

Navigating the Twin Transition Paradox: How Enterprise Digitalization Induces the Carbon Rebound Effect and the Mitigating Role of Energy Governance

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ABSTRACT

This study examines how enterprise digitalization affects carbon emissions through three channels: technical energy-efficiency gains, independent output growth, and efficiency-induced production expansion. Using panel data from 600 Chinese manufacturing firms across three industries over the period 2016 to 2025, the analysis employs two-way fixed effects regressions with enterprise-clustered standard errors and enterprise-block bootstrap inference. Technical energy-efficiency gains are derived from energy audit records, while digitalization and energy governance are measured through structured enterprise questionnaires. The results show that higher levels of digitalization are associated with larger technical energy-efficiency gains. These gains are in turn positively associated with output expansion after the separate contribution of digitalization to output has been accounted for. Energy governance weakens this transmission, with the marginal output response to efficiency gains declining from 1.28 at a governance level of 0.25 to 0.63 at 0.75. The counterfactual decomposition yields an aggregate carbon rebound estimate of 92.91 percent, though the 95 percent bootstrap interval ranges from 75.04 to 110.54 percent, crossing the complete-rebound threshold. Realized carbon savings thus remain uncertain in magnitude. These findings contribute to research on digital management and carbon governance by distinguishing efficiency-induced rebound from independent scale effects and by showing that internal energy governance can moderate the expansion channel through which efficiency gains translate into additional emissions.

Keywords: Enterprise Digitalization, Carbon Rebound, Energy Governance, Producer Rebound, Manufacturing Firms

1. Introduction

1.1 Digital and Low-Carbon Transformation

Manufacturing enterprises confront two concurrent transformation agendas. The first involves integrating digital technologies into business operations, data management, and decision processes (Verhoef et al., 2021). The second centers on reducing energy consumption and carbon emissions in response to tightening regulatory requirements (Beier et al., 2020). These two agendas share a common premise: that digital technologies can improve operational efficiency and thereby reduce the resource intensity of production.

This premise, however, rests on an incomplete chain of reasoning. A reduction in energy intensity does not automatically produce a proportional reduction in absolute energy use or total carbon emissions. When a firm becomes more energy-efficient, the effective cost of energy services falls, and the firm may respond by expanding production to capture the cost advantage (Sorrell, 2009; Brockway et al., 2021). In the context of enterprise digitalization, the challenge is compounded by the fact that digital technologies may also contribute to output growth through channels unrelated to energy efficiency, such as market access and coordination improvements (Daryono et al., 2024). Evidence at the macroeconomic level links digital economy development to larger carbon rebound in Chinese provinces and cities (Huang and Lin, 2025; Zhu and Lan, 2023), while firm-level studies report mixed results depending on the type of technology and economic context (Axenbeck et al., 2024; Kopp et al., 2023; Shang et al., 2023). This coexistence of efficiency improvement and potential emission increases defines the twin transition paradox addressed in this study.

1.2 Research Problem and Boundary

Three gaps motivate this research. First, firm-level studies typically estimate the net association between digitalization and emissions, bundling together technical efficiency improvements, independent output growth, and efficiency-induced expansion without separating these channels. Second, while external environmental regulations have been shown to mitigate energy rebound (Du et al., 2023), whether internal energy governance achieves comparable effects remains untested. Third, the estimation uncertainty of firm-level rebound calculations is rarely reported, leaving readers unable to assess whether the data support partial rebound, complete rebound, or backfire. The analysis operates at the enterprise boundary, where operational emissions are determined by production volume, energy intensity, and emission factor; wider economic feedback through inter-firm competition or supply-chain reallocation lies outside this scope.

1.3 Research Objectives and Contributions

This study addresses three research questions:

RQ1: How do the technical energy-efficiency gains, independent output growth, and cost-induced expansion associated with enterprise digitalization separately affect enterprise energy use and carbon emissions?

RQ2: Relative to a counterfactual in which only technical efficiency improvements occur, how much carbon-saving potential is offset by output expansion?

RQ3: Can internal energy governance weaken the positive association between technical energy-efficiency gains and enterprise output, and what is the estimation uncertainty of this moderating effect?

The analysis draws on panel data from 600 Chinese manufacturing firms spanning three industries over 2016 to 2025. Digitalization and energy governance are measured through structured questionnaires, and technical energy-efficiency gains are derived from energy audit records. The estimation framework uses two-way fixed effects regressions with enterprise-clustered standard errors and enterprise-block bootstrap for counterfactual decomposition.

The study makes three contributions: an explicit three-channel decomposition of the carbon effect of digitalization, the introduction of internal energy governance as a moderator of the expansion channel, and the transparent reporting of bootstrap confidence intervals for the aggregate rebound rate.

The paper proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and methods. Section 4 reports the results. Section 5 discusses the implications, and Section 6 concludes.

2. Literature Review and Hypothesis Development

2.1 Enterprise Digitalization and Energy Demand

Enterprise digitalization refers to the progressive integration of digital technologies into business data management, operational processes, coordination mechanisms, and decision-making routines (Verhoef et al., 2021). This definition distinguishes the digitalization of business operations from narrower conceptions limited to hardware acquisition or broader conceptions that encompass industry-level structural change. Beier et al. (2020) observe that the sustainability implications of digital transformation depend on how technologies interact with organizational practices and socioeconomic conditions, cautioning against the assumption that technological advancement automatically delivers environmental benefits.

The energy consequences of digitalization operate through multiple pathways. Lange et al. (2020) identify four channels through which digital technologies affect energy demand: the direct energy consumption of digital devices and infrastructure, productivity improvements that stimulate economic growth, energy efficiency gains in production processes, and structural changes in the composition of economic output. The net effect is ambiguous because efficiency gains and structural shifts may be partially or fully offset by increased device energy use and growth-related demand increases.

Empirical evidence at the firm and industry levels confirms this ambiguity. Matthess et al. (2023), using panel data from fifteen European countries and eight manufacturing sectors, find that industrial robots are associated with lower energy intensity, whereas broader digital capital investment shows a reversed association. Axenbeck et al. (2024) report similar heterogeneity in German manufacturing firms, where the relationship between digitalization and energy demand varies by firm size, technology type, and regional characteristics, with increased electricity demand being a common outcome. These findings indicate that the energy effect of digitalization is neither uniform across technologies nor consistent across firms.

On the carbon emission side, Shang et al. (2023) find that digital transformation, measured through annual report text analysis, is associated with lower carbon intensity among Chinese listed firms, operating through green innovation and internal control channels. Kopp et al. (2023), differentiating between firm-related and household-related digitalization indicators across European and OECD countries, report a net reduction in emissions on average, although the effect reverses in lower-income country groups. These studies capture the net association between digitalization and emissions without isolating the specific channel through which efficiency improvements may be offset by behavioral responses.

The present study focuses on the first link in the rebound chain: whether digitalization is associated with improvements in technical energy efficiency. When firms digitalize their operations, the improved monitoring, scheduling, and process control can reduce the energy required per unit of output, holding production volume constant. This technical efficiency gain is the engineering-level improvement that forms the starting point for potential rebound. Based on the evidence that digitalization can improve process efficiency despite its heterogeneous net effect on total energy demand, the first hypothesis is:

H1. Enterprise digitalization is positively associated with technical energy-efficiency gains.

2.2 Producer Rebound and Output Expansion

The rebound effect describes the phenomenon whereby realized energy savings fall short of the savings predicted by engineering calculations when technological improvements reduce the energy required per unit of output or service. Sorrell and Dimitropoulos (2008) provide a foundational treatment of rebound definitions at the microeconomic level, distinguishing between the reduction in energy intensity, the change in the effective price of energy services, and the demand response that follows. They also note that the economic boundary, capital cost, and time horizon of measurement affect the interpretation of rebound magnitudes. Sorrell (2009) evaluates the evidence for backfire, the condition in which rebound exceeds 100

percent and energy consumption increases despite efficiency improvement, concluding that the supporting evidence depends on the scope and measurement approach of each study.

In the production context, the mechanism operates through cost reduction. An improvement in technical energy efficiency lowers the unit cost of energy services to the firm. If the firm responds by expanding output to exploit the cost advantage, total energy consumption may increase relative to the efficiency-only counterfactual. Saunders (2013), using data from thirty US industrial sectors, estimates producer rebound within a cost function framework and finds that the magnitude varies across industries, with input substitution and scale effects playing distinct roles. Saunders et al. (2021), in a review spanning forty years of energy efficiency research, note that while efficiency improvements generally yield social benefits, behavioral and economic responses shape the extent to which technical potential translates into actual savings.

Firm-level evidence from several countries supports the existence of producer rebound, though estimates of magnitude diverge considerably. Berner, Lange, and Silbersdorff (2022) use data from over 16,000 German manufacturing firms and report a modest rebound of approximately 4.5 to 5.3 percent, conditional on firm efficiency and investment levels. Lu and Wang (2024), analyzing Chinese manufacturing and service firm data from 2013 to 2016, report substantially larger direct rebound rates of 33.5 percent in manufacturing and 57.9 percent in services, accompanied by an additional output expansion effect of 19.3 percent in manufacturing. Du et al. (2025) exploit input tariff reductions following China's accession to the World Trade Organization and find that lower input costs amplify firm-level energy rebound, with output expansion identified as the primary channel rather than input substitution.

The variation in estimates reflects differences in the scope of adjustment, measurement period, and identification strategy. Amjadi et al. (2022) emphasize the temporal dimension, showing that rebound in Swedish manufacturing exhibits different patterns in the short run and the long run, with adjustment dynamics affecting interpretation. At the economy-wide level, Berner, Bruns, et al. (2022) apply structural factor-augmented vector autoregressions and estimate that macroeconomic feedback may offset a substantial portion of technical energy savings in European countries and the United States. Stern (2020) and Brockway et al. (2021) further emphasize that economy-wide rebound estimates are sensitive to model structure and time horizon, and that no single number represents the rebound effect across all contexts. Tan and Walheer (2025) propose a nonparametric production-based decomposition of energy rebound that connects observed changes to efficiency, technology, and input factors, reinforcing the need to separate different sources of production adjustment.

For the purposes of this study, the relevant question is whether technical energy-efficiency gains are associated with enterprise output expansion when the independent contribution of digitalization to output has been accounted for separately. The cost-reduction mechanism predicts that efficiency gains lower the effective unit cost of energy services, creating an incentive for the firm to increase production volume. Gillingham et al. (2016) caution that the existence of rebound does not automatically imply that efficiency investments are undesirable, since the welfare evaluation depends on the full set of costs and benefits rather than on the energy saving alone. This point is important for interpretation: a positive association between efficiency gains and output does not mean that digitalization fails to deliver net benefits. It means only that the energy and carbon savings are smaller than a pure engineering estimate would suggest.

Based on the producer rebound framework and the empirical evidence that efficiency improvements are associated with output expansion at the firm level, the second hypothesis is:

H2. Technical energy-efficiency gains are positively associated with enterprise output, conditional on the separate output contribution of digitalization.

2.3 Organizational Control and Energy Governance

If efficiency gains create incentives for output expansion, the question arises whether organizational mechanisms can constrain this response. Ouchi (1979) provides a foundational framework for understanding how organizations design control mechanisms, arguing that the choice among market, bureaucratic, and clan controls depends on the measurability of performance and the alignment of goals. Applied to energy management, this perspective suggests that firms can institute formal controls over energy use through responsibility assignment, budgeting, investment review, and corrective action procedures, and that the effectiveness of these controls depends on the availability of relevant information and the clarity of accountability structures.

Energy management systems provide the organizational infrastructure for such controls. The ISO 50001 standard establishes a plan-do-check-act cycle for energy management, encompassing energy policy, planning, implementation, performance monitoring, and management review. Fuchs et al. (2020), analyzing 72 ISO 50001 award cases, identify management commitment, energy culture, data availability, and professional capability as important organizational conditions for effective energy management. Jin et al. (2021) develop an energy management maturity model that links ISO 50001 to Chinese enterprise practices, decomposing energy management capability into identifiable developmental stages and management activities ranging from initial awareness to continuous improvement.

Empirical evidence on formal energy management and energy performance is generally supportive. Fitzgerald et al. (2023) find that manufacturing facilities operating ISO 50001 systems achieve deeper and more sustained energy savings over multiple years, attributing the result to continuous monitoring and improvement processes. E.Z. Wang and Pan (2025), matching ISO 50001 certification with Chinese manufacturing firm data through propensity score matching and difference-in-differences analysis, report that certification is associated with lower energy intensity, although not with a shift toward cleaner energy sources. These findings indicate that energy management arrangements can improve energy performance, though they do not directly identify whether the improvement operates through better technical efficiency, reduced output expansion, or both channels simultaneously.

This analysis specifically addresses the moderation of the efficiency-to-expansion channel. If energy governance imposes constraints on how firms use efficiency gains, for instance by requiring that expansion plans account for additional energy demand, that energy budgets cap total consumption, and that deviations from targets trigger corrective action, then the marginal incentive to expand output in response to lower energy costs should be attenuated. External environmental regulation provides analogous evidence for this logic. Du et al. (2023), using China's pollution reduction mandates under the Eleventh Five-Year Plan as a quasi-experiment, find that stricter regulatory requirements are associated with smaller firm-level energy rebound, indicating that binding constraints can alter the behavioral response to efficiency gains. Chen et al. (2020) similarly show that energy regulation contributed to lower energy intensity and shifts in energy structure among Chinese manufacturing firms, with research and development activities and resource reallocation toward more efficient producers serving as transmission channels.

The complementarity between digital technologies and environmental management also merits consideration. Liu et al. (2024) report that digital transformation is associated with improved carbon emission reduction performance among Chinese listed firms and that external oversight from government and investors strengthens this association. Z. Wang et al. (2025), using a cross-level model with 650 Chinese manufacturing firms, find that environmental management systems condition the energy-saving effects of different digital technologies. These studies suggest that governance mechanisms interact with technological capabilities in shaping environmental outcomes, though the specific moderation of the efficiency-to-expansion path through internal energy governance measures has not been directly tested.

Based on organizational control theory and the evidence that external constraints and management systems can alter the behavioral response to efficiency improvements, the third hypothesis is:

H3. Energy governance weakens the positive association between technical energy-efficiency gains and enterprise output.

2.4 Integrated Framework and Evidence Boundaries

The three hypotheses together describe a sequential mechanism: digitalization improves technical energy efficiency (H1), efficiency gains induce output expansion (H2), and energy governance moderates the expansion response (H3). The model simultaneously accounts for the independent contribution of digitalization to output through non-energy channels such as market expansion, coordination improvement, and product development. This independent scale effect is not part of the rebound mechanism, and conflating it with efficiency-induced expansion would overstate the rebound rate.

The carbon rebound rate is defined as the ratio of the expansion-induced carbon offset to the technical carbon-saving potential. A rebound rate below 100 percent indicates that some technical savings are realized in practice; a rate at or above 100 percent indicates complete offset or backfire. The counterfactual emissions under the efficiency-only scenario are computed by applying the improved technical energy intensity to the baseline output level before expansion, using the same industry-year emission factor. This approach follows the logic of Sorrell and Dimitropoulos (2008), who emphasize that rebound should be measured relative to a well-defined engineering counterfactual within consistent economic boundaries.

Existing research at the macro and meso levels provides contextual evidence for these mechanisms. Huang and Lin (2025) use a stochastic frontier approach to show that digital economy development is associated with larger energy rebound across Chinese provinces, with urbanization and regional differences conditioning the relationship. Zhang et al. (2025) construct a computable general equilibrium model to assess the energy, economic, and emission effects of digitalization, reporting that output and income expansion can offset efficiency gains and that carbon pricing helps contain the rebound. Zhu and Lan (2023) document a positive association between urban digital economy development and carbon rebound in Chinese cities, discussing substitution, income, and output effects. Peng and Qin (2024) report a nonlinear relationship between digitalization and electricity rebound at the city level, with different dimensions of digital development exhibiting distinct patterns.

These macro-level findings are informative but cannot be directly transferred to the enterprise level. Provincial and city data aggregate across firms, industries, and households, capturing inter-sectoral resource reallocation and cross-firm competition effects that do not apply within a single enterprise. The present study operates at the firm level, where the relevant mechanisms are the individual firm's own production decisions, energy management practices, and technology choices.

Several streams of adjacent research inform the broader context of this study. Santarius et al. (2023) develop the concept of digital sufficiency, arguing that improving the per-unit efficiency of digital services is insufficient to reduce aggregate resource consumption without also addressing the scale and pattern of use. This perspective supports the inclusion of absolute energy budgets and expansion review in the governance construct, where total consumption matters alongside unit efficiency. Lai et al. (2023) find through case studies of six manufacturing enterprises that digitalization supports green supply chain innovation, but that organizational conditions including management support and internal coordination determine the extent of environmental benefit. Sun (2026) similarly emphasizes the role of supply chain coordination and regulatory alignment in achieving low-carbon outcomes in the automotive industry.

Research in the digital management and service innovation domain further supports the integration of digital capabilities with organizational practices. Abu Bakir and Alma'abreh (2026) show that business intelligence capabilities relate to sustainable performance through green logistics practices, indicating that digital tools require organizational implementation channels to affect outcomes. Daryono et al. (2024) find that digital business model transformation is associated with enterprise performance through green

intellectual capital, suggesting that the output growth associated with digitalization may operate through multiple organizational pathways beyond energy cost reduction. Tang and Koornwinder-gott (2025) illustrate how data-driven approaches can support circular business models, providing an example of carbon information entering operational sustainability decisions. X. Wang and Md Kassim (2025) report a positive association between digital service innovation and industrial low-carbon transformation at the provincial level, although the aggregate indicators used in their analysis do not isolate firm-level rebound dynamics.

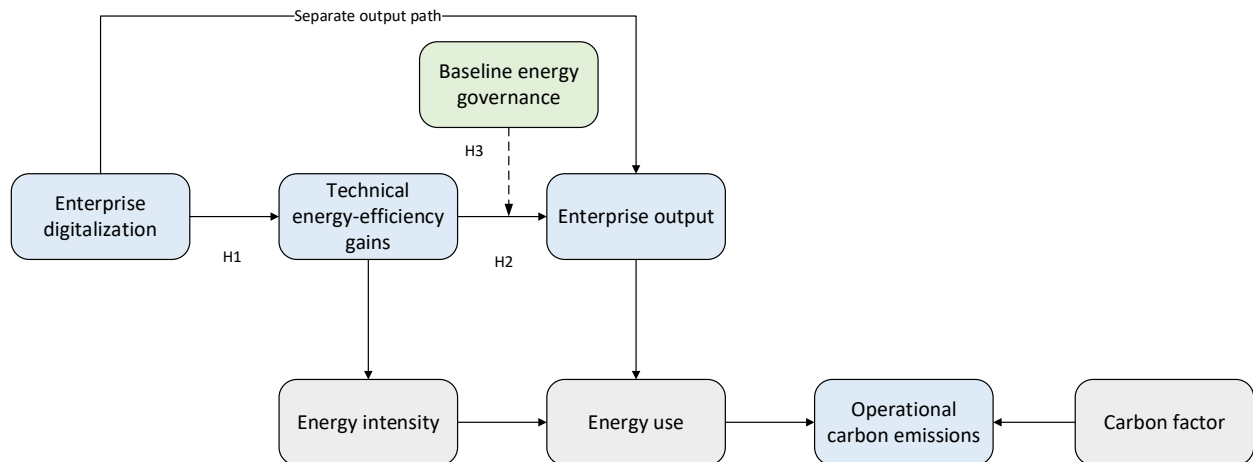


Figure 1. Conceptual Framework of Digitalization, Efficiency Gains, and Energy Governance

3. Research Methodology

3.1 Sample and Data Collection

The sample consists of 600 manufacturing firms from three industries in China, selected through cooperation with industry associations and provincial energy conservation supervision centers. Each firm had maintained continuous energy audit records since at least 2015 and had participated in annual enterprise digitalization and energy governance surveys conducted for this research program. The three industries, designated by anonymized codes to protect firm-level confidentiality, represent sectors with varying levels of energy intensity and digital technology adoption. Each industry contributes 200 firms to the sample.

The data span the period 2015 to 2025. The year 2015 serves as the initialization period during which baseline energy governance was measured; the analysis sample covers 2016 to 2025, providing a planned panel of 6,000 firm-year observations across 600 enterprises. Five categories of data were assembled:

First, enterprise digitalization was captured through a twelve-item annual questionnaire administered to production managers and information system managers, covering four dimensions of digital implementation: data integration, business operations, coordination, and decision support. Each dimension includes three items rated on a five-point scale ranging from 1 (not implemented) to 5 (fully implemented).

Second, baseline energy governance was measured through a separate twelve-item questionnaire administered in 2015, covering responsibility assignment, energy budgeting, investment appraisal, and corrective feedback, again with three items per dimension on a five-point scale.

Third, technical energy-efficiency gains were derived from energy audit reports that firms submit to provincial energy conservation supervision centers under regulatory requirements. The technical gain is defined as the log ratio of prior-period energy intensity to current-period technical energy intensity as documented in the engineering audit assessment.

Fourth, enterprise output, energy consumption, and employment were obtained from corporate annual reports and industry statistical records. Carbon emissions were calculated as the product of energy consumption and industry-year emission factors sourced from official emission accounting databases.

Fifth, control variables include a demand index constructed from industry output growth, a log energy price index from official price statistics, and log employment from corporate annual reports.

Missing observations arise from item nonresponse in the digitalization questionnaire, incomplete energy audit submissions, and firm attrition over the panel period. No imputation was applied; each model uses the subsample for which all required variables are jointly available. Resulting sample sizes range from 5,215 firm-years for the common descriptive statistics sample to 6,000 firm-years for models using the full-information specification.

3.2 Construct Operationalization

Enterprise digitalization is operationalized as a formative index of twelve items spanning four dimensions. Data integration captures structured record storage, cross-system data sharing, and data quality maintenance. Business operations covers digital scheduling, real-time status monitoring, and process coverage of major workflows. Coordination measures cross-department handoffs, task synchronization across units, and partner-facing digital channels. Decision support assesses managerial use of digital reports, data-driven adjustments, and decision traceability to underlying records. The composite score is the unweighted mean of the four dimension means, rescaled to the unit interval. A valid score requires at least two of three items answered within each dimension and all four dimensions available. The analysis uses the lagged value, that is, the prior-year digitalization score, to reduce simultaneity with current-period outcomes.

Baseline energy governance is operationalized through twelve items across four dimensions, measured once at the start of the observation period. Responsibility covers explicit assignment of energy management duties, decision authority specification, and role-level accountability. Budgeting captures total energy consumption targets, business-unit energy allowances, and capacity-linked budget checks. Investment appraisal assesses whether new projects estimate additional energy demand, follow energy review procedures, and require pre-approval energy supply arrangements. Corrective feedback measures target-versus-actual monitoring, deviation accountability, and follow-up verification of corrective actions. The composite index uses the same aggregation rule as digitalization. Because governance was measured at baseline and remains fixed throughout the panel, its main effect is absorbed by the enterprise fixed effect; the estimable governance term enters through its interaction with the time-varying technical efficiency gain.

Both constructs use formative indicators developed for this study. They are intended to capture the breadth of organizational implementation rather than to reflect a single latent trait. Future applications should assess their content coverage and predictive relevance in independent settings.

3.3 Estimation Models and Carbon Counterfactuals

The analysis proceeds through three regression models and a counterfactual decomposition.

The efficiency model regresses the technical energy-efficiency gain S on lagged digitalization D and controls X , with enterprise and year fixed effects:

$$S_{it} = \alpha_i + \gamma_t + \beta_1 D_{i,t-1} + \beta_2 X_{it} + \epsilon_{it}$$

where α_i and γ_t are enterprise and year effects, and X includes the demand index, log energy price index, and log employment.

The output model regresses log enterprise output on lagged digitalization, the technical efficiency gain, the interaction of the efficiency gain with baseline governance G , and controls:

$$\ln(Q_{it}) = \alpha_i + \gamma_t + \delta_1 D_{i,t-1} + \delta_2 S_{it} + \delta_3 (S_{it} \times G_i) + \delta_4 X_{it} + u_{it}$$

The coefficient δ_2 captures the output response to efficiency gains when governance equals zero. The marginal output response at governance level g is $\delta_2 + \delta_3 * g$. H2 is tested at the prespecified governance level of 0.50, and H3 corresponds to $\delta_3 < 0$.

The emission model regresses log operational carbon emissions on lagged digitalization, the interaction of digitalization with governance, and controls:

$$\ln(C_{it}) = \alpha_i + \gamma_t + \phi_1 D_{i,t-1} + \phi_2 (D_{i,t-1} \times G_i) + \phi_3 X_{it} + v_{it}$$

This model does not include current output or current intensity as regressors, since these are endogenous to the digitalization and governance decisions under study.

For the counterfactual decomposition, baseline carbon emissions are defined as:

$$C_0 = Q_0 \times I_0 \times F$$

where Q_0 is output before efficiency-induced expansion, I_0 is prior-period intensity, and F is the industry-year emission factor. Technical-efficiency-only emissions and operational emissions are defined as:

$$C_{\text{eff}} = Q_0 \times I_1 \times F$$

$$C_1 = Q_1 \times I_1 \times F$$

where I_1 is post-improvement technical intensity and Q_1 is observed output including any expansion response. The technical carbon-saving potential, realized savings, and expansion-induced offset are respectively:

$$C_0 - C_{\text{eff}}, \quad C_0 - C_1, \quad C_1 - C_{\text{eff}}$$

The aggregate rebound rate is:

$$\text{Aggregate Rebound} = \frac{\sum (C_1 - C_{\text{eff}})}{\sum (C_0 - C_{\text{eff}})}$$

The summation is taken over all firm-year observations for which the potential saving exceeds one percent of baseline emissions, excluding records with negligible denominators. Alternative thresholds of 0.5 and 2 percent are examined in sensitivity analysis. Emissions under a counterfactual that removes all digitalization channels, including the independent scale effect, are also computed to distinguish the total carbon effect of digitalization from the efficiency-specific rebound rate.

3.4 Inference and Sensitivity

All regressions include enterprise and year fixed effects. Standard errors are clustered at the enterprise level (Cameron and Miller, 2015), and t-statistics use degrees of freedom equal to the number of enterprises minus one. Imai and Kim (2021) note that two-way fixed effects regressions rely on specific assumptions about additive unobserved heterogeneity and do not automatically deliver nonparametric causal identification. The fixed effects in this analysis absorb time-invariant firm differences and common year

shocks but do not fully resolve endogeneity from time-varying unobservables that simultaneously affect digitalization, governance, and output decisions.

The three primary hypothesis tests (H1, H2 at governance = 0.50, and H3) are adjusted using the Holm correction for multiple comparisons. The counterfactual decomposition uses 999 iterations of enterprise-block bootstrap, resampling entire firm histories with replacement and reassigning cluster identifiers when a firm is drawn more than once. Confidence intervals are percentile-based, and the bootstrap standard error supports asymptotic Wald diagnostics.

Sensitivity analysis covers six dimensions: (1) replacing the full-information digitalization measure with the survey-based questionnaire index; (2) re-estimating on the matched subsample to isolate measurement from composition effects; (3) setting the governance interaction to zero to check for spurious moderation recovery; (4) examining weaker and stronger expansion assumptions; (5) allowing governance to affect technical efficiency gains rather than only the expansion channel; and (6) replacing additive year effects with industry-by-year fixed effects to absorb sector-specific time trends. MacKinnon et al. (2023) inform the cluster-robust inference diagnostics, Cinelli and Hazlett (2020) provide the framework for omitted variable bias assessment, and Morris et al. (2019) establish reporting guidelines for estimation diagnostics.

A limited conditional check is additionally conducted over 200 iterations: the regressors are held at their observed values while the output disturbance is regenerated, allowing the bias, root mean squared error, empirical standard deviation, average clustered standard error, and 95 percent interval coverage of the governance interaction estimate to be evaluated. This check applies only to the output equation under fixed regressors and does not constitute a comprehensive validation of all model components.

4. Results

4.1 Sample Characteristics and Measurement Quality

The common sample for descriptive statistics comprises 5,215 firm-year observations from 581 enterprises for which all analysis variables are jointly available over the 2016 to 2025 period. Table 1 reports the means, standard deviations, and pairwise Pearson correlations.

The mean lagged digitalization score is 0.45 on the unit interval, indicating that the average firm has implemented roughly half of the assessed digital capabilities. Baseline energy governance averages 0.42, with comparable dispersion (SD = 0.24). Log output (mean 8.32) and log energy use (mean 8.44) are strongly correlated ($r = 0.90$), as expected from the mechanical relationship between production volume and energy consumption. Log carbon emissions correlate at 0.97 with log energy use, reflecting the proportional link through emission factors. Digitalization shows moderate positive correlations with output ($r = 0.32$), energy use ($r = 0.26$), and emissions ($r = 0.24$), while governance exhibits near-zero correlations with the continuous outcome variables, consistent with its time-invariant baseline nature being absorbed by enterprise fixed effects in regression models.

Table 1: Descriptive Statistics and Correlations

Variable	Mean	Standard Deviation	1	2	3	4	5	6	7	8
1. Lagged Enterprise	0.45	0.27	1.00							

Variable	Mean	Standard Deviation	1	2	3	4	5	6	7	8
Digitalization										
2. Baseline Energy Governance	0.42	0.24	0.22	1.00						
3. Log Reported Output	8.32	0.93	0.32	0.03	1.00					
4. Log Reported Energy Use	8.44	1.06	0.26	0.04	0.90	1.00				
5. Log Reported Carbon Emissions	9.10	1.16	0.24	0.04	0.84	0.97	1.00			
6. Demand Index	0.01	0.48	0.04	0.04	0.10	0.09	0.09	1.00		
7. Log Energy Price Index	0.00	0.14	0.02	-0.03	-0.02	-0.02	-0.03	0.01	1.00	
8. Log Employment	4.57	0.58	0.26	0.03	0.96	0.83	0.76	0.00	0.00	1.00

Note: N = 5,215 firm-year observations from 581 enterprises using the common non-missing sample over 2016 to 2025. All logarithms are natural logarithms.

Table 2 reports item-level measurement information for the 24 questionnaire items. For the twelve digitalization items, valid response rates range from 93.4 to 94.4 percent across the 6,600 planned records (600 firms times 11 years including the baseline year), with item means spanning 2.42 to 3.58 on the five-point scale. Items covering advanced digital capabilities such as decision traceability and cross-department process automation tend to have lower means than those capturing basic data storage and sharing, indicating that implementation depth varies across firms. For the twelve governance items measured on the 600-firm baseline, valid response rates range from 92.8 to 95.7 percent, and item means range from 2.10 to 3.61. Items related to corrective feedback procedures and investment appraisal show the lowest means, indicating that these governance dimensions are less commonly implemented at the mature level.

Table 2: Item-Level Measurement and Data Quality

Construct	Item Wording	Planned Records	Valid Responses	Mean	Standard Deviation	Missing (%)
Enterprise Digitalization	Core business records are stored in structured digital formats.	6600	6195	3.58	1.32	6.14
Enterprise Digitalization	Required data can be shared across business systems.	6600	6222	3.10	1.41	5.73
Enterprise Digitalization	Business data are updated and checked using consistent rules.	6600	6161	2.88	1.43	6.65
Enterprise Digitalization	Production or service tasks are scheduled through digital systems.	6600	6203	3.01	1.40	6.02
Enterprise Digitalization	The status of key operations can be checked promptly in digital systems.	6600	6230	2.65	1.43	5.61
Enterprise Digitalization	Digital systems cover the execution of major business processes.	6600	6190	2.49	1.36	6.21
Enterprise Digitalization	Cross-department handoffs are carried out through shared digital platforms.	6600	6222	3.08	1.44	5.73
Enterprise Digitalization	Order or task progress is synchronize	6600	6219	2.68	1.37	5.77

Construct	Item Wording	Planned Records	Valid Responses	Mean	Standard Deviation	Missing (%)
	d across relevant departments					
Enterprise Digitalization	Routine information exchange with business partners uses digital channels. Managers use digital reports in routine decisions. System data are analyzed before business adjustments. Important operating decisions can be traced to the data records used.	6600	6170	2.52	1.42	6.52
Enterprise Digitalization		6600	6198	3.16	1.39	6.09
Enterprise Digitalization		6600	6221	2.69	1.40	5.74
Enterprise Digitalization		6600	6178	2.42	1.35	6.39
Baseline Energy Governance	Responsibility for energy management matters is explicitly assigned. The responsible energy manager has clearly specified decision authority. Accountability for energy management tasks can be traced to specific roles. The enterprise sets a	600	571	3.61	1.28	4.83
Baseline Energy Governance		600	567	3.00	1.45	5.50
Baseline Energy Governance		600	570	2.73	1.41	5.00
Baseline Energy Governance		600	574	2.79	1.37	4.33

Construct	Item Wording	Planned Records	Valid Responses	Mean	Standard Deviation	Missing (%)
Baseline Energy Governance	budget for total energy consumption. Business units have explicit energy consumption allowances. Added capacity requires checking the available total energy budget.	600	568	2.48	1.40	5.33
Baseline Energy Governance	Investment appraisal includes estimates of additional energy demand. Digitalization and capacity projects follow explicit energy review procedures.	600	573	2.18	1.23	4.50
Baseline Energy Governance	Energy supply and budget arrangements must be specified before project approval. Actual energy use is regularly compared with established targets.	600	574	2.44	1.34	4.33
Baseline Energy Governance	Deviations from energy targets require documented	600	571	2.10	1.20	4.83
Baseline Energy Governance		600	561	2.36	1.35	6.50
Baseline Energy Governance		600	574	3.21	1.37	4.33
Baseline Energy Governance		600	569	2.84	1.41	5.17

Construct	Item Wording	Planned Records	Valid Responses	Mean	Standard Deviation	Missing (%)
Baseline Energy Governance	reasons and accountability. Corrective energy management actions are subject to follow-up checks.	600	557	2.53	1.36	7.17

Note: Enterprise Digitalization items are measured annually from 2015 to 2025 (planned: 600 firms times 11 years = 6,600 records). Baseline Energy Governance items are measured once in 2015 (planned: 600 records). Missing percentage is calculated against planned records.

4.2 Digitalization and Technical Efficiency

Table 3 presents the results of regressing technical energy-efficiency gains on lagged digitalization and control variables. The dependent variable is expressed as 100 times the log intensity reduction, so that reported coefficients and standard errors correspond to percentage log-point changes. All models include enterprise and year fixed effects, with standard errors clustered by enterprise.

Under the full-information specification (6,000 firm-years, 600 enterprises), the coefficient on lagged digitalization is 19.83 (SE = 0.35, $t = 57.07$, $p < .001$, 95% CI [19.15, 20.51]), indicating a strong positive association between digitalization and technical efficiency improvements. The R-squared after double demeaning is 0.49. Under the survey-based specification (5,753 firm-years, 600 enterprises), the coefficient attenuates to 8.47 (SE = 0.25, $t = 34.06$, $p < .001$, 95% CI [7.98, 8.96]), with an R-squared of 0.25. This attenuation is expected when measurement error in the questionnaire-derived digitalization index biases the coefficient toward zero. In both specifications, the control variables do not show statistically significant associations with technical efficiency gains, as expected given that these controls capture demand and cost conditions rather than technology adoption. H1 is supported in both specifications.

Table 3: Digitalization and Technical Energy-Efficiency Gains

Specification	Predictor	Coefficient	Standard Error	t	p Value	95% Confidence Interval
Full-Information Specification	Lagged Enterprise Digitalization	19.83	0.35	57.07	$p < .001$	[19.15, 20.51]
Full-Information Specification	Demand Index	0.02	0.05	0.31	$p = .756$	[-0.09, 0.12]
Full-Information Specification	Log Energy Price Index	0.10	0.16	0.60	$p = .546$	[-0.22, 0.42]
Full-Information Specification	Log Employment	0.17	0.27	0.61	$p = .543$	[-0.37, 0.70]
Survey-Based Measures	Lagged Enterprise	8.47	0.25	34.06	$p < .001$	[7.98, 8.96]

Specification	Predictor	Coefficient	Standard Error	t	p Value	95% Confidence Interval
	Digitalization					
Survey-Based Measures	Demand Index	-0.02	0.07	-0.22	p = .824	[-0.15, 0.12]
Survey-Based Measures	Log Energy Price Index	0.22	0.22	1.03	p = .303	[-0.20, 0.65]
Survey-Based Measures	Log Employment	0.10	0.32	0.31	p = .756	[-0.53, 0.72]

Note: The dependent variable is Technical Energy-Efficiency Gain ($100 \times \log$ intensity reduction). All specifications include enterprise and year fixed effects; standard errors are clustered by enterprise.

4.3 Output Expansion and Governance

Table 4 reports the output expansion model, which tests H2 and H3. The dependent variable is 100 times log enterprise output. The technical efficiency gain coefficient represents the output response when governance equals zero; the H2 test at the prespecified governance level of 0.50 is reported in Table 7.

Under the full-information specification, the coefficient on the technical efficiency gain is 159.83 (SE = 17.79, $t = 8.98$, $p < .001$), representing the output response at zero governance. The interaction with baseline energy governance is -128.99 (SE = 29.55, $t = -4.37$, $p < .001$), indicating that governance substantially weakens the efficiency-to-expansion association. The direct digitalization channel shows a coefficient of 5.48 (SE = 2.81, $t = 1.95$, $p = .052$), which does not reach the conventional five percent significance level but is consistent with a modest independent contribution of digitalization to output.

Under the survey-based specification (5,361 firm-years, 581 enterprises), the efficiency gain coefficient is 146.87 (SE = 17.61, $t = 8.34$, $p < .001$), and the governance interaction is -96.11 (SE = 33.84, $t = -2.84$, $p = .005$). The direct digitalization coefficient is 3.44 (SE = 2.39, $t = 1.44$, $p = .151$), not significant at conventional levels. The demand index is the strongest control in both specifications, consistent with market conditions being the primary driver of output variation. The energy price index shows a negative association with output in both specifications, indicating that higher energy prices coincide with lower production levels.

Table 4: Efficiency-Induced Output Expansion and Energy Governance

Specification	Predictor	Coefficient	Standard Error	t	p Value	95% Confidence Interval
Full-Information Specification	Lagged Enterprise Digitalization	5.48	2.81	1.95	p = .052	[-0.04, 10.99]
Full-Information Specification	Technical Energy-Efficiency Gain	159.83	17.79	8.98	p < .001	[124.89, 194.78]
Full-Information Specification	Technical Energy-Efficiency Gain x Baseline	-128.99	29.55	-4.37	p < .001	[-187.02, -70.96]

Specification	Predictor	Coefficient	Standard Error	t	p Value	95% Confidence Interval
Energy Governance						
Full-Information Specification	Demand Index	18.35	0.37	49.50	$p < .001$	[17.62, 19.08]
Full-Information Specification	Log Energy Price Index	-10.84	1.27	-8.52	$p < .001$	[-13.33, -8.34]
Full-Information Specification	Log Employment	0.58	1.67	0.35	$p = .728$	[-2.70, 3.87]
Survey-Based Measures	Lagged Enterprise Digitalization	3.44	2.39	1.44	$p = .151$	[-1.26, 8.13]
Survey-Based Measures	Technical Energy-Efficiency Gain	146.87	17.61	8.34	$p < .001$	[112.29, 181.46]
Survey-Based Measures	Technical Energy-Efficiency Gain x Baseline Energy Governance	-96.11	33.84	-2.84	$p = .005$	[-162.58, -29.64]
Survey-Based Measures	Demand Index	19.15	0.62	30.93	$p < .001$	[17.94, 20.37]
Survey-Based Measures	Log Energy Price Index	-9.12	1.99	-4.58	$p < .001$	[-13.02, -5.21]
Survey-Based Measures	Log Employment	-0.68	2.41	-0.28	$p = .779$	[-5.42, 4.06]

Note: The dependent variable is $100 \times \text{Log Enterprise Output}$. All models include enterprise and year fixed effects, with standard errors clustered by enterprise.

4.4 Operational Carbon Emissions

Table 5 reports the reduced-form emission model, which regresses 100 times log operational carbon emissions on lagged digitalization, its interaction with governance, and controls. This specification estimates the net association between digitalization and emissions without decomposing the underlying channels.

Under the full-information specification, the digitalization coefficient is 18.80 (SE = 4.65, $t = 4.05$, $p < .001$), indicating that higher digitalization is associated with greater carbon emissions when governance is at zero. The interaction with governance is -29.20 (SE = 8.10, $t = -3.60$, $p < .001$), indicating that governance attenuates this association. Under the survey-based specification, the digitalization coefficient is 5.35 (SE = 3.81, $t = 1.40$, $p = .161$), and the interaction is -11.88 (SE = 6.74, $t = -1.76$, $p = .079$). Neither coefficient reaches the conventional five percent significance threshold in the survey-based version, though the

direction is consistent with the full-information results. The attenuation across specifications again reflects the effect of measurement error in the questionnaire-derived digitalization index.

The positive net association between digitalization and emissions in the full-information specification indicates that the output expansion and independent growth effects of digitalization outweigh the technical efficiency gains in their impact on absolute emissions. This net effect, however, is not the same as the efficiency-induced rebound rate, which requires the counterfactual decomposition reported next.

Table 5: Digitalization and Operational Carbon Emissions

Specification	Predictor	Coefficient	Standard Error	t	p Value	95% Confidence Interval
Full-Information Specification	Lagged Enterprise Digitalization	18.80	4.65	4.05	$p < .001$	[9.68, 27.93]
Full-Information Specification	Lagged Enterprise Digitalization x Baseline Energy Governance	-29.20	8.10	-3.60	$p < .001$	[-45.12, -13.29]
Full-Information Specification	Demand Index	18.39	0.39	47.02	$p < .001$	[17.62, 19.15]
Full-Information Specification	Log Energy Price Index	-10.99	1.35	-8.14	$p < .001$	[-13.64, -8.34]
Full-Information Specification	Log Employment	0.81	1.78	0.46	$p = .647$	[-2.67, 4.30]
Survey-Based Measures	Lagged Enterprise Digitalization	5.35	3.81	1.40	$p = .161$	[-2.13, 12.83]
Survey-Based Measures	Lagged Enterprise Digitalization x Baseline Energy Governance	-11.88	6.74	-1.76	$p = .079$	[-25.12, 1.36]
Survey-Based Measures	Demand Index	19.31	0.62	31.29	$p < .001$	[18.10, 20.52]
Survey-Based Measures	Log Energy Price Index	-7.66	2.55	-3.00	$p = .003$	[-12.68, -2.65]
Survey-Based Measures	Log Employment	0.00	3.45	0.00	$p = .999$	[-6.78, 6.79]

Note: The dependent variable is $100 \times \text{Log Operational Carbon Emissions}$. All models include enterprise and year fixed effects, with standard errors clustered by enterprise.

4.5 Carbon Rebound and Uncertainty

Table 6 presents the counterfactual decomposition of carbon rebound using the full-information specification. Direct estimates are calculated from firm-level accounting identities using observed output, technical intensity, and emission factor data. Fitted estimates are derived from the behavioral model, and bootstrap inference is based on 999 enterprise-block resamples. The z-statistics and p values for level quantities test against a null of zero; the rebound rate tests against the complete-rebound threshold of 100 percent.

The total technical carbon-saving potential is estimated at 11.11 million tonnes CO₂ (direct estimate: 11.33), representing the emission reduction that would occur if firms captured the full technical efficiency improvement without expanding output. The expansion-induced carbon offset is 10.32 million tonnes (direct: 8.77), indicating that most of the technical savings potential is absorbed by production expansion. Realized carbon savings are estimated at 0.79 million tonnes with a 95 percent percentile interval of [-1.15, 2.96], meaning that the savings estimate is not statistically distinguishable from zero.

The aggregate carbon rebound rate is estimated at 92.91 percent with a bootstrap interval of [75.04, 110.54] percent. This interval spans the complete-rebound threshold, so the data do not allow a definitive determination of whether partial savings are realized or whether backfire occurs. The primary threshold excludes 8 firm-year records with negligible saving potential, representing 0.04 percent of baseline emissions; results under the 0.5 percent and 2 percent thresholds are substantively identical after rounding.

The decomposition also considers the counterfactual in which all digitalization channels are removed. The independent digitalization scale effect is estimated at 3.21 million tonnes CO₂ (95% CI [0.20, 6.38]), and the total digitalization carbon effect is 2.42 million tonnes (95% CI [-0.08, 4.89]). The total effect interval crosses zero, reflecting uncertainty about whether digitalization increases absolute emissions after all channels are combined.

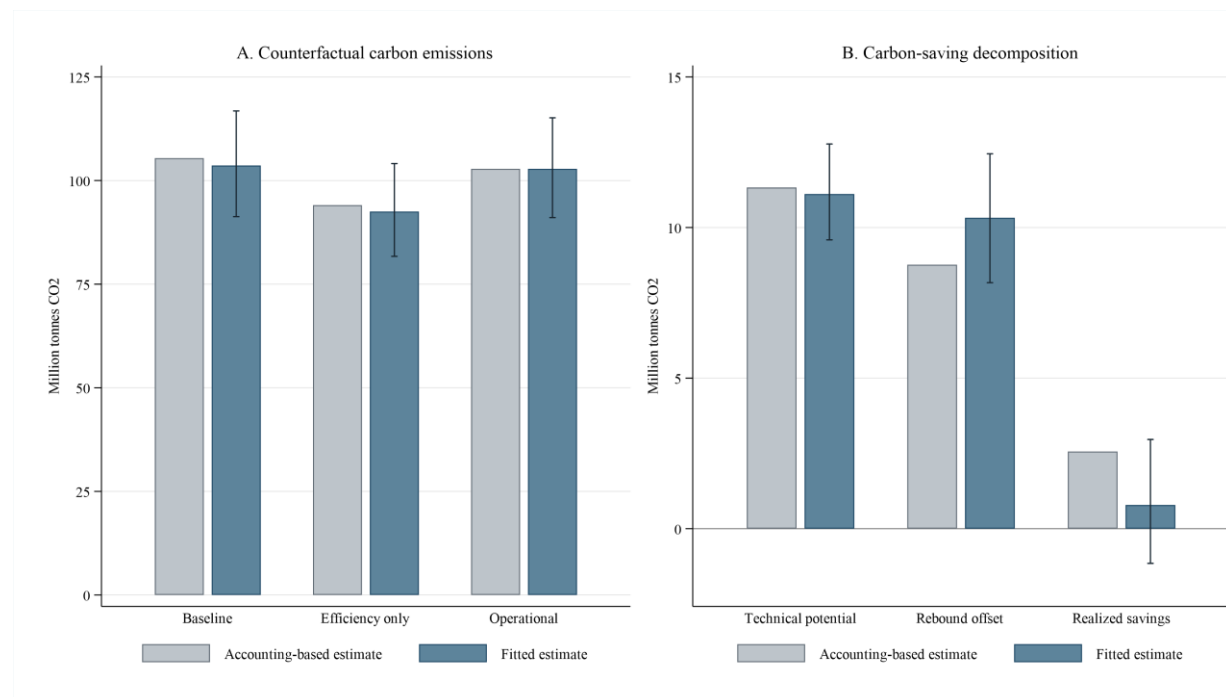


Figure 2. Counterfactual Carbon Emissions and Rebound Decomposition

Table 6: Counterfactual Decomposition of Carbon Rebound

Measure	Unit	Records	Direct Estimate	Fitted Estimate	Bootstrap Standard Error	Null Value	z	p Value	95% Percentile Interval
Baseline Carbon Emissions	Million Tonnes CO2	6000	105.40	103.63	6.41	0.00	16.17	p < .001	[91.29, 116.81]
Technical-Efficiency-Only Carbon Emissions	Million Tonnes CO2	6000	94.07	92.52	5.63	0.00	16.43	p < .001	[81.72, 104.11]
Operational Carbon Emissions	Million Tonnes CO2	6000	102.84	102.84	6.20	0.00	16.59	p < .001	[91.06, 115.14]
Technical Carbon-Saving Potential	Million Tonnes CO2	6000	11.33	11.11	0.81	0.00	13.65	p < .001	[9.59, 12.77]
Realized Carbon Savings	Million Tonnes CO2	6000	2.56	0.79	1.03	0.00	0.76	p = .445	[-1.15, 2.96]
Expansion-Induced Carbon Offset	Million Tonnes CO2	6000	8.77	10.32	1.12	0.00	9.25	p < .001	[8.17, 12.45]
Aggregate Carbon Rebound (1% Threshold)	%	5992	77.37	92.91	9.13	100.00	-0.78	p = .437	[75.04, 110.54]
Carbon Emissions Without Digitalization	Million Tonnes CO2	6000	100.67	100.42	6.18	0.00	16.24	p < .001	[88.31, 112.86]
Independent Digitalization	Million Tonnes CO2	6000	4.73	3.21	1.57	0.00	2.04	p = .042	[0.20, 6.38]

Measure	Unit	Records	Direct Estimate	Fitted Estimate	Bootstrap Standard Error	Null Value	z	p Value	95% Percentile Interval
Scale Effect Total Digitalization Carbon Effect Aggregate Carbon Reboun	Million Tonnes CO2	6000	2.17	2.42	1.24	0.00	1.95	p = .051	[-0.08, 4.89]
d (0.5% Threshold) Aggregate Carbon Reboun	%	6000	77.37	92.91	9.13	100.00	-0.78	p = .437	[75.04, 110.54]
d (2% Threshold)	%	5890	77.35	92.87	9.13	100.00	-0.78	p = .435	[75.02, 110.49]

Note: Direct estimates are based on firm-level accounting identities, while fitted estimates use behavioral model coefficients. Confidence intervals are based on 999 enterprise-block bootstrap resamples.

4.6 Conditional Responses

Table 7 reports the marginal effect of technical efficiency gains on log enterprise output at three prespecified governance levels, computed from the full-information output model using the coefficient covariance matrix. These estimates use the original log-elasticity scale rather than the 100-times scale of Table 4.

At governance level 0.25, the marginal effect is 1.28 (SE = 0.12, $t = 10.61$, $p < .001$, 95% CI [1.04, 1.51]), indicating a strong positive output response to efficiency gains under weak governance. At governance level 0.50, the response declines to 0.95 (SE = 0.09, $t = 10.56$, $p < .001$, 95% CI [0.78, 1.13]). At governance level 0.75, the effect further diminishes to 0.63 (SE = 0.11, $t = 5.59$, $p < .001$, 95% CI [0.41, 0.85]). The difference between high and low governance (0.75 minus 0.25) is -0.64 (SE = 0.15, $t = -4.37$, $p < .001$, 95% CI [-0.94, -0.35]).

H2 is formally tested at governance = 0.50, where the marginal effect is positive and significant. After Holm correction across the three primary tests, all three hypotheses (H1, H2, H3) are supported at $p < .001$. The monotonic decline in the output response across governance levels is consistent with the interpretation that energy governance constrains the extent to which efficiency gains translate into production expansion.

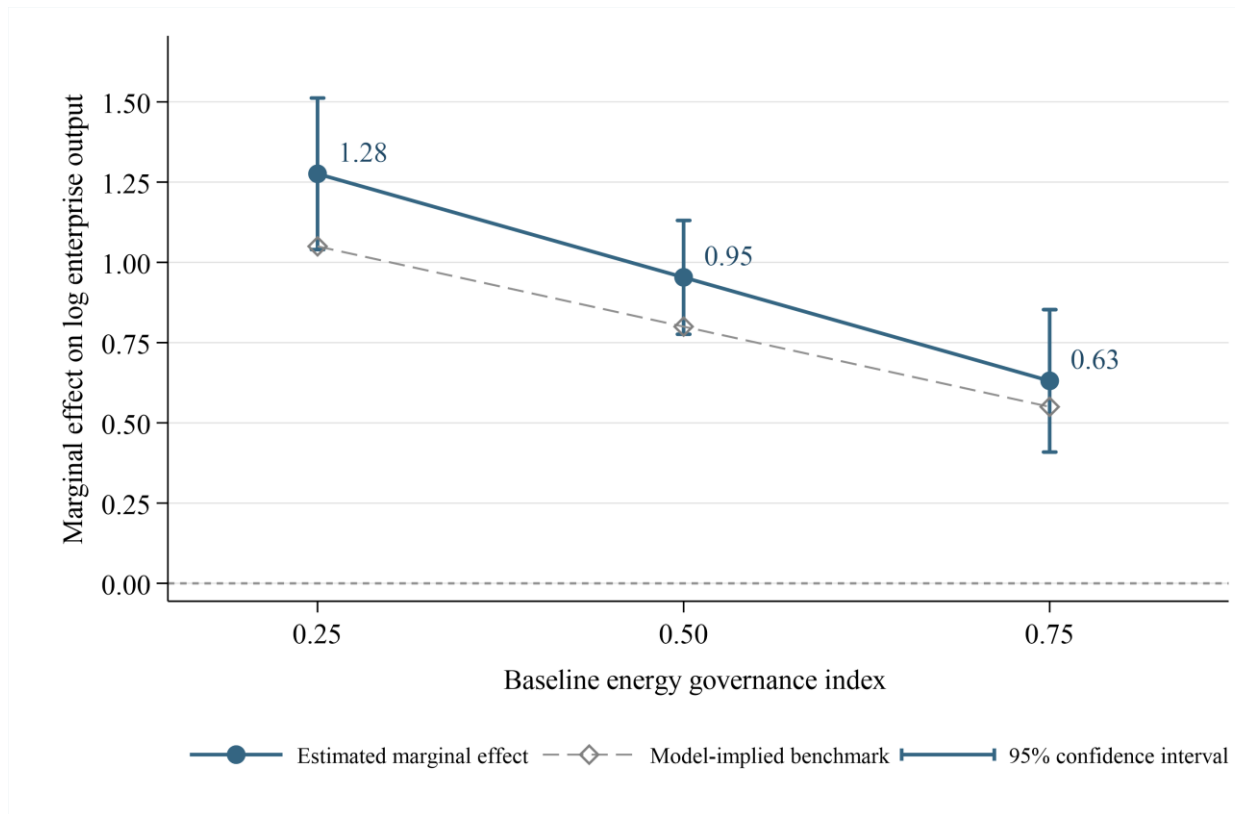


Figure 3. Conditional Output Responses Across Energy Governance Levels

Table 7: Conditional Output Responses Across Governance Levels

Governance Level or Contrast	Direct Estimate	Marginal Effect	Standard Error	t	p Value	95% Confidence Interval
0.25	1.05	1.28	0.12	10.61	$p < .001$	[1.04, 1.51]
0.50	0.80	0.95	0.09	10.56	$p < .001$	[0.78, 1.13]
0.75	0.55	0.63	0.11	5.59	$p < .001$	[0.41, 0.85]
0.75 minus 0.25	-0.50	-0.64	0.15	-4.37	$p < .001$	[-0.94, -0.35]

Note: Marginal effects are computed from the full-information output model. The scale is the original log-elasticity. Holm-corrected p values for H1–H3 are all below .001.

4.7 Sensitivity and Estimation Diagnostics

Table 8 reports the governance interaction estimate from the output model under alternative specifications and structural scenarios. All coefficients are presented in the original log-output scale.

The benchmark interaction estimate is -1.29 (SE = 0.30, $t = -4.37$, $p < .001$, 95% CI [-1.87, -0.71]). The survey-based specification yields -0.96 (SE = 0.34, $t = -2.84$, $p = .005$), which is attenuated but remains significant. Estimating the full-information model on the same 5,361 observations used in the survey-based specification produces an interaction of -1.46 (SE = 0.32, $t = -4.58$, $p < .001$), confirming that the attenuation in the survey-based result reflects measurement properties rather than sample composition.

Under the null scenario in which governance does not moderate the expansion response (reference value 0.00), the estimated interaction is -0.29 (SE = 0.30, $t = -0.98$, $p = .327$), not significant and close to zero. This result indicates that the estimation procedure does not spuriously recover a moderation effect when

none is present in the data. Under weaker and stronger expansion scenarios, the estimated interactions are -0.59 ($p = .046$) and -0.69 ($p = .020$), tracking the differences in reference values.

Allowing governance to affect technical efficiency gains as well as the expansion channel produces an unchanged interaction estimate of -1.29 ($SE = 0.27$), indicating that the moderation result in the expansion equation is not sensitive to this alternative pathway. Replacing additive year effects with industry-by-year fixed effects also leaves the estimate unchanged at -1.29 ($SE = 0.29$).

The conditional diagnostic (200 iterations, fixed regressors, regenerated output disturbance) reports a mean bias of 0.05, RMSE of 0.34, empirical standard deviation of 0.33, average clustered standard error of 0.32, and a 95 percent interval coverage rate of 94.50 percent with a Monte Carlo standard error of 1.61 percentage points. These results indicate adequate standard error calibration and interval coverage for the governance interaction under the maintained assumptions.

Table 8: Sensitivity of the Governance Moderation Estimate

Specification or Scenario	Records	Enterprises	Reference Value	Interaction Estimate	Standard Error	t	p Value	95% Confidence Interval
Benchmark	6000	600	-1.00	-1.29	0.30	-4.37	$p < .001$	[-1.87, -0.71]
Survey-Based Measures and Missingness	5361	581	Not Applicable	-0.96	0.34	-2.84	$p = .005$	[-1.63, -0.30]
Full-Information on Survey Complete Cases	5361	581	-1.00	-1.46	0.32	-4.58	$p < .001$	[-2.08, -0.83]
No Governance Moderation	6000	600	0.00	-0.29	0.30	-0.98	$p = .327$	[-0.87, 0.29]
Weaker Expansion	6000	600	-0.30	-0.59	0.30	-2.00	$p = .046$	[-1.17, -0.01]
Stronger Expansion	6000	600	-0.40	-0.69	0.30	-2.33	$p = .020$	[-1.27, -0.11]
Governance Also Changes Technical Gains	6000	600	-1.00	-1.29	0.27	-4.71	$p < .001$	[-1.83, -0.75]
Industry-by-Year Fixed Effects	6000	600	-1.00	-1.29	0.29	-4.38	$p < .001$	[-1.87, -0.71]

Note: All coefficients are reported on the original log-output scale. Reference values represent expected interaction parameters under each scenario; p values are based on exploratory two-sided tests.

5. Discussion

5.1 Interpretation and Comparison with Prior Research

All three hypotheses receive support in the main specification. The H1 result is consistent with evidence that digitalization improves process efficiency through monitoring, scheduling, and resource allocation (Lange et al., 2020), although the effect varies by technology type (Matthess et al., 2023; Axenbeck et al., 2024). The attenuation from 19.83 to 8.47 between specifications reflects classical measurement error and underscores the sensitivity of digitalization-energy estimates to measurement approach. Shang et al. (2023) report that digital transformation is associated with lower carbon intensity, which is compatible with H1 once intensity reduction and absolute emission change are distinguished.

The expansion channel finding aligns with Lu and Wang (2024), who report direct rebound of 33.5 percent and output expansion of 19.3 percent for Chinese manufacturing firms, and with Du et al. (2025), who identify output expansion as the primary rebound channel. The estimated rebound rate of 92.91 percent exceeds the German firm-level estimates of Berner, Lange, and Silbersdorff (2022), likely reflecting differences in energy pricing, growth pressures, and estimation scope. Stern (2020) and Brockway et al. (2021) note that rebound magnitudes are sensitive to methodology and time horizon, cautioning against direct cross-study comparison.

The governance moderation extends the work of Du et al. (2023), who show that external regulation reduces firm-level rebound, to internal organizational mechanisms. This finding complements E.Z. Wang and Pan (2025) and Fitzgerald et al. (2023) on energy management systems and adds that governance can operate specifically on the expansion channel. The bootstrap interval of [75.04, 110.54] percent spans the complete-rebound threshold, so the data are consistent with both partial savings and marginal backfire. Gillingham et al. (2016) note that rebound does not render efficiency investments valueless; the present results indicate serious offset risk rather than a precise rebound magnitude.

5.2 Theoretical Implications

The study contributes to theory in three ways. First, decomposing the carbon effect of digitalization into technical efficiency, independent scale, and efficiency-induced expansion channels provides a more precise application of the producer rebound framework (Sorrell and Dimitropoulos, 2008; Saunders, 2013), preventing the conflation of market-driven growth with efficiency-induced expansion. Second, introducing internal energy governance as a moderator of the expansion channel extends the organizational control perspective (Ouchi, 1979) into the rebound literature, connecting to the digital sufficiency argument that efficiency improvements require complementary scale constraints (Santarius et al., 2023). Third, the transparent reporting of bootstrap intervals for the rebound rate addresses a methodological gap where point estimates are often presented without uncertainty assessment.

5.3 Managerial Implications

For energy budget planners, the results suggest that absolute consumption ceilings may be more effective than intensity-ratio targets when efficiency improvements coincide with output growth. For project evaluators, incorporating energy demand estimates into digitalization project approval represents a concrete procedural step to constrain the expansion response. For operations managers, regular comparison of actual energy use against targets and documented accountability for deviations provide monitoring mechanisms that limit unreflected expansion. The study does not estimate governance costs or optimal governance intensity; the managerial task is to make expansion decisions with explicit awareness of their energy and carbon consequences.

5.4 Uncertainty and Measurement Implications

The gap between the full-information and survey-based specifications illustrates how measurement properties affect estimated relationships: the digitalization coefficient attenuates from 19.83 to 8.47 in the efficiency model, and the governance interaction from -1.29 to -0.96 in the output model, suggesting that survey-based coefficients may represent lower bounds on the true associations. The bootstrap interval for realized carbon savings spans zero (0.79, 95% CI [-1.15, 2.96]) because when expansion offsets most of the technical potential, the realized saving becomes a small residual with amplified uncertainty. The baseline governance measurement, fixed at 2015, cannot capture within-firm changes over the panel period and may attenuate the interaction estimate if firms strengthened their governance during the observation window.

6. Conclusion

6.1 Main Conclusion

This study examined how enterprise digitalization affects carbon emissions through three channels and whether internal energy governance moderates the expansion response to efficiency gains. Using panel data from 600 Chinese manufacturing firms over 2016 to 2025, the analysis found that digitalization is positively associated with technical energy-efficiency gains (H1), that these gains are associated with output expansion conditional on the separate contribution of digitalization to output (H2), and that energy governance weakens this expansion response (H3). The aggregate carbon rebound estimate is 92.91 percent, with a bootstrap interval spanning 75.04 to 110.54 percent that crosses the complete-rebound threshold. The core finding is that technical energy improvements from digitalization are largely offset by production expansion, but that firms with stronger energy governance arrangements experience smaller output responses to efficiency gains.

6.2 Limitations and Future Research

Several limitations should inform interpretation. The formative indicators for digitalization and governance were developed for this study and require validation in independent samples. The baseline governance measurement cannot capture within-firm changes over the observation period. The two-way fixed effects approach controls for time-invariant firm characteristics and common shocks but does not fully resolve endogeneity from time-varying confounders (Imai and Kim, 2021). The analysis operates at the enterprise boundary and does not capture inter-firm competition, supply-chain reallocation, or wider macroeconomic feedback (Brockway et al., 2021). The conditional diagnostic covers only the output equation under fixed regressors.

Future research could extend this framework in several directions. Collecting repeated governance measures would allow investigation of whether governance improvements alter the rebound trajectory over time. Applying the three-channel decomposition to specific digital technologies (Matthess et al., 2023) rather than aggregate digitalization would identify which investments carry the greatest rebound risk. Examining these mechanisms in service sectors, logistics systems, and supply-chain contexts (Lai et al., 2023; Sun, 2026) would test generalizability beyond manufacturing. Incorporating governance implementation costs would enable a welfare analysis balancing emission reductions against administrative burden. Amjadi et al. (2022) and Tan and Walheer (2025) provide alternative dynamic and production-based decomposition approaches that could complement the fixed-effects framework used here. Studies in other country contexts, building on evidence such as the provincial-level analyses of Huang and Lin (2025) and Peng and Qin (2024) and the city-level work of Zhu and Lan (2023), would help assess the external validity of the governance moderation finding across different institutional environments.

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