2)** **REC**	**(3)** **REC**	**(4)** **REC**	**(5)** **REC**	**(6)** **REC**
AIsoftware_2	-0.334*	0.448**	0.367**	-0.566**	0.265	0.177
	(-1.70)	(2.35)	(2.07)	(-2.51)	(1.46)	(0.67)
*AIsoftware_2*TRADESCH_CO2*	0.422***					
	(5.92)					
*AIsoftware_2*TRADESCH_RENEW*		0.132*				
		(1.84)				
*AIsoftware_2*TAXCO2*			0.301***			
			(3.71)			
*AIsoftware_2*TAXDIESEL*				0.349***		
				(4.88)		
*AIsoftware_2*TAXNOX*					0.206**	
					(2.66)	
*AIsoftware_2*TAXSOX*						0.136
						(1.38)
N	342	342	342	342	342	342

Notes: Similar as Table 2.

Table 10. Moderating effects of non-market-based environment policies

Panel A				
	(1) **REC**	**(2)** **REC**	**(3)** **REC**	**(4)** **REC**
AIsoftware_1	-3.798***	-0.421	-0.734*	-0.512
	(-4.32)	(-0.75)	(-1.86)	(-1.12)
*AIsoftware_1*ELV_DIESELSO*	0.738***			
	(4.96)			
*AIsoftware_1*ELV_NOX*		0.179		
		(1.67)		
*AIsoftware_1*ELV_PM*			0.221***	
			(3.38)	
*AIsoftware_1*ELV_SOX*				0.203**
				(2.13)
N	342	342	342	342
Panel B				
	(1) **REC**	**(2)** **REC**	**(3)** **REC**	**(4)** **REC**
AIsoftware_2	-2.134***	-0.208	-0.428	-0.336
	(-4.36)	(-0.51)	(-1.45)	(-0.89)
*AIsoftware_2*ELV_DIESELSO*	0.467***			
	(5.47)			
*AIsoftware_2*ELV_NOX*		0.150*		
		(1.97)		
*AIsoftware_2*ELV_PM*			0.175***	
			(3.31)	
*AIsoftware_2*ELV_SOX*				0.177**
				(2.28)
N	342	342	342	342

Notes: Similar as Table 2.

Table 11. Moderating effects of policy support for renewable technologies

	(1) **REC**	**(2)** **REC**	**(3)** **REC**	**(4)** **REC**	**(5)** **REC**	**(6)** **REC**
AIsoftware_1	0.423*	0.429**	-0.496**			
	(1.87)	(2.25)	(-2.12)			
AIsoftware_2				0.426*	0.465**	-0.200
				(1.88)	(2.41)	(-0.89)
*AIsoftware_1*FIT_SOLAR*	0.026					
	(0.48)					

Table 11. Continued

	(1) REC	(2) REC	(3) REC	(4) REC	(5) REC	(6) REC
*AIsoftware_1*FIT_WIND*		0.032				
		(0.63)				
*AIsoftware_1*RD_SUB*			0.414***			
			(5.90)			
*AIsoftware_2*FIT_SOLAR*				0.043		
				(0.86)		
*AIsoftware_2*FIT_WIND*					0.036	
					(0.71)	
*AIsoftware_2*RD_SUB*						0.305***
						(5.17)
N	342	342	342	342	342	342

Notes: Similar as Table 2.

Figure 1. Robust tests for possible confounders

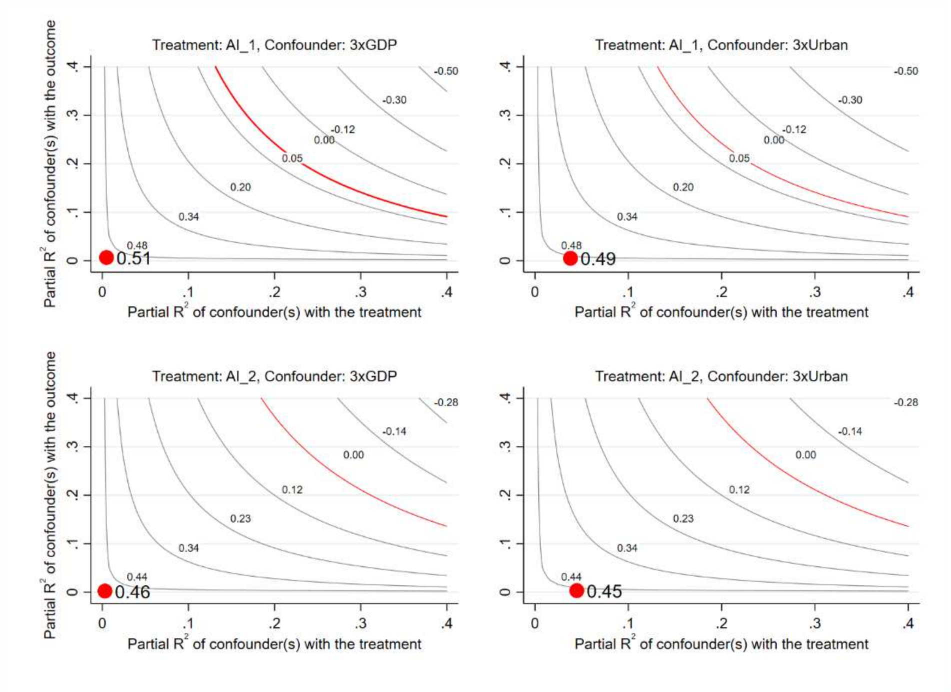

Figure 2. Moderating effects of environmental policies