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# *National AI Strategies and the Green Transition: Cross-Country Evidence from Staggered Difference-in-Differences and Double Machine Learning*

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***Abstract.*** National artificial intelligence (AI) strategies have proliferated since 2017, yet whether they advance the green transition remains unknown. We exploit the staggered adoption of national AI strategies by 59 countries within an 85-country panel over 2000–2021, combining two-way fixed effects (TWFE), Callaway–Sant'Anna difference-in-differences, and double machine learning (DML). Strategy adoption raises the renewable energy share of consumption by 1.87 percentage points in fixed-effects estimates and by 1.47 points in dynamic event-study aggregation, and reduces the $CO_2$ intensity of GDP (−0.026 kg per 2017 PPP dollar), a result corroborated by a significant decline in $CO_2$ emissions per capita. In contrast, we find no robust effect on the share of environment-related patents: pre-trends are rejected and point estimates switch sign across estimators. Green-patenting effects are concentrated, albeit imprecisely, in high-income economies, and carbon-intensity reductions are larger where renewable endowments are high. DML estimates for green patenting are sensitive to the choice of learner. National AI strategies appear to green the energy mix before they green the innovation base.

***Keywords:*** Artificial intelligence, Green transition, National AI strategy, Staggered difference-in-differences, Double machine learning

## 1. Introduction

Artificial intelligence (AI) is widely viewed as a general-purpose technology that reshapes productivity, industrial structure, and labour markets [1-3]. Since Canada launched the first national AI strategy in 2017, more than sixty governments have followed, making AI a central object of industrial policy [4, 5]. Whether these state-led AI agendas also accelerate the green transition is a first-order policy question on which systematic causal evidence is scarce.

Micro-level evidence suggests they might. AI adoption enhances corporate green innovation capability [6], green transformation [7], and ESG performance [8], predominantly among Chinese listed firms; AI and digitalisation have been linked to lower carbon emissions across 66 countries [9], at Chinese firms undergoing digital transformation [10], and in Chinese AI-policy pilot zones [11]. Such returns arise only when adoption is embedded in complementary organisational and institutional change [12].

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Two gaps remain. First, existing causal evidence is firm- or region-level and largely single-country; to our knowledge no study provides cross-country quasi-experimental estimates of national AI strategies—arguably the most salient AI-era policy instrument—on green outcomes. Second, staggered adoption renders conventional two-way fixed effects (TWFE) estimands potentially misleading under treatment-effect heterogeneity [13-16], while machine-learning causal tools [17-20] have rarely been combined with staggered designs in this setting.

This paper fills these gaps. We construct an unbalanced panel of 85 countries over 2000–2021, in which 59 countries adopted a national AI strategy between 2017 and 2022 and 26 never did. We estimate the effect of adoption on three green-transition outcomes—the share of environment-related patents, the $CO_2$ intensity of GDP, and the renewable energy share of consumption—using TWFE, heterogeneity-robust Callaway–Sant'Anna estimators, and double machine learning (DML) with continuous digitalisation treatments. Adoption significantly raises the renewable share and lowers carbon intensity, with parallel trends supported for both, but has no robust effect on green patent shares, for which pre-trends are rejected and estimates are sign-unstable. Effects concentrate in high-income countries and, for carbon intensity, in countries with high renewable endowments.

Our contributions are threefold. First, we provide the first cross-country causal evidence on national AI strategies and the green transition, treating their staggered roll-out as a quasi-natural experiment with cross-verified treatment timing. Second, we apply heterogeneity-robust staggered estimators where conventional TWFE is fragile, and we transparently report where identification fails, including rejected pre-trends and placebo exercises. Third, we combine difference-in-differences with DML and causal forests, documenting both the promise and the learner sensitivity of ML-based causal inference for green outcomes.

Section 2 describes the data and methodology, Section 3 reports the empirical results, and Section 4 concludes.

## 2. Data and methodology

### 2.1. Data and sample

We assemble an unbalanced country–year panel of 85 countries over 2000–2021 (1,618 observations). The first outcome is the green patent share: environment-related patent families (family size $\geq 2$, fractional counting by inventor country) as a percentage of all patent families, from the OECD ENV.EPI statistics [21], winsorised at the 1st/99th percentiles; country-years with fewer than ten families are dropped. The second outcome is the $CO_2$ intensity of GDP (kg per 2017 PPP dollar) from the World Bank's World Development Indicators [22]; we also examine the renewable energy consumption share and $CO_2$ emissions per capita. Controls include log GDP per capita, log population, FDI net inflows, trade openness, energy intensity, log resident patent applications, and R&D expenditure (interpolated within country; 79 of 1,618 observations imputed, with a flag).

Table 1. Descriptive statistics, 85 countries, 2000–2021

| Variable | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Green patent share (%, wins.) | 1618 | 11.899 | 5.562 | 1.943 | 32.589 |
| $CO_2$ intensity of GDP (kg/2017 PPP $) | 1603 | 0.559 | 0.507 | 0.048 | 5.170 |
| Renewable energy consumption (%) | 1618 | 19.499 | 17.261 | 0.000 | 87.000 |
| Internet users (% pop.) | 1618 | 53.013 | 29.741 | 0.140 | 100.000 |

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Table 1. (continued)

| | | | | | |
|---|---|---|---|---|---|
| Fixed broadband (per 100) | 1563 | 16.074 | 13.475 | 0.000 | 47.943 |
| ln GDP per capita | 1618 | 9.427 | 1.165 | 6.486 | 11.630 |
| ln population | 1618 | 16.752 | 1.652 | 12.547 | 21.070 |
| Energy intensity (MJ/2017 PPP $) | 1618 | 4.562 | 2.153 | 1.090 | 15.780 |
| R&D expenditure (% GDP) | 1618 | 1.187 | 0.999 | 0.016 | 5.832 |

Notes. Ever-treated countries adopt a national AI strategy in 2017–2022. The green patent share is winsorised at the 1st/99th percentiles. R&D expenditure is interpolated within country and imputed where missing (79 of 1,618 obs.; flag included). Full descriptive statistics, including group means, are available upon request.

Treatment is the adoption of a national AI strategy. Adoption years are cross-verified across sources, using the Stanford AI Index Report 2023 [5] as the primary source and correcting individual countries to official-document years where they diverge. Fifty-nine countries adopted in 2017–2022; 26 never-adopters serve as controls, with Thailand (a 2022 adopter) grouped among controls in the staggered designs. Table 1 reports descriptive statistics; the average green patent share is 11.9%, whereas never-treated countries exhibit higher carbon intensity (0.714 vs. 0.504 kg per 2017 PPP dollar), motivating the explicit modelling of selection below.

## 2.2. Econometric strategy

Our baseline is the TWFE specification (1), where AIStrategy equals one from the adoption year onward, α and λ denote country and year fixed effects, and standard errors are clustered by country.

$$Y_{it} = \alpha_i + \lambda_t + \beta \cdot AIStrategy_{it} + \gamma' X_{it} + \varepsilon_{it} \quad (1)$$

Because staggered adoption renders β a potentially non-convex weighted average of group-time effects [13], our preferred estimates use the Callaway and Sant'Anna [14] group-time ATT(g,t) estimator with never-treated controls, a universal base period, and doubly robust estimation, aggregated into overall and dynamic (event-study) ATTs; inference uses a country-cluster bootstrap (399 replications), and pre-trends are assessed by Wald tests. We complement these with the Sun and Abraham [15] interaction-weighted estimator. We further deploy double/debiased machine learning in a partially linear model [19], treating digitalisation (internet users and fixed broadband subscriptions per 100 people) as a continuous treatment, with five-fold cross-fitting repeated three times and OLS-TWFE, Lasso, and random-forest learners. Heterogeneity is examined through interaction TWFE by income group (World Bank classification) and renewable-energy endowment (above/below the pre-2015 sample median), and through a causal forest (CausalForestDML, 1,000 trees).

# 3. Empirical results

## 3.1. Baseline TWFE estimates

Table 2 reports equation (1). Strategy adoption has a statistically insignificant effect on the green patent share (0.092, SE 0.663) and on $CO_2$ intensity (0.010, SE 0.019), but raises the renewable energy share by 1.874 percentage points (SE 0.792; p = 0.018)—an economically meaningful effect relative to the sample mean of 19.5%.

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Table 2. Baseline two-way fixed effects estimates of national AI strategy adoption

| | (1) Green patent share | (2) $CO_2$ intensity | (3) Renewable share |
|---|---|---|---|
| AI strategy (post) | 0.092 (0.663) | 0.010 (0.019) | 1.874** (0.792) |
| ln GDP p.c. | −1.443 (2.035) | 0.120 (0.135) | −18.618*** (4.148) |
| ln population | 2.235 (4.298) | 0.286* (0.158) | −21.881*** (5.417) |
| FDI (% GDP) | −0.007*** (0.002) | −0.000 (0.000) | −0.001 (0.002) |
| Trade openness | 0.001 (0.008) | 0.001* (0.000) | 0.019 (0.023) |
| Energy intensity | 0.029 (0.327) | 0.165*** (0.050) | −0.760 (0.766) |
| ln resident patents | −0.053 (0.461) | −0.000 (0.015) | −0.885 (0.720) |
| R&D (% GDP) | 1.515** (0.640) | 0.067 (0.049) | 0.800 (1.078) |
| Country FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| N | 1618 | 1603 | 1618 |
| $R^2$ | 0.388 | 0.975 | 0.967 |

Notes. Country-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All columns include country and year fixed effects and the full control set.

### 3.2. Heterogeneity-robust staggered estimates

reports Callaway–Sant'Anna estimates; Figure 1 plots the corresponding event-study paths. For the renewable share, the overall ATT is positive but imprecise (0.734, SE 0.505), while the dynamic aggregation is significant at 1.472 (SE 0.585), with parallel trends comfortably supported (Wald p = 0.674) and a visibly monotone post-adoption build-up in Fig. 1, Panel C. For $CO_2$ intensity, the overall ATT is −0.026 (SE 0.016, significant at 10%) and the dynamic ATT is −0.034 (SE 0.021); pre-trends are not rejected (p = 0.521), and Fig. 1, Panel B shows post-adoption coefficients trending downward. Strategy adoption thus shifts the energy mix and lowers carbon intensity, consistent with AI-enabled grid management, demand forecasting, and energy-efficiency applications.Table 3

For the green patent share, the evidence does not support a causal effect, and we report this null transparently. The overall ATT is statistically insignificant (0.309, SE 0.742), the pre-trend Wald test is rejected (p = 0.032), and Fig. 1, Panel A shows pre-adoption coefficients of unstable sign. Alternative estimators disagree: a covariate-adjusted doubly robust implementation yields −2.633 (SE 1.575, significant at 10%) and the Sun–Abraham estimator yields −5.023 (SE 3.414, insignificant). We therefore characterise the green-innovation effect as lacking robust evidence rather than as positive or negative.

Table 3. Callaway–Sant'Anna staggered difference-in-differences estimates

| Outcome | Overall ATT | SE | Dynamic-agg. ATT | SE | Pre-trend Wald p | N |
|---|---|---|---|---|---|---|
| Green patent share | 0.309 | 0.742 | 0.820 | 0.991 | 0.032 | 1618 |
| $CO_2$ intensity | −0.026* | 0.016 | −0.034 | 0.021 | 0.521 | 1603 |

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Table 3. (continued)

| | | | | | | |
|---|---|---|---|---|---|---|
| Renewable share | 0.734 | 0.505 | 1.472** | 0.585 | 0.674 | 1618 |
| Green share, covariate-adj. | −2.633* | 1.575 | — | — | — | 1618 |
| Green share, Sun–Abraham | −5.023 | 3.414 | — | — | — | 1618 |

Notes. Inference is based on a country-cluster bootstrap (399 replications); estimates use never-treated controls, a universal base period, and doubly robust estimation.

Table 4. Double/debiased machine learning estimates

| Outcome Y | Treatment D | OLS-TWFE | DML-Lasso | DML-RandomForest |
|---|---|---|---|---|
| Green patent share | Internet users (%) | −0.056*** (0.017) | −0.038*** (0.014) | 0.054*** (0.008) |
| Green patent share | Broadband (per 100) | −0.009 (0.039) | 0.057*** (0.021) | 0.132*** (0.014) |
| $CO_2$ intensity | Internet users (%) | −0.0016*** (0.0005) | −0.0017*** (0.0004) | 0.0007** (0.0003) |

Notes. The DML coefficient is the effect of a one-unit increase in the continuous digitalisation treatment D, estimated in a partially linear model with X = full controls plus country and year dummies, five-fold cross-fitting (three repetitions). Lasso and random-forest learners disagree in sign for the patent-share outcome, indicating sensitivity to the functional form of the nuisance functions; these results are suggestive only.

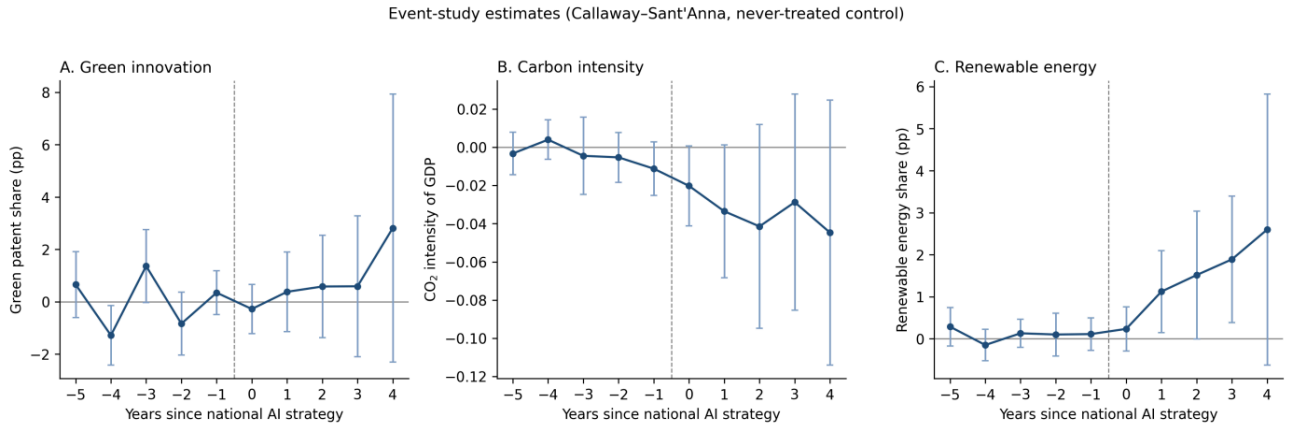



Figure 1. Event-study estimates around national AI strategy adoption, based on Callaway–Sant'Anna group-time ATTs aggregated by event time with never-treated controls, for the green patent share (Panel A), $CO_2$ intensity of GDP (Panel B), and renewable energy share (Panel C). Whiskers denote 95% confidence intervals from a country-cluster bootstrap (399 replications). Pre-treatment coefficients are jointly insignificant for Panels B and C (Wald p = 0.521 and 0.674) but not for Panel A (p = 0.032)

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### 3.3. Double machine learning

treats digitalisation as a continuous treatment. Internet penetration is negatively associated with $CO_2$ intensity under OLS-TWFE (−0.0016, SE 0.0005) and Lasso (−0.0017, SE 0.0004), though the sign flips under random forests (0.0007, SE 0.0003). For the green patent share, OLS and Lasso agree (−0.056 and −0.038, both significant at 1%) but random forests reverse the sign (0.054, SE 0.008); broadband estimates are similarly learner-dependent. Because nuisance-function flexibility changes conclusions, we read the DML results as suggestive only Table 4 [20].

### 3.4. Heterogeneity

examine effect heterogeneity. The green-patent effect differs by income group: −1.178 (SE 1.024) in non-high-income versus 0.596 (SE 0.701) in high-income countries, a marginally significant difference of 1.774 (SE 1.016). Causal-forest group ATEs point the same way—1.451 [−0.944, 3.845] for high-income versus −0.403 [−3.903, 3.096] for non-high-income countries—though both intervals span zero. For carbon intensity, reductions concentrate in countries with high pre-existing renewable shares (−0.044, SE 0.021, significant at 5%, versus 0.010, SE 0.023 in the low-share group; interaction difference 0.055, SE 0.030, marginally significant). Absorptive capacity and a favourable energy mix thus condition the green dividends of AI strategies.Tables 5–6 and Figure 2

Table 5. Heterogeneity of the AI strategy effect: interaction TWFE estimates

| Outcome | Group | Effect, low group | Effect, high group | Difference | N |
|---|---|---|---|---|---|
| Green share | High-income | −1.178 (1.024) | 0.596 (0.701) | 1.774* (1.016) | 1618 |
| Green share | High renewable share | −0.256 (0.743) | 0.515 (0.924) | 0.771 (1.002) | 1612 |
| $CO_2$ intensity | High-income | −0.029 (0.027) | 0.023 (0.028) | 0.052 (0.047) | 1603 |
| $CO_2$ intensity | High renewable share | −0.016 (0.019) | 0.039 (0.029) | 0.055* (0.030) | 1597 |

Notes. Country-clustered standard errors in parentheses; * p<0.1. Effect = post × group indicator; all columns include country and year fixed effects and the full control set. For reference, subsample TWFE regressions give, for $CO_2$ intensity, −0.044 (SE 0.021) in high-renewable-share and 0.010 (SE 0.023) in low-renewable-share countries.

Table 6. Causal forest estimates of group ATEs on the green patent share

| Group | ATE | 95% CI | N |
|---|---|---|---|
| All | 0.705 | [−2.185, 3.595] | 1618 |
| High-income | 1.451 | [−0.944, 3.845] | 964 |
| Non-high-income | −0.403 | [−3.903, 3.096] | 648 |
| High renewable share | 0.631 | [−2.645, 3.908] | 788 |
| Low renewable share | 0.776 | [−1.688, 3.241] | 824 |

Notes. Group average treatment effects from a causal forest (CausalForestDML, 1,000 trees, discrete treatment) on the green patent share.

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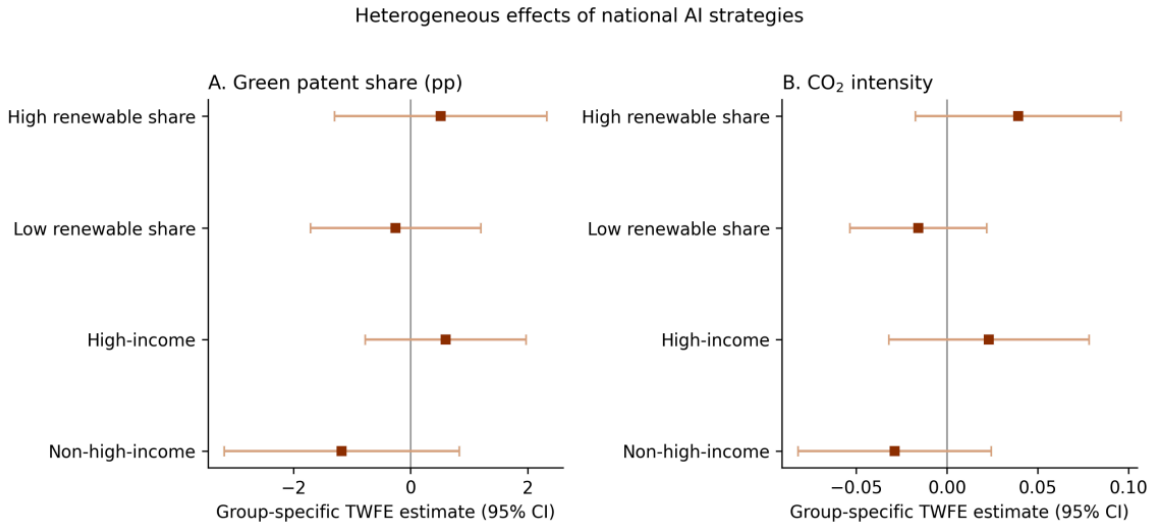



Figure 2. Group-specific TWFE estimates (post × group indicator interactions) of the effect of national AI strategy adoption on the green patent share (Panel A) and $CO_2$ intensity of GDP (Panel B), split by World Bank income classification and by pre-2015 median renewable energy share. Whiskers denote 95% confidence intervals based on country-clustered standard errors

### 3.5. Robustness and limitations of identification

Three checks qualify our conclusions. First, replacing the outcome with $CO_2$ emissions per capita in the TWFE specification yields −0.483 (SE 0.196, significant at 5%), corroborating the decarbonisation finding on an alternative measure. Second, dropping the COVID year 2020 leaves conclusions unchanged (green share 0.229, SE 0.782; $CO_2$ intensity 0.022, SE 0.022; both insignificant). Third, a placebo exercise randomising adoption timing 500 times yields permutation p-values of 0.702 (green share) and 0.560 ($CO_2$ intensity): TWFE point estimates cannot be distinguished from randomly timed pseudo-treatments. We therefore rest our inference on the heterogeneity-robust estimators with passing pre-trends and treat the TWFE magnitudes as descriptive. Residual uncertainty in adoption-year coding, the modest country count, and a single 2022 adopter (Thailand) that contributes no post-treatment years further qualify the design.

## 4. Conclusion

Exploiting the staggered adoption of national AI strategies across 85 countries, we find that these strategies raise the share of renewable energy in consumption and reduce the carbon intensity of output, but deliver no robust increase in green patenting. The green transition induced by AI policy appears to proceed through the energy structure before—and perhaps instead of—the innovation base. For policymakers, the implication is that AI strategies are not a substitute for dedicated green-innovation instruments: without complementary R&D support and demand-pull policies for clean technology, the innovation leg of the green transition may lag. Our design is deliberately conservative: we report rejected pre-trends, estimator disagreement, and weak placebo performance where they occur. Future work should revisit these questions with post-2021 data, within-country firm-level linkages between AI adoption and green patenting, and designs that separate strategy adoption from concurrent environmental policies.

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## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used generative AI tools to assist with literature verification, language editing, and drafting support. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## Data availability

The World Development Indicators (World Bank) and OECD patent statistics (ENV.EPI/DF_PAT_DEV) are publicly available. The AI strategy adoption coding, derived from the Stanford HAI AI Index Report 2023 and official government documents, and the replication codes are available from the corresponding author upon reasonable request.

## References

[1] Damioli, G., Van Roy, V., Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review, 11*(1), 1–25. https://doi.org/10.1007/s40821-020-00172-8

[2] Yang, C.-H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy, 51*(6), 104536. https://doi.org/10.1016/j.respol.2022.104536

[3] Aldasoro, I., Gambacorta, L., Pal, R., Revoltella, D., Weiss, C., Wolski, M. (2026). AI adoption, productivity and employment: Evidence from European firms. BIS Working Papers No. 1325, Bank for International Settlements, Basel.

[4] Radu, R. (2021). Steering the governance of artificial intelligence: National strategies in perspective. *Policy and Society, 40*(2), 178–193. https://doi.org/10.1080/14494035.2021.1929728

[5] Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Ngo, H., Niebles, J. C., Parli, V., Shoham, Y., Wald, R., Clark, J., Perrault, R. (2023). The AI Index 2023 annual report. AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA.

[6] Zhong, K., Song, L. (2025). Artificial intelligence adoption and corporate green innovation capability. *Finance Research Letters, 72*, 106480. https://doi.org/10.1016/j.frl.2024.106480

[7] Weng, M. (2025). Green innovation through artificial intelligence technology: Enhancing environmental, social, and governance performance. *Finance Research Letters, 75*, 106921. https://doi.org/10.1016/j.frl.2025.106921

[8] Zhou, X., Li, G., Wang, Q., Li, Y., & Zhou, D. (2025). Artificial intelligence, corporate information governance and ESG performance: Quasi-experimental evidence from China. *International Review of Financial Analysis, 102*, 104087. https://doi.org/10.1016/j.irfa.2025.104087

[9] Zhong, J., Zhong, Y., Han, M., Yang, T., & Zhang, Q. (2024). The impact of AI on carbon emissions: Evidence from 66 countries. *Applied Economics, 56*(25), 2975–2989. https://doi.org/10.1080/00036846.2023.2203461

[10] Shang, Y., Raza, S. A., Huo, Z., Shahzad, U., & Zhao, X. (2023). Does enterprise digital transformation contribute to the carbon emission reduction? Micro-level evidence from China. *International Review of Economics & Finance, 86*, 1–13. https://doi.org/10.1016/j.iref.2023.02.019

[11] Lin, B., & Zhu, Y. (2025). The impact of artificial intelligence policy on green innovation of firms. *Energy Economics, 148*, 108524. https://doi.org/10.1016/j.eneco.2025.108524

[12] Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights into the past, current, and future trajectories. *Journal of Management Studies, 58*(5), 1159–1197. https://doi.org/10.1111/joms.12639

[13] Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics, 225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

[14] Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics, 225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

[15] Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics, 225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

[16] Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A., & Sant'Anna, P. H. C. (2026). Difference-in-differences designs: A practitioner's guide. *Journal of Economic Literature, 64*(2), 498–557. https://doi.org/10.1257/jel.20251650

DOI: 10.54254/2755-2721/2026.38687

[17] Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives, 31*(2), 87–106. https://doi.org/10.1257/jep.31.2.87
[18] Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics, 11*, 685–725. https://doi.org/10.1146/annurev-economics-080217-053433
[19] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal, 21*(1), C1–C68. https://doi.org/10.1111/ectj.12097
[20] Baiardi, A., & Naghi, A. A. (2024). The value added of machine learning to causal inference: Evidence from revisited studies. *The Econometrics Journal, 27*(2), 213–234. https://doi.org/10.1093/ectj/utae004
[21] OECD. (2023). Environment-related technology patent statistics (ENV.EPI, DF_PAT_DEV). *OECD Environment Statistics (database)*, OECD Publishing, Paris. https://stats.oecd.org
[22] World Bank. (2024). World development indicators. *World Bank*. https://databank.worldbank.org/source/world-development-indicators, Washington, DC.