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Can Artificial Intelligence Fix Bad Environmental Regulation? Evidence from Green Total Factor Productivity in China

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Abstract. Environmental regulation is often assumed to work the same way regardless of how it is designed — yet this study shows that command-and-control and market-incentive instruments pull green productivity in opposite directions, and that artificial intelligence (AI) does not treat them equally either. Drawing on panel data from 281 Chinese prefecture-level cities over 2012–2024, this study finds that command-and-control regulation, measured through text analysis of local government work reports, significantly suppresses green total factor productivity (GTFP) by raising compliance costs, while market-incentive regulation, measured as the ratio of pollutant discharge fee revenue to GDP, significantly promotes it by channeling price signals into innovation. GTFP is estimated using the SBM-ML index, which incorporates labor, capital, and energy inputs together with industrial pollution as an undesirable output. Interaction-term estimates further show that local AI development attenuates the negative effect of command-and-control regulation while amplifying the positive effect of market-incentive regulation — AI acts as a "buffer" for coercive regulation and an "amplifier" for market-based regulation, rather than a uniform productivity booster. The findings suggest that AI cannot simply substitute for well-designed environmental policy, but it can make both good and bad policy design matter less — or more — than they otherwise would.

Keywords: *environmental regulation; green total factor productivity; artificial intelligence; digital economy; moderating effect*

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1. Introduction

China's 2022 Party Congress work report explicitly calls for advancing green development and a harmonious coexistence between humanity and nature. Against this backdrop, green total factor productivity (GTFP) — an indicator that jointly accounts for economic growth and the resource-and-environmental cost of that growth — has become a central benchmark for reconciling economic expansion with ecological sustainability, and the question of how to raise it has drawn sustained policy and academic attention.

Environmental regulation is not a single policy lever but a family of instruments with different logics, and the literature has long disagreed about which logic actually raises productivity. Regulators rely principally on command-and-control (CAC) instruments — mandatory technical standards, emission limits, and administrative permits — and market-incentive instruments, such as pollutant discharge fees and emissions trading, but developing-country regulators often lack the capacity to implement, monitor, and enforce either type consistently [1]. Porter argued that well-designed regulation can pay for itself by inducing efficiency-enhancing innovation [2], [3], yet subsequent panel-data evidence found only a weak link between compliance spending and measured innovation output [4].

Evidence from China largely mirrors this ambiguity: some studies find environmental regulation improves GTFP through digital-economy channels [5], others link government environmental governance to high-quality growth without a clear productivity dividend [6], and still others show that market-based instruments such as pollutant discharge permit trading raise energy-use efficiency even where command-and-control tools do not [7]. What is largely missing is a joint test of both instrument types within the same empirical framework — and an account of how a rapidly diffusing general-purpose technology might be changing the calculus for each.

Read together, this literature shows two consistent patterns rather than a single verdict. First, the debate has shifted over time from asking whether environmental regulation helps productivity in the aggregate — the original Porter-hypothesis exchange [2], [3] contested by [4] — toward asking which instrument does

so, since command-and-control and market-incentive tools rest on different behavioral logics and, on the China evidence summarized above, do not even share the same sign of effect [5], [6], [7]. Second, despite this shift toward instrument-specific analysis, almost every study still estimates command-and-control and market-incentive regulation in separate models, separate samples, or separate papers rather than jointly, which leaves open how a city government should weigh investment in one instrument against the other when, as in virtually every Chinese city, both are simultaneously in force. Table 1 places these studies and the AI-related evidence discussed next side by side to make this trajectory explicit.

Table 1. Representative Studies on Environmental Regulation, Artificial Intelligence, and (Green) Total Factor Productivity

Study	Data & Method	Regulatory Instrument(s)	Role of AI	Key Finding	Relation to This Study
Porter & van der Linde [2], [3]	Conceptual / cross-industry	Regulation (undifferentiated)	Not considered	Well-designed regulation can induce offsetting "innovation compensation"	Untested empirically at the instrument level
Jaffe & Palmer [4]	US panel, compliance spending vs. patents	Aggregate compliance cost	Not considered	Weak link between compliance spending and innovation output	Predates instrument disaggregation and AI
Blackman, Li & Liu [1]	Cross-country review, developing economies	CAC and market reviewed jointly	Not considered	Monitoring / enforcement capacity constrains both instrument types	No productivity outcome or AI channel tested
Song & Qi [5]; Shi & Li [7]	China city panel	CAC (digital-economy channel) / market (permit trading), studied separately	Not considered	Instrument-specific effects differ, but each is modeled alone	No joint CAC-vs-market test in one framework
Xie et al. [23]; Yang & Liu [24]	China province/city panel, EBM / DEA	Aggregate ER index, entered as moderator of AI's effect	Industrial-intelligence index	ER attenuates ("substitutes for") AI's gains; AI raises GTFP only past an ER threshold	ER left undifferentiated; moderation runs ER→AI, not instrument-specific AI→ER
Tu et al. [25]; Jia et al. [26]; Wang et al. [27]; Zhang et al. [28]	China city/province panel, text-mining of work reports	Government "attention" (frequency, TF-IDF, weighted-dictionary, Word2vec)	Not modeled	Attention indices predict green/productivity outcomes; measurement moves toward semantic, weighted methods	Attention proxy not benchmarked against a market-incentive counterpart; no AI-moderation test
This study	China prefecture-city panel; SBM-ML DEA + Python NLP text index + AI-enterprise count	CAC (text-based) and market-incentive (fee-based), modeled jointly	AI development level, tested as an asymmetric moderator of each instrument	Reported in Section 3	Disentangles CAC and market-incentive instruments in one framework; tests asymmetric AI moderation of each; documents the CAC text-mining pipeline (Sec. 2.2)

That technology is artificial intelligence (AI). A separate and fast-growing literature shows that AI-driven automation reshapes productivity and factor demand well beyond the environmental domain [8], and, closer to this paper's concern, that AI adoption is associated with higher green total factor productivity in Chinese cities and firms through channels such as industrial-structure upgrading, green innovation, and reduced resource misallocation [9], [10], [11], [12]. What this literature has not yet resolved is whether AI's productivity dividend is uniform across regulatory environments, or whether it interacts differently with coercive versus price-based instruments — a question that matters because the two instrument types work through very different mechanisms and, on the evidence above, do not even have the same sign of effect on productivity to begin with.

A closely related and more recent strand tests this interaction directly, but from the opposite direction and with an undifferentiated regulation measure: Xie et al. [23] enter environmental regulation as a moderator of industrial intelligence's effect on GTFP and find a substitution effect — stronger regulation attenuates AI's productivity gains — while Yang and Liu [24] find that industrial intelligence raises GTFP only once regulatory stringency crosses a threshold. Both studies confirm that AI and environmental regulation interact, which motivates H2 below, but both treat "environmental regulation" as a single aggregate index and place it as the moderator of AI's effect rather than asking whether AI moderates regulation differently depending on the instrument's own logic. Since command-and-control and market-incentive instruments have already been shown to pull GTFP in opposite directions [5]–[7], collapsing them into one aggregate index in an AI-interaction model risks averaging over two effects that may not just differ in magnitude but in sign — precisely the ambiguity this study is designed to resolve.

This leaves three specific gaps that motivate the present study. First, no study to date jointly estimates command-and-control and market-incentive regulation's effects on GTFP alongside an AI-moderation test for each, within a single empirical framework and sample; existing work either compares instruments without an AI channel [5]–[7] or tests an AI channel without disaggregating instruments [23], [24]. Second,

because the sign of the regulation–productivity relationship is instrument-specific, an aggregate AI×regulation interaction term cannot distinguish a genuine "buffer" role (AI softening a harmful effect) from an "amplifier" role (AI strengthening a beneficial one) — a distinction with directly opposite policy implications that this study's instrument-specific interaction terms (models 3–6) are designed to recover.

Third, on the measurement side, the government-work-report text-mining literature has moved from simple keyword-frequency ratios [13] toward semantically weighted and machine-learning-based measures of policy attention [25]–[28]; this study's command-and-control index sits within that methodological lineage, and Section 2.2 documents the full natural-language-processing pipeline — corpus construction, Chinese segmentation, stopword filtering, sentence-level keyword matching, and index computation — used to construct it, together with the alternative, more semantically rich measures this pipeline could be extended toward in future work.

This study addresses these three gaps by jointly modeling both regulatory instruments, testing their interaction with local AI development separately, and detailing the text-based construction of the command-and-control measure that much of the existing literature treats as a black box.

This gap matters because AI-enabled data collection, monitoring, and predictive analytics are increasingly embedded in environmental governance, and could plausibly change both how costly compliance is for regulated firms and how efficiently market-based instruments transmit price signals into innovation decisions. Whether AI complements or substitutes for a given regulatory tool has direct implications for how governments sequence environmental policy alongside digital-economy investment — pouring AI resources into monitoring a command-and-control regime is a very different policy bet than pouring them into an emissions-trading platform, and the evidence to tell them apart has been thin.

Using panel data from 281 Chinese prefecture-level cities from 2012 to 2024, this study (1) tests the direct effects of command-and-control and market-incentive environmental regulation on GTFP, and (2) tests whether the level of local AI development moderates each of these effects differently. The remainder of the paper is organized as follows. Section 2 develops the theoretical framework and hypotheses, describes variable measurement, and presents the empirical model. Section 3 reports and discusses the regression results. Section 4 concludes with a discussion of policy implications and limitations.

2. Method

2.1 Theoretical Framework and Research Hypotheses

Command-and-control environmental regulation typically intervenes directly in firms' production decisions by imposing mandatory technical standards, emission ceilings, or administrative licensing requirements. According to compliance-cost theory, meeting these requirements forces firms to divert resources that could otherwise fund productivity-enhancing technical innovation, and regulators in developing economies often lack the monitoring capacity to enforce such standards efficiently, which raises the cost of compliance further without necessarily improving environmental outcomes [1]. Rigid, uniform standards can also discourage firms from pursuing abatement effort beyond the mandated threshold, producing an insufficient "innovation compensation" effect and thereby constraining GTFP growth [5], [6].

Market-incentive environmental regulation instead internalizes environmental externalities into firms' operating costs through price signals and market mechanisms, encouraging firms to lower abatement costs — or even gain a first-mover advantage — by developing green technology and optimizing production processes [2], [3]. Because firms retain flexibility to choose their own cost-minimizing abatement path, this type of regulation can simultaneously improve environmental performance and raise productivity and competitiveness, a pattern consistent with firm- and city-level evidence that carbon-pricing and emissions-trading pilots raise total factor productivity in China [18], [19], [20], [21].

The rapid development of the digital economy is opening new pathways for how environmental regulation is enforced. Command-and-control regulation traditionally relies on government-mandated standards and inspection, which are vulnerable to information lags and coarse-grained monitoring — a capacity constraint that is especially binding in exactly the kind of rapidly industrializing settings this study examines [1] — pushing firms toward reactive, box-ticking compliance strategies that raise compliance costs and drag down productivity. AI-driven big-data analytics and Internet-of-Things technology can enable real-time collection, transmission, and verification of environmental data, lowering government information-gathering and enforcement costs.

This narrows the scope for firms to exploit information asymmetries to evade regulation, pushing them from passive compliance toward proactive innovation, which should dampen the productivity-suppressing

effect of command-and-control regulation. Predictive models can also help regulators dynamically adjust policy and avoid the resource misallocation associated with "one-size-fits-all" rules — consistent with city-level evidence that AI development interacts with environmental-governance regimes rather than acting on GTFP in isolation [10], [14].

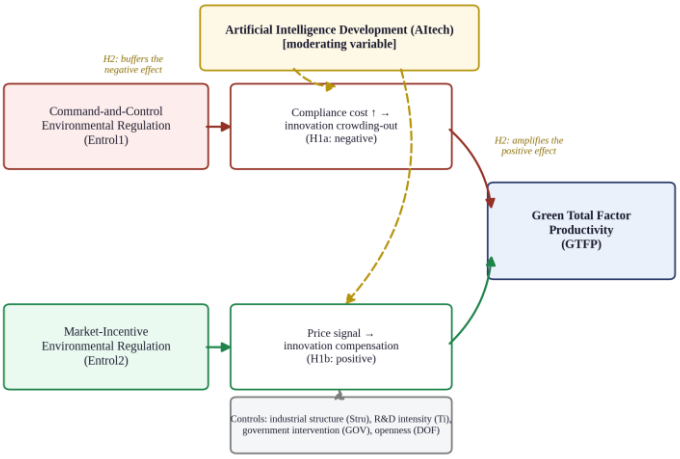


Figure 1. Conceptual framework linking environmental regulation, artificial intelligence, and green total factor productivity

Market-incentive regulation, in turn, depends on the efficiency of price signals and market activity to induce innovation, and its effectiveness hinges on how efficiently the underlying market operates and how freely information flows. AI technology can improve the precision and responsiveness of market mechanisms and thereby amplify the positive effect of market-incentive regulation on GTFP — a channel consistent with broader evidence that AI-driven automation reshapes firm productivity through better allocation of resources and faster diffusion of efficient technology [8], [9], [11], [12].

For instance, intelligent algorithms can integrate fragmented environmental-market data to improve the pricing and matching of emissions-trading schemes, and supply-demand-forecasting platforms can raise the real-time efficiency of emissions trading, lower transaction costs, and allocate abatement costs more rationally. This reinforces the innovation-compensation effect of market incentives, amplifying the returns firms capture from green innovation and encouraging higher R&D investment.

2.2 Construction of the Command-and-Control Regulation Index via Text Mining

Because Entrol1 is the study's core measure of command-and-control regulatory intensity and is built entirely from unstructured text rather than a published statistic, this subsection details the natural-language-processing (NLP) pipeline used to construct it, extending the brief description in [13] into the six stages summarized in Figure 2. The procedure follows the text-mining approach standard in the government-attention literature [13], [25]–[28], implemented in Python.

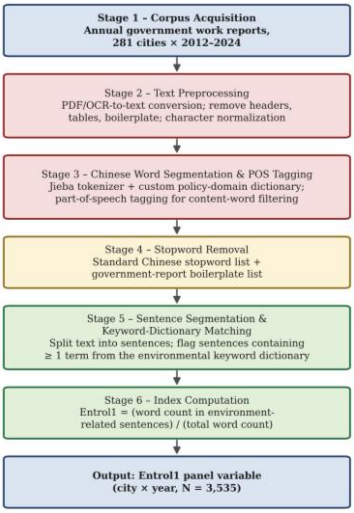


Figure 2. Python-based natural-language-processing pipeline

This dictionary-based, sentence-level counting procedure is deliberately conservative: it treats every dictionary hit as equally informative and does not weight sentences by semantic intensity, sentiment, or policy-instrument specificity. More recent work in this literature has moved toward richer alternatives — TF-IDF-weighted keyword extraction [28], weighted-dictionary methods that score semantic strength rather than raw frequency [27], and unsupervised Word2Vec embeddings that measure attention as semantic similarity to a concept vector rather than exact-string matching [26]. Because these alternatives can shift both the level and the ranking of the resulting index, Entrol1 as constructed here should be read as a transparent, replicable baseline measure of command-and-control intensity rather than the only defensible one, and a natural robustness extension would recompute Entrol1 under a TF-IDF or embedding-based weighting scheme and re-estimate models (1) and (3) to confirm that the sign and significance of Entrol1 and Entrol1×AItech are not artifacts of the counting rule chosen at Stage 5.

2.3 Variable Definition and Measurement

The dependent variable is green total factor productivity (GTFP). Following the slacks-based measure of efficiency [16] and its extension to the Malmquist-Luenberger index in the presence of undesirable outputs [17], this study treats labor, capital, and energy as inputs, regional GDP as the desirable output, and industrial sulfur dioxide, industrial soot and dust, and industrial wastewater discharge as undesirable outputs, and estimates GTFP using the SBM-ML index method.

The core explanatory variable is environmental regulation. Prior studies typically classify environmental regulation into administrative-command and economic-constraint forms; this study focuses on the command-and-control and market-incentive types. Command-and-control regulation (Entrol1) is measured by the frequency of environment-related terms in local government work reports, which is widely used to capture the degree of policy emphasis local governments place on environmental governance; Section 2.2 details the Python-based text-mining pipeline used to construct this index from the text of local government work reports. Market-incentive regulation (Entrol2) is measured as the ratio of pollutant discharge fee revenue to GDP. Because city-level discharge-fee data are frequently missing, and because this fee is levied primarily on industrial wastewater discharge, this study follows the weighting approach of [14]: provincial discharge-fee totals are disaggregated to the city level using each city's share of its province's industrial wastewater discharge as the weight.

The moderating variable is the level of local AI development (AItech), proxied by the number of registered AI enterprises in each city, since AI firms are the primary agents that develop and apply AI technology. Following [15], the control variables are industrial structure (Stru), R&D investment intensity (Ti), government intervention (GOV), and the degree of economic openness (DOF). Table 2 summarizes the definition and measurement of all variables.

Table 2. Definition and Measurement of Key Variables

Variable	Symbol	Measurement
Green total factor productivity	GTFP	SBM-ML index; inputs: labor, capital, energy; desirable output: regional GDP; undesirable outputs: industrial SO_2, soot and dust, and wastewater discharge
Command-and-control regulation	Entrol1	Share (by word count) of environment-related sentences in municipal government work reports, obtained through Python-based text segmentation
Market-incentive regulation	Entrol2	Ratio of pollutant discharge fee revenue to GDP; missing city data imputed from provincial totals weighted by each city's share of provincial industrial wastewater discharge
AI development level (moderator)	AItech	Number of registered AI enterprises in the city
Industrial structure	Stru	Control variable
R&D investment intensity	Ti	Control variable
Government intervention	GOV	Control variable
Degree of openness	DOF	Control variable

2.4 Model Specification

To test H1a and H1b, this study specifies models (1) and (2):

$$GTFP_{it} = \alpha_0 + \alpha_1 Entrol1_{it} + \Sigma City + \Sigma Year + \text{Controls}_{it} + \varepsilon_{it} \quad (1)$$

$$GTFP_{it} = \beta_0 + \beta_1 Entrol2_{it} + \Sigma City + \Sigma Year + \text{Controls}_{it} + \varepsilon_{it} \quad (2)$$

where $GTFP_{it}$ is the dependent variable, $Entrol1_{it}$ and $Entrol2_{it}$ are the core explanatory variables (command-and-control and market-incentive regulation, respectively), $Controls_{it}$ is the vector of control variables, *City* and *Year* denote city and year fixed effects, and ε_{it} is the idiosyncratic error term.

To test H2, interaction terms between environmental regulation and AI development are added, yielding models (3) and (4):

$$GTFP_{it} = \gamma_0 + \gamma_1 Entrol1_{it} + \gamma_2 AItech_{it} + \gamma_3 Entrol1_{it} \times AItech_{it} + \Sigma Controls_{it} + \varepsilon_{it} \quad (3)$$

$$GTFP_{it} = \omega_0 + \omega_1 Entrol2_{it} + \omega_2 AItech_{it} + \omega_3 Entrol2_{it} \times AItech_{it} + \Sigma Controls_{it} + \varepsilon_{it} \quad (4)$$

where $AItech_{it}$ is the moderating variable (AI development level), and γ_0, γ_1, γ_2, γ_3, ω_{0-3} are parameters to be estimated.

3. Results and Discussion

3.1 Baseline Regression Results

Table 3 reports the estimation results for all six models. In columns (1) and (2), the baseline specifications, the coefficients on command-and-control regulation (Entrol1) and market-incentive regulation (Entrol2) are both significant at the 1% level after controlling for a set of macro-level covariates and city/year fixed effects. Command-and-control regulation carries a negative coefficient (−0.039, t = −3.40), consistent with H1a: firms bearing the cost of meeting mandatory standards and administrative licensing tend to satisfy the minimum compliance threshold rather than proactively pursue green transformation, while the informational and monitoring burden the policy places on local government further dampens productivity — a pattern consistent with the capacity constraints documented for command-and-control enforcement in developing economies more broadly [1].

Market-incentive regulation carries a positive coefficient (0.139, t = 4.24), consistent with H1b: pollutant discharge fees and emissions-trading mechanisms provide a continuous incentive for firms to adopt cleaner technology and improve efficiency, which supports GTFP growth. The direction and rough magnitude of this effect line up with firm- and city-level estimates of emissions-trading schemes raising total factor productivity in China by roughly 5 to 22 percent [18], [19], [20], [21]. Both coefficients remain stable in sign, magnitude, and significance across columns (3)–(6), which add the AI interaction terms and the full set of controls, further supporting H1a and H1b.

Table 3. Regression Results of the Mechanism Test (dependent variable: GTFP)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Entrol1	−0.039***		−0.045***		−0.044***	
	(−3.40)		(−3.86)		(−3.77)	
Entrol2		0.139***		0.193***		0.199***
		(4.24)		(3.85)		(4.06)
Digieco	0.145***	0.087	0.156***	0.097		
	(3.36)	(0.92)	(4.45)	(1.02)		
Entrol1×AItech			0.199*		0.210**	
			(2.57)		(2.72)	
Entrol2×AItech				0.717***		0.734***
				(3.16)		(3.30)
Controls	Yes	Yes	No	No	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3535	3535	3535	3535	3535	3535
R^2	0.673	0.688	0.676	0.680	0.678	0.682

*Note: t-statistics in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively*

3.2 Moderating Effect of Artificial Intelligence

Columns (3) and (4) introduce the AI interaction terms without control variables, and columns (5) and (6) add the full set of controls. The coefficient on AI development level (AItech) is positive and significant at the 1% level in every specification, indicating that AI development is independently associated with GTFP growth — consistent with city- and firm-level evidence that AI adoption raises green and total factor productivity through innovation and resource-allocation channels [9], [10], [11], [12]. More importantly, the interaction term Entrol1×AItech is positive and significant (0.199 without controls, 0.210 with

controls), showing that as local AI adoption deepens, the productivity-suppressing effect of command-and-control regulation is significantly attenuated — consistent with AI reducing both firms' compliance costs and the government's monitoring and enforcement costs under command-and-control regulation, precisely the capacity bottleneck identified as central to CAC's weaker performance in developing settings [1], freeing up resources for green innovation.

The interaction term Entrol2×AItech is also positive and significant, and considerably larger in magnitude (0.717 without controls, 0.734 with controls), showing that AI development strengthens the positive effect of market-incentive regulation on GTFP. Figure 3 visualizes these four interaction coefficients. Together, these results support H2 and indicate that the moderating role of AI is asymmetric: AI does more to amplify a market-based instrument that is already working in the intended direction than it does to offset a coercive instrument working against it.

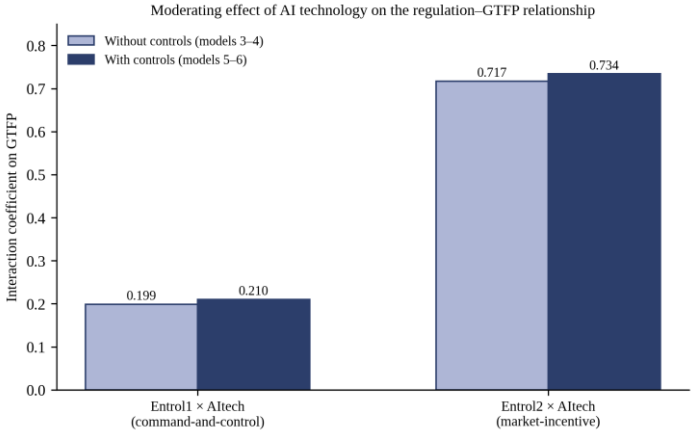


Figure 3. Moderating effect of AI technology on the regulation–GTFP relationship, with and without controls.

3.3 Discussion

These results indicate that the productivity effect of environmental regulation is instrument-specific, echoing evidence that regulation-productivity effects vary substantially across industries and firms rather than following a single sign [22]. Market-incentive regulation promotes GTFP mainly by channeling economic signals into firm-level green innovation and resource reallocation, while command-and-control regulation constrains GTFP because of the compliance costs and enforcement burden it imposes. AI technology plays a distinct role in each channel: for market-incentive regulation, AI functions as an "amplifier" that strengthens the innovation-inducing effect of price signals; for command-and-control regulation, AI functions as a "buffer" that lowers compliance and monitoring costs and softens — without fully reversing — the negative effect. In other words, AI is not a universal fix for weak environmental policy: it narrows the gap between well-designed and poorly designed instruments rather than closing it.

These findings should be interpreted with several caveats in mind. The AI-enterprise count used to proxy AItech captures the scale of the local AI industry rather than the intensity with which AI is actually applied inside environmental governance or regulated firms, so the estimated moderating effect may partly reflect the broader economic development that co-occurs with AI clustering. In addition, the number of AI enterprises is unlikely to be strictly exogenous to city-level productivity and regulatory capacity, so the interaction coefficients reported here are best read as conditional associations rather than clean causal moderation effects unless supported by an explicit identification strategy (e.g., an instrument for local AI development or a quasi-experimental design, in the spirit of the causal designs used to identify the productivity effects of automation and emissions trading elsewhere in this literature [8], [18]). Future work could test the robustness of these findings using alternative AI-intensity proxies, such as AI-related patents or firm-level AI-adoption surveys, together with an explicit identification strategy for the AI variable.

4. Conclusion

Using panel data from 281 Chinese prefecture-level cities for 2012–2024, this study examines how command-and-control and market-incentive environmental regulation affect GTFP and how the level of local AI development moderates each relationship. Three findings emerge. First, the productivity effect of environmental regulation depends on the policy instrument used: market-incentive regulation significantly promotes GTFP by channeling economic signals into firm-level green innovation and resource

optimization, while command-and-control regulation significantly suppresses GTFP because of the compliance costs and enforcement burden it imposes on firms and local government alike. Second, AI development is independently and positively associated with GTFP. Third, AI plays an asymmetric moderating role: it functions as a "buffer" that softens the negative effect of command-and-control regulation, and as an "amplifier" that strengthens the positive effect of market-incentive regulation.

These findings suggest a differentiated policy pathway for aligning environmental governance with the diffusion of AI. Rather than applying a single "one-size-fits-all" strategy, city governments seeking to accelerate green productivity growth may gain more from investing in AI-enabled monitoring, disclosure, and emissions-trading infrastructure — which directly reinforces the price-signal channel — while using AI-based risk profiling and dynamic standard-setting to reduce the compliance burden that command-and-control regulation places on already-compliant firms. AI, on this evidence, is best understood not as a substitute for good regulatory design but as a multiplier of whatever design choice a government has already made.

The results reported here are based on observational panel data and interaction-term estimates and, as discussed above, do not by themselves establish that AI development causally moderates the regulation–productivity relationship. Future research could strengthen causal identification through instrumental-variable or quasi-experimental designs, test alternative measures of AI intensity, and extend the analysis beyond China to assess whether the buffering and amplifying roles of AI generalize to other regulatory and institutional settings.

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