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Technology dividend or governance black box? Digital transformation and ESG performance in Chinese energy firms

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Abstract. Using 610 firm-year observations on 122 Chinese listed energy firms over 2020–2024, this paper examines the relationship between digital transformation and ESG performance, the mediating role of internal control quality and the moderating role of government subsidies. Digital transformation is positively associated with ESG performance in the controlled specification (coefficient 0.138, $t = 2.32$). Internal control quality carries a significant indirect effect of 0.035 (95% CI [0.008, 0.063]), while the direct effect becomes insignificant. Government subsidies strengthen the association (interaction coefficient 0.0452, $t = 2.34$). Industry analysis shows a stronger association in gas utilities than in power generation. The estimate becomes insignificant with firm fixed effects, and several alternative specifications are also insignificant; the findings therefore support a conditional association rather than a causal effect. The results highlight governance upgrading and the scale of public support as relevant considerations in energy-sector digitalisation.

Keywords: digital transformation, ESG performance, energy firms, internal control quality, government subsidies, mediation effect

1. Introduction

Global climate governance has moved from scientific consensus to institutional implementation. The emission-reduction pathway set out under the United Nations Framework Convention on Climate Change and China's own "dual carbon" timetable jointly constitute the external constraint on the transformation of the energy system. Because China's resource endowment has long been coal-dominated, its carbon emissions are heavily concentrated in energy production and conversion, and the pace of decarbonisation in the energy sector consequently governs the pace at which the national targets can be met.

Running parallel to this institutionalisation is the deepening embedding of digital technology in the energy sector. The combination of smart sensors, edge computing and the industrial internet has shifted dispatch from experience-based to data-driven operation, allowing unit efficiency, line losses and emission intensity to be optimised in real time, while digital twins and predictive maintenance extend the service life of key equipment. More importantly, digital technology has changed how environmental information is produced. Energy consumption and emission data that were once compiled manually after the fact are now captured

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automatically by internet-of-things devices and calculated on a consistent basis, which both narrows the scope for selective disclosure and lowers the cost of external verification. The effect of digitalisation therefore extends beyond production efficiency to reshape the production and transmission of ESG information—an observation that provides the initial rationale for treating governance rather than technology as the core mechanism.

Whether digital transformation actually raises the ESG performance of energy firms is, however, unresolved. One strand of work emphasises a "technology dividend": by optimising processes, improving resource allocation and strengthening information transmission and risk identification, digital technology supplies a new source of ESG improvement and can systematically reshape green innovation capacity. A second strand stresses a "cost constraint": digitalisation demands continuous investment in infrastructure, systems and organisational change, and for capital-intensive energy firms with specific assets and long replacement cycles such investment may compete with green governance for scarce resources in the short run.

Two gaps motivate this study. First, most studies concentrate on financial performance, innovation efficiency and total factor productivity, leaving the non-financial ESG dimension comparatively neglected, and the work that does address ESG rarely goes beyond estimating a main effect. Second, the functional status of internal control is contested: some studies treat it as a transmission channel through which digitalisation first improves the information environment and control quality and only then affects ESG, whereas others treat it as a contextual condition that amplifies the ESG effect of digitalisation.

This paper addresses three questions: whether digital transformation is associated with ESG performance, whether internal control quality mediates this association, and whether government subsidies moderate it. This study estimates panel regressions, bootstraps the indirect effect, and tests a mean-centred subsidy interaction. Alternative measures, sample restrictions and endogeneity checks assess the sensitivity of the results.

The paper contributes in three respects. It focuses on the energy sector, a setting of high carbon intensity and strong regulation in which the marginal effect of digitalisation on ESG is likely to differ systematically from that in the full sample or in manufacturing, and for which the structural features of capital intensity and asset specificity have not been well captured. It re-specifies internal control from a moderator, as treated in much of the existing literature, to a mediator, thereby providing fresh evidence on the "digitalisation–governance–ESG" pathway and addressing the disagreement over its functional status. Finally, it incorporates government subsidies into a unified framework and adjudicates between the competing predictions of synergy and crowding-out, supplying an empirical basis for the design of fiscal instruments.

2. Literature review and hypotheses

2.1. Economic consequences of digital transformation

Digital transformation is commonly defined as the reconstruction of processes, products and business models through big data, artificial intelligence, cloud computing and blockchain, accompanied by upgrades in leadership and management practice [1]. Its measurement has converged on textual indicators built from annual reports: Wu et al. [2] construct a five-dimensional lexicon covering artificial intelligence, cloud computing, blockchain, big data and digital technology applications, and take the log of the summed keyword frequency, whereas Yuan et al. [3] count the occurrence of some two hundred policy-derived terms.

On efficiency, digital technology has been shown to reduce search costs, accelerate decision-making and improve factor allocation. Liu et al. [4] find that the digitalisation of management raises input-output efficiency, while Qi and Cai [5] show that the performance consequences for manufacturers are multiple rather than uniformly positive. On innovation, Jin et al. [6] document a positive effect on green innovation among

Chinese manufacturers, and Shen and Tan [7] identify parallel "incremental" and "quality-enhancing" effects. On organisational boundaries, Yuan et al. [3] find that digitalisation lowers external transaction costs and pushes firms towards specialisation rather than vertical integration, Li et al. [8] trace its diffusion along supply chains, and Yi et al. [9] document a performance-driving effect in capital markets. Digitalisation is not, however, unambiguously beneficial. Pang and Liu [10] describe a "digitalisation–innovation paradox" that depends on absorptive capacity, Wang et al. [11] counterpose "data-driven" against "competence curse" trajectories, and Lu et al. [12] report an inverted-U relationship between digitalisation and core technological capability. The economic consequences of digitalisation are thus conditional and non-linear.

More recently the focus has shifted from efficiency to governance. Digital technology renders environmental and social behaviour observable, traceable and verifiable, and thereby changes how ESG information is produced and transmitted. Yi et al. [13] established an early link between corporate governance and disclosure quality; in a digital setting this link is amplified, because authorisation, segregation of duties and similar controls move from manual execution to system-embedded routines, reducing both execution error and the scope for selective disclosure. Xiao et al. [14] provide supply-chain evidence that the digitalisation of customers raises the ESG performance of suppliers, implying a governance spillover that crosses firm boundaries, and Cao et al. [15] show through a resource-orchestration lens that what matters for green transformation is not the technology itself but how firms orchestrate digital resources.

2.2. Internal control and ESG performance

Among external factors, environmental regulation has received most attention. Li and Xiao [16] find that heterogeneous regulatory instruments generate differentiated incentives for green innovation, and Qi et al. [17] show, using green patent data, that emissions trading schemes induce green innovation. Li and Zhu [18] approach the question from the angle of information infrastructure and find that its improvement raises ESG performance. With respect to subsidies, Zhang et al. [19] use Chinese listed firms over 2010–2023 to show that subsidies promote green innovation and that ESG ratings encourage green R&D, with subsidies playing a significant moderating role and with pronounced differences between state-owned and private firms.

Among internal factors, ownership structure and financial condition dominate. Concentration of ownership affects CSR through the monitoring incentives and capacity of large shareholders, while leverage affects the resources available for ESG investment through repayment pressure. Notably, attention has begun to shift towards non-financial governance mechanisms. Yan et al. [20] find, for Chinese A-share firms over 2009–2021, that internal control quality is significantly associated with the level of ESG disclosure, most strongly in the governance dimension, and that media attention positively moderates the relationship, with negative coverage exerting the stronger influence. Their results, validated through lagged specifications, propensity score matching and instrumental variables, provide comparatively reliable evidence that internal control is an important antecedent of ESG.

Internal control is the system of arrangements and processes designed to secure operating efficiency, reliable financial reporting and compliance[1]. Agency theory identifies it as a core governance mechanism for mitigating conflicts of interest, constraining managerial opportunism and safeguarding the integrity of information [21].

[1] COSO (2013), Internal Control—Integrated Framework, Committee of Sponsoring Organizations of the Treadway Commission, Durham, NC. This institutional framework supplies supplementary background to the definition of internal control.

The literature disagrees on how to position internal control within the digitalisation–ESG relationship. One group treats it as a mediator. Hu et al. [22] find that digitalisation improves ESG performance by raising the level of internal control; Wang et al. [23], studying the energy sector, specify internal control quality, external market attention and government subsidies simultaneously as mediators and identify these as potential transmission channels; and Dai et al. [24] identify internal control as a channel linking reverse mixed-ownership reform to ESG performance.

A second group treats internal control as a moderator. In their study in the International Journal of Managerial Finance, Li et al. [1] specify green innovation capacity, information disclosure and investment efficiency as mediators but internal control and government regulation as moderators, finding that stronger internal control amplifies the positive effect of digitalisation on ESG.

The two specifications rest on different logics. If internal control mediates, digitalisation first improves the governance infrastructure and the effect is then transmitted to ESG through governance quality—a process mechanism. If it moderates, internal control is a pre-existing contextual condition that governs the efficiency with which digital investment is converted—a boundary condition. Related MSCI-based evidence also identifies innovation capability, information interaction and financial performance as channels linking digital transformation to ESG responsibility performance [25].

2.3. The moderating role of government subsidies

Institutional theory holds that strategic behaviour is embedded in an institutional environment that alters the costs and benefits of particular actions and hence their marginal effects [26]. Government subsidies operate through precisely this mechanism. Digital upgrading and green technology investment are both large in scale and long in payback, imposing a substantial financing burden on energy firms, and subsidies ease that constraint by supplementing cash flow and lowering project financing costs.

The effect of subsidies is not, however, uniformly positive. Prior work suggests that they can induce strategic compliance, with firms undertaking formalistic investment directed at visible elements rather than substantive governance improvement—in the digital domain, heavy equipment purchase combined with light process re-engineering. Subsidies may also crowd out a firm's own spending on green and digital projects. Zhang et al. [19] find pronounced differences between state-owned and private firms in the effect of subsidies on green innovation, indicating substantial heterogeneity. Two competing predictions therefore coexist, "synergistic amplification" and "substitution crowding-out", and their relative strength is an empirical question.

2.4. Hypotheses

The resource-based view supplies the basic rationale for a positive association. Barney [27] argues that sustained competitive advantage derives from resources that are valuable, rare, difficult to imitate and non-substitutable, and digital capability satisfies all four criteria in the setting examined here. It is valuable because, once embedded in production and governance processes, digital systems generate a continuing flow of data assets and analytical capacity that supports efficiency improvement and risk identification. It is rare because few energy firms have achieved end-to-end digitalisation. It is difficult to imitate because digital capability embodies a large body of tacit knowledge and organisational routine with considerable causal ambiguity. And it is non-substitutable because digital infrastructure is tightly coupled with existing equipment, processes and personnel, giving it a path-dependent character that cannot easily be replicated in the short run.

The effect is moreover multi-levered. In the environmental dimension, smart sensors and real-time monitoring raise the precision with which energy use and emissions are managed; in the social dimension,

supply-chain traceability and compliance review improve the efficiency of social responsibility fulfilment; and in the governance dimension, data trails and automated disclosure enhance transparency and regulatory conformity. A single resource thus acts on all three pillars at once, making it an important source of ESG advantage. Existing evidence is consistent: Xue and Zhu [28], using Chinese listed energy firms over 2010–2023, find that digitalisation raises green total factor productivity both directly and indirectly through improved ESG performance, and Zhou et al. [29] confirm a positive effect of digitalisation on corporate sustainability among Chinese listed firms. The following hypothesis is therefore proposed:

H1. Digital transformation significantly improves the ESG performance of energy firms.

This study proposes that the effect operates to a considerable extent through internal control, for two reasons. First, digitalisation changes how control activities are executed. Through process standardisation, real-time data and controllable permissions, authorisation, segregation of duties and budgetary control move from manual execution to system embedding, compressing the space for human manipulation and reducing execution error and symbolic risk. Internal control thereby operates more effectively instead of remaining a textual artefact.

Second, digitalisation improves risk assessment and information communication. Digital technology allows firms to identify, assess and manage environmental, social and governance risks more promptly, and pushes internal control objectives from a traditional compliance orientation towards value creation. This extension creates a substantive connection between the control system and ESG management, because the reliability of the non-financial data on which ESG information rests depends directly on the rigour of control processes [20].

Taken together, the chain can be stated as follows. Digitalisation lowers the cost of producing internal information and the cost to outsiders of verifying it, making managerial behaviour more observable and allowing internal control to function more effectively; a well-functioning control system in turn sediments technical digital capability into institutional capability, shifting ESG investment from project-by-project response to routine governance, which finally registers as an improved rating.

H2. Internal control quality mediates the relationship between digital transformation and the ESG performance of energy firms.

This study expects the synergistic effect to dominate in the current Chinese energy context, for three reasons. First, subsidies are accompanied by process supervision that limits the scope for formalistic investment. Digital and green upgrading projects in energy firms are typically incorporated into local government assessments of industrial upgrading and energy saving, and awards are accompanied by relatively strict process monitoring and acceptance requirements. The finding of Sun et al. [30] that policy empowerment drives digitalisation illustrates that the effectiveness of institutional supply depends substantially on the rigour with which policy is executed.

Second, the specificity of energy assets raises the efficiency of fund conversion. Once deployed, digital systems cannot readily be redeployed elsewhere, which lowers the probability of arbitrage or diversion and raises the chance that funds are converted into genuine governance capability. Because green and digital investment in energy firms exhibits economies of scale, the marginal leverage of subsidy funds may be more pronounced.

Third, energy firms are generally larger and comparatively well governed, and thus possess the organisational conditions needed to convert external resources into internal capability. They are consequently more likely to direct subsidies towards substantive process re-engineering and governance upgrading rather than equipment purchase alone, a point that resonates with the finding of Wang et al. [23] that subsidies act as a channel for improving ESG performance in the energy sector.

H3. Government subsidies positively moderate the effect of digital transformation on the ESG performance of energy firms.

3. Data and methodology

3.1. Sample and data

The initial sample comprises all Chinese A-share listed energy firms over 2020–2024, covering oil, coal, power generation, gas and new energy. Following established practice, the sample excludes financial and insurance firms, observations carrying ST or *ST status, and observations with missing key variables, arriving at a balanced panel of 122 firms and 610 firm-year observations. The baseline regression uses 578 observations, the mediation test 561, the moderation test 544 and the lagged instrumental-variable specification 459.

ESG performance is measured by the Huazheng ESG rating, which is converted from the nine rating grades (C, CC, CCC, B, BB, BBB, A, AA, AAA) to scores from 1 to 9. Internal control quality is the DIB internal control index for Chinese listed firms. Digital transformation is taken from the CSMAR digital economy database and constructed as the natural logarithm of one plus the summed frequency of keywords across five dimensions: artificial intelligence, blockchain, cloud computing, big data and digital technology applications. Government subsidies are taken from the CSMAR government subsidy database, and financial and governance data are from CSMAR.

3.2. Variables

Control variables—To mitigate omitted variable bias, the models control for the growth rate of Management Expenses (MgmtG), Asset Turnover (Turnover), the Leverage Ratio (Lev) and Ownership Concentration (Top1), capturing operating efficiency, asset utilisation, financial risk and ownership structure respectively. Table 1 summarises the definitions, measurement and data sources of all variables.

Table 1. Variable definitions

Type	Variable	Symbol	Definition	Source
Dependent	ESG performance	ESG	Huazheng ESG rating converted to a 1–9 score	Huazheng
Independent	Digital transformation	DT	ln(total frequency of five keyword categories + 1)	CSMAR
Mediating	Internal control quality	IC	DIB internal control index	DIB
Moderating	Government subsidies	Subsidy	Total government subsidies (RMB 100 million)	CSMAR
Control	Management expense growth	MgmtG	(current − previous) / previous management expenses	CSMAR
	Asset turnover	Turnover	Operating revenue / average total assets	CSMAR
	Leverage ratio	Lev	Total liabilities / total equity	CSMAR
	Ownership concentration	Top1	Shareholding of the largest shareholder (%)	CSMAR

Notes: DT and Subsidy are mean-centred before the interaction term is constructed.

3.3. Model specification

To examine the association between digital transformation and ESG performance, this study estimates Equation (1):

$$ESG_it = \beta_0 + \beta_1 DT_it + \sum \beta_jControls_j, it + \varepsilon_it \quad (1)$$

To test H2, this study follows the three-step procedure of Wen et al. [31] and supplements it with bootstrap inference. Equation (2) estimates the association between digital transformation and internal control quality, while Equation (3) includes both variables to estimate their associations with ESG performance:

$$IC_it = \alpha_0 + aDT_it + \sum \beta_jControls_j, it + \varepsilon_it \quad (2)$$

$$ESG_it = c_0' + c'DT_it + bIC_it + \sum \beta_jControls_j, it + \varepsilon_it \quad (3)$$

To test H3, Equation (4) introduces a mean-centred interaction between digital transformation and government subsidies into the baseline model:

$$ESG_it = \beta_0 + \beta_1 DT_it + \beta_2 Subsidy_it + \beta_3 (DT_it \times Subsidy_it) + \sum \beta_jControls_j, it + \varepsilon_it \quad (4)$$

where i and t index firms and years, Controls is the vector of control variables, and ε is a random disturbance. Standard errors are heteroskedasticity-robust. Year fixed effects are assessed as a separate robustness check.

The main specifications emphasise between-firm associations, while year and firm fixed effects are examined in the sensitivity analyses. Firm effects control for time-invariant firm characteristics but absorb the cross-sectional variation central to this comparison. The firm-fixed-effects estimate is reported in Table 10, and interpretation is confined to conditional associations.

4. Empirical results

4.1. Descriptive statistics

Table 2 reports the descriptive statistics. The mean ESG score is 3.526 with a standard deviation of 1.331, corresponding to a rating between CCC and B, which indicates that Chinese listed energy firms perform moderately weakly on ESG and have considerable room for improvement.

Table 2. Descriptive statistics

Variable	*N*	Mean	SD	Min	Max
ESG score	610	3.526	1.331	0.0	8.0
Digital Transformation (DT)	580	0.737	0.799	0.0	3.664
Internal Control index (IC)	561	609.815	173.792	0.0	844.9
Government subsidies (RMB m)	548	11,149.6	29,654.5	2.4	275,370.6
Management expense growth	601	0.107	0.392	−0.852	5.343
Asset turnover	603	0.428	0.442	0.016	4.751
Leverage ratio	603	1.994	4.890	−31.809	74.911
Largest shareholder (%)	583	39.036	16.729	7.138	76.128

4.2. Correlation analysis

Table 3 reports positive pairwise correlations between digital transformation and ESG performance (r = 0.082), digital transformation and internal control quality (r = 0.101), and internal control quality and ESG

performance (r = 0.255). These descriptive associations motivate the regression analysis but do not establish mediation or causality.

Table 3. Correlation matrix

	ESG	DT	IC	Subsidy	MgmtG	Turnover	Lev	Top1
ESG	1							
DT	0.082**	1						
IC	0.255***	0.101**	1					
Subsidy	0.321***	0.015	0.160***	1				
MgmtG	−0.015	−0.001	0.100**	−0.002	1			
Turnover	−0.065	−0.022	0.059	−0.040	0.037	1		
Lev	−0.088**	−0.091**	−0.133***	0.060	−0.057	−0.038	1	
Top1	0.138***	−0.122***	0.256***	0.202***	0.035	−0.043	−0.034	1

Notes: ***, ** and * denote significance at the 1, 5 and 10 per cent levels. Coefficients are computed on the valid observations for each pair (pairwise deletion).

4.3. Baseline regression

Table 4 reports the unadjusted association on 580 firm-year observations; the controlled estimate of 0.138 is considered alongside the mediation and robustness analyses.

Digital transformation enters with a coefficient of 0.119 (t = 1.987, p = 0.047). With controls, the coefficient is 0.138 (t = 2.32), consistent with H1. These estimates describe conditional associations rather than within-firm causal effects.

Table 4. Baseline regression of digital transformation on ESG performance

Variable	Coefficient	Std. error	Standardised	t	p	VIF
Constant	3.588	0.065	—	55.167	0.000***	—
Digital transformation	0.119	0.060	0.082	1.987	0.047**	1.000
R^2	0.007					
Adjusted R^2	0.005					
F	F(1,578) = 3.947, p = 0.047					
Durbin–Watson	1.252					
N	580					

Notes: The dependent variable is the ESG score. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

4.4. Mediation analysis: internal control quality

Table 5 and Figure 1 report the estimates of Equations (2) and (3). The analysis follows the stepwise procedure of Wen et al. [31], estimating first the total effect of digitalisation on ESG performance, then its effect on internal control quality, and finally both together, comparing the direct and total effects to establish mediation.

Path a shows that digital transformation raises internal control quality by 20.550 points (t = 2.26, p = 0.024), significant at the 5 per cent level, with a standardised coefficient of 0.095. This accords with how digitalisation works: through process standardisation, real-time data and controllable permissions,

authorisation, segregation of duties and budgetary control move from manual execution to system embedding, leaving an auditable trail and raising the effectiveness of internal control.

Path b shows that internal control quality raises ESG performance by 0.002 points (t = 6.19, p < 0.001), significant at the 1 per cent level, with a standardised coefficient of 0.255, the largest of the three paths. Meanwhile the direct effect of digitalisation falls from a total effect of 0.123 to 0.088 and loses significance (t = 1.51, p = 0.132), indicating that its influence on ESG performance operates to a considerable extent through internal control: once control quality is held constant, the independent influence of digitalisation weakens markedly.

The bootstrap indirect effect is 0.035 with a 95 per cent confidence interval of [0.008, 0.063], supporting H2. The direct effect is insignificant, but this does not establish that internal control is the only transmission channel. The stepwise procedure identifies a statistical transmission relationship; causal mediation requires stronger assumptions [32].

Table 5. Mediation test: internal control quality

Path	Coefficient	Std. error	t	p	95% CI
c: DT → ESG (total effect)	0.123*	0.060	2.041	0.042	[0.005, 0.241]
a: DT → IC	20.550*	9.092	2.260	0.024	[2.691, 38.410]
b: IC → ESG (controlling DT)	0.002***	0.000	6.192	< 0.001	[0.001, 0.002]
a × b: indirect effect (bootstrap)	0.035*	0.014	2.503	0.012	[0.008, 0.063]
c′: DT → ESG (direct effect)	0.088	0.059	1.509	0.132	[−0.027, 0.204]

Notes: N = 561. The models control for year effects. Bootstrap intervals are percentile intervals; an interval excluding zero indicates a significant indirect effect. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

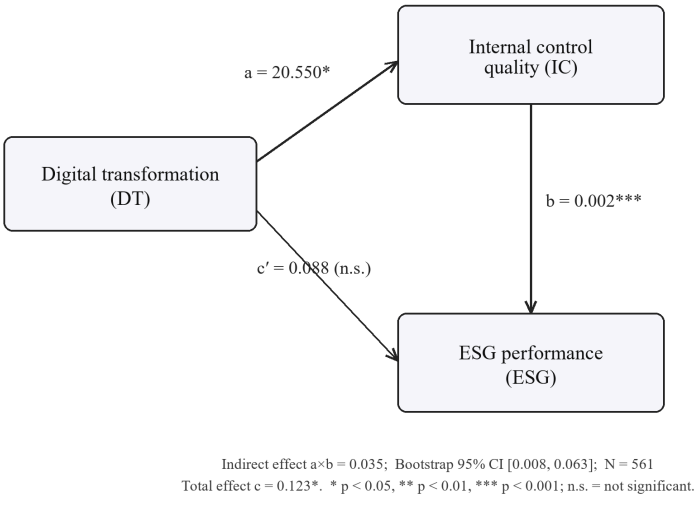


Figure 1. Mediation path through internal control quality

Notes: N = 561; ***, ** and * denote significance at the 1, 5 and 10 per cent levels; n.s. denotes not significant.

4.5. Moderation analysis: government subsidies

Table 6 and Figure 2 report the estimates of Equation (4) on 544 firm-year observations.

Both variables are mean-centred. This mitigates differences in scale and the collinearity between the interaction and its constituents, and it allows the main effect to be read as the effect of digitalisation at the mean level of subsidies. It should be noted that internal control quality and government subsidies play different roles in the model: the former lies on the causal chain between digitalisation and ESG performance and is a mediator, whereas the latter does not alter the chain itself but affects the strength of the relationship and is a moderator. The distinction, and the corresponding tests, follow Baron and Kenny [33], while the moderating effect is identified through the interaction and simple slopes recommended by Aiken and West [34].

In column (1) digital transformation enters with a coefficient of 0.1435 (t = 2.34, p = 0.020), significantly positive at the 5 per cent level and consistent with the baseline. In column (2) government subsidies enter with a coefficient of 0.1210 (t = 7.52, p < 0.001), significant at the 1 per cent level: each additional RMB 100 million of subsidy raises the ESG score by 0.121 points, so subsidies themselves improve ESG performance.

Once the interaction is included in column (3), it enters with a coefficient of 0.0452 (t = 2.34, p = 0.020), significantly positive at the 5 per cent level: each additional RMB 100 million of subsidy raises the marginal effect of digitalisation on ESG by 0.045 points. R^2 rises from 0.136 to 0.144 with an incremental F of 5.48 (p = 0.020); the gain in explanatory power is modest but statistically significant. Decomposing the effect into simple slopes, the slope of digitalisation is −0.014 (t = −0.18, p = 0.861) when subsidies are one standard deviation below the mean, essentially no promotion; 0.120 (t = 2.06, p = 0.040) at the mean; and 0.255 (t = 3.13, p = 0.002) one standard deviation above the mean, a markedly stronger effect. The ESG effect of digitalisation thus rises monotonically with the level of subsidy.

Table 6. Moderating effect of government subsidies (dependent variable: ESG score)

Variable	(1)	(2)	(3)
Digital transformation (centred)	0.1435**	0.1220**	0.1201**
	(2.34)	(2.08)	(2.06)
Government subsidies (centred, RMB 100 m)	—	0.1210***	0.1134***
		(7.52)	(6.95)
DT × Subsidy	—	—	0.0452**
			(2.34)
Controls	Yes	Yes	Yes
N	544	544	544
R^2	0.044	0.136	0.144
Adjusted R^2	0.036	0.126	0.133
ΔR^2	—	0.091	0.009
ΔF	—	56.61***	5.48**

Notes: All columns estimate Equation (4), corresponding respectively to excluding subsidies, adding the subsidy main effect, and adding the centred interaction. t statistics in parentheses. Controls comprise management expense growth, asset turnover, the leverage ratio and the largest shareholder's stake. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

This pattern is consistent with the direction of existing work. Li et al. [1] likewise use an interaction to characterise how external institutional conditions moderate the ESG effect of digitalisation and supplement it with simple-slope analysis; Zhang et al. [19] specify subsidies directly as a moderator and find that they amplify the conversion of ESG ratings into green innovation. On the mechanism, Guo [35] shows that subsidies perform a signalling function, transmitting information about project quality and policy support to

outside investors and drawing in subsequent social capital, which accords with the interpretation advanced here that subsidies relax financing constraints and amplify the ESG effect of digitalisation. Subsidies therefore act as a synergistic amplifier rather than a substitute.

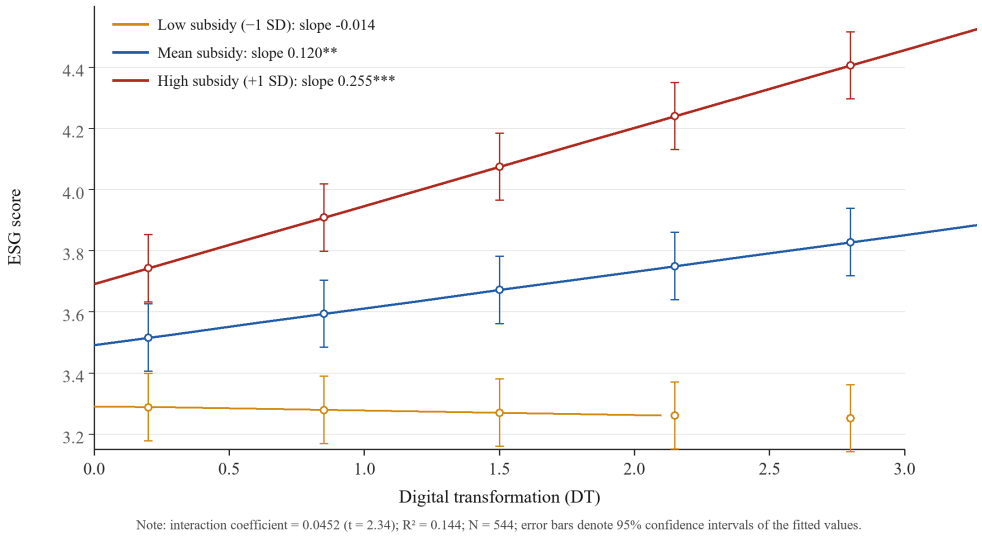


Figure 2. Moderating effect of government subsidies

Notes: The three lines show the fitted relationship between digital transformation and ESG performance at the mean and at plus or minus one standard deviation of government subsidies. Error bars denote 95 per cent confidence intervals of the fitted values. $N = 544$, ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

4.6. Industry heterogeneity

For industry membership, each firm is assigned the industry classification most recently disclosed over the sample period, which is extrapolated to all years. The sample is then divided into power and gas utilities—subject to stronger price regulation and emissions oversight—and neighbouring industries; results appear in Table 7. In the regulated subsample the coefficient on digital transformation is 0.171 ($t = 2.60$, $p = 0.010$), significant at the 1 per cent level, whereas in neighbouring industries it is 0.048 ($t = 0.37$, $p = 0.716$) and insignificant.

The source of this difference is not regulatory intensity as such. Splitting the regulated subsample further, the coefficient reaches 0.686 in gas production and supply ($t = 4.53$, $p < 0.001$) but only 0.029 in power and heat generation ($t = 0.40$, $p = 0.692$); a test of the difference in slopes shows that the gap of 0.647 is itself significant at the 1 per cent level ($t = 4.16$).

Table 7. Industry heterogeneity (dependent variable: ESG score)

Panel A: subsample regressions					
Subsample	DT coefficient	*t*	*p*	Firms	*N*
Power and gas (regulated)	0.1707***	2.60	0.010	110	528
Neighbouring industries	0.0479	0.37	0.716	10	50

Table 7. Continued

Panel B: disaggregating the regulated sector					
Subsample	DT coefficient	*t*	*p*	Firms	*N*
Power and heat generation	0.0288	0.40	0.692	80	386
Gas production and supply	0.6856***	4.53	0.000	30	142
Panel C: tests of slope differences					
Test	Coefficient difference	Std. error	*t*	*p*	
DT × Gas (base: power)	0.6466***	0.1556	4.16	0.000	
DT × Neighbouring (base: power)	0.0212	0.1661	0.13	0.899	

Notes: All columns control for management expense growth, asset turnover, the leverage ratio and the largest shareholder's stake. Industry classification is extrapolated from each firm's most recent disclosure to all years. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

4.7. Robustness checks

To assess the sensitivity of the baseline result to measurement and specification, and following Li et al. [1], this study conducts robustness checks on three fronts: alternative measures of the explanatory variable, alternative measures of the dependent variable, and other specifications. Results appear in Tables 8 and 9.

Alternative measures of digital transformation—Digitalisation is re-measured in four ways. First, a dummy for whether the firm discloses any digital keyword enters with a coefficient of 0.2664 (t = 2.80, p = 0.005), significant at the 1 per cent level. Second, raw keyword frequency enters positively (0.0132) but insignificantly (p = 0.268), confirming that the raw distribution is heavily right-skewed and that the logarithmic transformation is necessary. Third, using ln(frequency) without adding one and dropping zero observations yields a positive but insignificant coefficient (0.0084, p = 0.914), reflecting the fall in sample size to 330 observations after removing 248 zero-frequency cases and the consequent loss of power. Fourth, adding the square of DT yields a significant positive linear term (0.3659, t = 2.48, p = 0.013) and a quadratic term of −0.1026 (t = −1.69, p = 0.092), indicating a marginally significant inverted-U pattern, so that the marginal ESG return to digitalisation declines at higher levels although the overall effect remains positive across the observed range.

Alternative measures of ESG—Rating agencies differ in scoring criteria, industry adjustments and data sources, which may introduce noise into the ESG measure. Two alternative measures are therefore adopted. Converting the ESG score into a within-year percentile rank yields a coefficient of 0.0339 (t = 2.57, p = 0.010), significant at the 5 per cent level. Dichotomising ESG at the within-year median and estimating a logit model yields a positive but insignificant coefficient (0.1455, p = 0.259), which may reflect the loss of ordinal information and the reduced variation induced by dichotomisation. Taken together, the positive effect of digitalisation survives under both the continuous and the rank measure, which retain the ordinal information in the rating.

Other specifications—Winsorising all continuous variables at the 1st and 99th percentiles yields a coefficient of 0.1184 (t = 2.00, p = 0.046), still significant at the 5 per cent level, so the result is not driven by extreme values. Adding year fixed effects raises the coefficient slightly to 0.1479 (t = 2.59, p = 0.010), indicating that the main result is not produced by a common time trend.

The significance of the interaction does, however, disappear when subsidies are measured coarsely: 0.0764 (p = 0.523) when using a dummy for above-median subsidy, 0.3215 (p = 0.117) when using the within-year percentile rank, and 0.0211 (p = 0.531) when the continuous digitalisation measure is replaced by a disclosure

dummy. This is unsurprising, since binary and rank measures discard the continuous information on subsidy scale and test power therefore falls in a sample of this size.

Table 8. Robustness checks of the main effect

Specification	DT coefficient	*t*	*p*	*N*
Baseline: DT = ln(1 + frequency)	0.1377**	2.32	0.021	578
Alt. X1: digital disclosure dummy (0/1)	0.2664***	2.80	0.005	578
Alt. X2: raw keyword frequency (unlogged)	0.0132	1.11	0.268	578
Alt. X3: ln(frequency), no +1, zeros dropped	0.0084	0.11	0.914	330
Alt. X4: DT squared (non-linearity test)	0.3659**	2.48	0.013	578
Alt. Y1: within-year percentile rank of ESG	0.0339**	2.57	0.010	578
Alt. Y2: ESG above within-year median (logit)	0.1455	1.13	0.259	578
Winsorising (1st/99th percentiles)	0.1184**	2.00	0.046	578
Adding year fixed effects	0.1479***	2.59	0.010	578
Adding Z-index and Herfindahl index	0.1589***	2.71	0.007	578

Notes: Unless stated otherwise every model controls for management expense growth, asset turnover, the leverage ratio and the largest shareholder's stake. Alt. X4 reports the linear DT term; its quadratic term is −0.1026 (t = −1.69, p = 0.092). Alt. Y2 reports logit coefficients and z statistics. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

Table 9. Robustness checks of the moderating effect (interaction term)

Specification	Interaction	*t*	*p*	*N*	Result
Baseline: subsidies (RMB 100 m)	0.0452**	2.34	0.020	544	—
Alt. M1: ln(subsidy)	0.0672**	2.16	0.031	544	Robust
Alt. M2: above within-year median (0/1)	0.0764	0.64	0.523	544	Insignificant
Alt. M3: within-year percentile rank (0–1)	0.3215	1.57	0.117	544	Insignificant
Alt. X: digital disclosure dummy (0/1)	0.0211	0.63	0.531	544	Insignificant
Winsorising (1st/99th percentiles)	0.0381**	1.99	0.047	544	Robust
Excluding 2020	0.0529**	2.53	0.012	448	Robust
Adding industry fixed effects	0.0471**	2.39	0.017	544	Robust
Power and gas subsample	0.0449**	2.26	0.024	494	Robust
Excluding ST and *ST observations	0.0425**	2.17	0.030	517	Robust

Notes: Every column reports the estimated interaction between digital transformation and government subsidies in Equation (4) and controls for management expense growth, asset turnover, the leverage ratio and the largest shareholder's stake. In the power and gas subsample the industry classification is extrapolated from each firm's most recent disclosure. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

4.8. Endogeneity and identification limits

Although the fixed-effect specification and a comparatively rich control set mitigate omitted variable bias, digital transformation decisions may still be endogenous through reverse causality, sample selection and unobserved shocks. This study therefore applies four complementary identification strategies and reports firm fixed effects as a supplementary check; results appear in Table 10.

Instrumental variables—Using the one-period lag of digital transformation as an instrument, the first stage yields a coefficient of 0.727 (t = 21.08) with a weak-instrument F statistic of 444.22, far above the conventional rule of thumb of 10 [36], so the instrument is relevant.

Heckman's two-step procedure [37]—Because some firms do not disclose digital keywords, sample selection bias is possible. The analysis estimates a probit selection equation for whether the keyword frequency is positive and include the inverse Mills ratio in the main equation.

Propensity score matching [38]—Treated firms are defined as those disclosing any digital keyword (n = 330), and controls as the remainder (n = 248). Propensity scores are estimated on the full control set, and comparable samples are constructed by 1:1 nearest-neighbour matching, kernel matching and radius matching.

The Heckman, kernel-matching, radius-matching and difference-in-differences estimates remain positive and significant, whereas the instrumental-variable estimate is insignificant. With firm fixed effects, the coefficient falls to 0.0106 and loses significance. The lagged instrument also requires an exclusion restriction that cannot be established here, and the short panel limits assessment of parallel trends. Staggered treatment timing also requires caution when interpreting conventional difference-in-differences estimates [39]. Taken together, the results support a conditional association across firms rather than a causal effect of within-firm digitalisation.

Table 10. Endogeneity tests

Specification	DT coefficient	t	p	N
Baseline (OLS)	0.1377**	2.32	0.021	578
Instrumental variables (lagged DT, 2SLS)	0.1244	1.23	0.218	459
Heckman two-step (with inverse Mills ratio)	0.1379**	2.32	0.021	578
PSM: 1:1 nearest neighbour	0.1127*	1.79	0.073	496
PSM: kernel matching	0.1255**	2.10	0.036	577
PSM: radius matching (caliper = 0.05)	0.1341**	2.25	0.025	571
Staggered DID (du × dt)	0.2200**	2.16	0.031	578
Firm fixed effects	0.0106	0.13	0.897	578

Notes: The first-stage weak-instrument F statistic is 444.22 ($p < 0.001$) and the Durbin–Wu–Hausman test yields $p = 0.978$. In the Heckman selection equation the leverage ratio enters with −0.0264 ($z = -4.35$, $p < 0.001$) and the inverse Mills ratio with 0.0089 ($t = 1.19$, $p = 0.234$). For PSM, treated firms are those with DT > 0 (n = 330) and controls those with DT = 0 (n = 248); 1:1 matching retains 248 pairs, or 496 observations. For the staggered DID the transformation year is the first year in which a firm reports any digital keyword, giving 98 treated firms. ***, ** and * denote significance at the 1, 5 and 10 per cent levels.

5. Conclusion and implication

Using 610 firm-year observations on 122 Chinese listed energy firms over 2020–2024, this paper finds a positive association between digital transformation and ESG performance. Internal control quality carries a significant indirect association, government subsidies positively moderate the relationship, and the industry estimates are strongest for gas utilities. The insignificant firm-fixed-effects estimate and sensitivity to some measurement choices limit causal interpretation.

For energy firms, the results suggest coordinating digital investment with internal control and ESG information systems. The industry differences also suggest that digital monitoring may be especially relevant to gas utilities, while generators need to consider their generation mix and capital investment alongside operational digitalisation. For policymakers, the subsidy interaction suggests examining how the scale and

design of public support complement digital upgrading. Support can be linked to verifiable governance and ESG outcomes, while recognising that the observational estimates do not establish the effects of a particular subsidy policy. For investors, digital intensity and internal control quality may inform comparisons across firms, with attention to industry differences. They are less reliable as evidence that a single firm's ESG performance will improve as it digitalises.

Several limitations should be acknowledged. Digital transformation is measured from keyword frequencies in annual reports. Although this is the prevailing approach, it remains sensitive to disclosure strategy and to choices in text mining, and future work could cross-validate with digital intangible assets, digital patents or the share of digital talent. The sample covers only five years, which suffices to identify an average effect but not to characterise the lag structure through which digital investment is converted into ESG performance; given the short panel, the analysis could not adequately test the parallel trends assumption underlying the staggered difference-in-differences design, there being only 58 pre-transformation observations, and dynamic effects could not be estimated robustly.

References

[1] Li, H., Dong, X., & Zhang, J. (2026). Empowering ESG performance through digital transformation: From the perspective of internal control and government regulation. *International Journal of Managerial Finance, 22*(2), 228–258. https://doi.org/10.1108/IJMF-04-2025-0211

[2] Wu, F., Hu, H., Lin, H., & Ren, X. (2021). Corporate digital transformation and capital market performance: Evidence from stock liquidity. *Management World, 37*(7), 130–144. (in Chinese)

[3] Yuan, C., Xiao, T., Geng, C., & Sheng, Y. (2021). Digital transformation and the division of labour within firms. *China Industrial Economics*, (9), 137–155. (in Chinese)

[4] Liu, S., Yan, J., Zhang, S., & Lin, H. (2021). Can the digitalisation of enterprise management improve input-output efficiency? *Management World, 37*(5), 170–190. (in Chinese)

[5] Qi, Y., & Cai, C. (2020). The multiple effects of digitalisation on the performance of manufacturing firms. *Study and Exploration*, (7). (in Chinese)

[6] Jin, Y., Wen, W., & He, Y. (2022). The impact of digital transformation on corporate green innovation: Evidence from Chinese manufacturing listed firms. *Finance and Trade Research, 33*(7), 69–83. https://doi.org/10.19337/j.cnki.34-1093/f.2022.07.006 (in Chinese)

[7] Shen, M., & Tan, W. (2022). Digitalization and green innovation performance of enterprises: Identification of double effects based on increment and quality improvement. *South China Journal of Economics, 41*(9), 118–138. https://doi.org/10.19592/j.cnki.scje.391819 (in Chinese)

[8] Li, Y., Lan, Q., & Wu, W. (2022). The supply-chain diffusion mechanism of customer firms' digital transformation. *China Industrial Economics*, (12), 146–165. (in Chinese)

[9] Yi, L., Wu, F., & Xu, S. (2021). The performance-driving effect of corporate digital transformation. *Securities Market Herald*, (8), 15–25. (in Chinese)

[10] Pang, R., & Liu, D. (2022). The paradox of digitalization and innovation: Does digitalization promote enterprise innovation? An explanation based on open innovation theory. *South China Journal of Economics, 41*(9), 97–117. https://doi.org/10.19592/j.cnki.scje.391844 (in Chinese)

[11] Wang, X., Zhang, X., & Niu, Y. (2022). "Data-driven" and "capability curse": The strategic paradox of enterprise digital transformation under the orientation of green innovation strategy upgrading. *R&D Management, 34*(4), 51–65. (in Chinese)

[12] Lu, R., Zhao, X., & Lyu, D. (2024). Enterprise digital transformation, managers' time orientation and core-technology competence: An inverted U-shape. *Science & Technology Progress and Policy, 41*(7), 11–20. https://doi.org/10.6049/kjjbydc.2022110352 (in Chinese)

[13] Yi, Z., Jiang, F., & Qin, Y. (2010). Product market competition, corporate governance and the quality of information disclosure. *Management World*, (1), 133–141. (in Chinese)

[14] Xiao, H., Shen, H., & Zhou, Y. (2024). Customer digitalization, supplier ESG performance and supply chain sustainability. *Economic Research Journal, 59*(3), 54–73. (in Chinese)

[15] Cao, Y., Li, X., Hu, H., Wan, G., & Wang, S. (2023). How does digitalisation promote the green transformation of manufacturing firms? An exploratory case study from the perspective of resource orchestration theory. *Management World, 39*(3), 96–112. (in Chinese)

[16] Li, Q., & Xiao, Z. (2020). Heterogeneous environmental regulation instruments and incentives for corporate green innovation: Evidence from green patents of listed firms. *Economic Research Journal, 55*(9), 192–208. (in Chinese)

[17] Qi, S., Lin, S., & Cui, J. (2018). Can emissions trading schemes induce green innovation? Evidence from green patent data of Chinese listed firms. *Economic Research Journal, 53*(12), 129–143. (in Chinese)

[18] Li, G., & Zhu, P. (2022). Does information infrastructure construction improve corporate ESG performance? *Finance and Economy*, (9), 52–61. https://doi.org/10.19622/j.cnki.cn36-1005/f.2022.09.005 (in Chinese)

[19] Zhang, J., Wu, Y., & Lin, L. (2025). Government subsidies, corporate ESG ratings, and green innovation. *Finance Research Letters, 84*, 107793. https://doi.org/10.1016/j.frl.2025.107793

[20] Yan, J., Hu, H., & Hu, Y. (2024). Does internal control improve enterprise environmental, social, and governance information disclosure? Evidence from China. *Corporate Social Responsibility and Environmental Management, 31*(5), 4980–4994. https://doi.org/10.1002/csr.2837

[21] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305–360.

[22] Hu, J., Han, Y., & Zhong, Y. (2023). How does corporate digital transformation affect ESG performance? Evidence from Chinese listed firms. *Review of Industrial Economics*, (1), 105–123. https://doi.org/10.19313/j.cnki.cn10-1223/f.20221104.001 (in Chinese)

[23] Wang, H., Zhang, Y., & Li, J. (2024). The impact of digital transformation on the ESG performance of energy firms. *Business Studies, 31*(6), 80–92. (in Chinese)

[24] Dai, F., Chen, C., & He, X. (2025). Reverse mixed-ownership reform, internal control quality and the ESG performance of private enterprises: An analysis of Shanghai and Shenzhen A-share private listed firms from 2013 to 2022. *Journal of Kunming University of Science and Technology (Natural Science), 50*(2), 173–187, 226. https://doi.org/10.16112/j.cnki.53-1223/n.2025.02.291 (in Chinese)

[25] Wang, H., Wang, S., Zhang, C., & Guo, L. (2023). Does digital transformation improve ESG responsibility performance? Empirical research based on MSCI index. *Foreign Economics & Management, 45*(6), 19–35. https://doi.org/10.16538/j.cnki.fem.20221128.202 (in Chinese)

[26] DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review, 48*(2), 147–160.

[27] Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

[28] Xue, D., & Zhu, Z. (2025). Digital transformation of energy enterprises, ESG performance, and green total factor productivity. *Finance Research Letters, 86*(Part A), 108398. https://doi.org/10.1016/j.frl.2025.108398

[29] Zhou, Z., Yuan, Z., & He, C. (2025). Can digital transformation promote firms' sustainable development? Evidence based on ESG performance. *International Review of Financial Analysis, 105*, 104434. https://doi.org/10.1016/j.irfa.2025.104434

[30] Sun, W., Mao, N., Lan, F., & Wang, L. (2023). Policy empowerment, digital ecosystem and corporate digital transformation: A quasi-natural experiment based on the national big data comprehensive pilot zones. *China Industrial Economics*, (9), 117–135. https://doi.org/10.19581/j.cnki.ciejournal.2023.09.007 (in Chinese)

[31] Wen, Z., Zhang, L., Hou, J., & Liu, H. (2004). Testing and application of the mediation effect. *Acta Psychologica Sinica, 36*(5), 614–620. (in Chinese)

[32] Jiang, T. (2022). Mediating and moderating effects in empirical research on causal inference. *China Industrial Economics*, (5), 100–120. (in Chinese)
[33] Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.
[34] Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage. Newbury Park, CA.
[35] Guo, Y. (2018). The signalling mechanism of government innovation subsidies and corporate innovation. *China Industrial Economics*, (9), 98–116. https://doi.org/10.19581/j.cnki.ciejournal.2018.09.016 (in Chinese)
[36] Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65*(3), 557–586.
[37] Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153–161.
[38] Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.
[39] Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics, 225*(2), 254–277.