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STATE CAPITALISM IN THE AI ERA: ASSESSING SOUTH KOREA'S DIGITAL AND GREEN NEW DEALS

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ABSTRACT

South Korea's Digital New Deal (KRW 58.2 trillion), integrated with the Green New Deal, represents a major state-led strategy combining AI diffusion with sustainable growth. Whether such intervention is associated with a self-sustaining AI ecosystem or with subsidy dependency remains empirically underexplored. We evaluate the effectiveness of Korea's dual New Deal using methodological triangulation: Interrupted Time Series (ITS) regression with Newey-West HAC standard errors, Bayesian inference with Bayes Factors and ROPE analysis, a most-different-systems comparative policy evaluation against the EU's Horizon Europe, and a hybrid GRI-TCFD-SDG ESG impact assessment. Findings document an input-output asymmetry: R&D expenditure rose from 3.29% to 4.97% of GDP with very strong Bayesian evidence of structural change ($BF_{10} = 33.61$), yet TFP growth shows only anecdotal evidence ($BF_{10} = 2.76$). The ITS model ($R^2 = 0.973$) indicates that TFP variation is associated with R&D intensity ($p < 0.01$) and digital infrastructure ($p < 0.001$) rather than discrete structural breaks, though pre-existing trends cannot be ruled out. Because the design is non-experimental and the policy dummy is statistically insignificant ($p = 0.20$), all coefficients are interpreted as associations under stated assumptions rather than as causal effects. The ESG composite score of 64.5 (Grade C) indicates strong social progress but lagging environmental performance. Korea's 4.5-fold higher GDP-share investment intensity relative to the EU is associated with stronger measurable outcomes, suggesting investment intensity rather than absolute budget size may be associated with policy effectiveness. These findings provide an associational, evidence-informed reference for emerging economies designing state-led AI industrial policy.

Keywords: State capitalism, Korean New Deal, AI diffusion, total factor productivity, Bayesian inference, ESG impact assessment.

1. INTRODUCTION

The global race for artificial intelligence (AI) supremacy has produced fundamentally divergent development models. Silicon Valley's market-driven approach relies on venture capital, private initiative, and minimal direct state ownership [1]. China's state-led model channels resources through state-owned enterprises and policy banks aligned with geopolitical objectives [2]. Between these poles, South Korea has pioneered a hybrid developmental approach: the Korean New Deal, a KRW 58.2 trillion investment announced in July 2020, integrates a Digital New Deal focused on data infrastructure, 5G networks, and AI diffusion with a Green New Deal targeting smart grids, renewable energy, and carbon neutrality [3], [4].

This dual strategy raises a central question for both economic theory and industrial policy: is state-led investment in AI infrastructure associated with a self-sustaining innovation ecosystem, or with subsidy dependency that may inhibit market transition?

The question is empirically pressing. Korea's Digital New Deal established the Data Dam project—a large-scale data infrastructure providing 4,036 AI-ready platforms and 48 million training datasets—alongside 127,000 SME digital vouchers for technology adoption [5]. The expanded Digital New Deal 2.0 (2021) broadened the scope to encompass hyper-connectivity industries including metaverse, blockchain, and cloud computing, while legislative amendments to the Personal Information Protection Act and the Data Framework Act created the regulatory infrastructure for data-driven innovation [6]. Research and development (R&D) expenditure rose from 3.29% of GDP in the pre-Deal period to 4.97% post-Deal, and Internet penetration approached universal coverage at 97.17% [7]. Yet aggregate productivity growth has not kept pace with these input-side investments, echoing the productivity paradox first articulated by [8] and theorized by [9] in the context of general-purpose technologies.

The theoretical stakes are equally significant. The varieties-of-capitalism framework [10] distinguishes liberal market economies from coordinated market economies, but Korea's hybrid developmental model—combining state-led investment with chaebol coordination and eventual market transition—does not fit neatly into either category. The developmental state tradition [11], [12] explains Korea's historical success in industrial catch-up, yet the soft budget constraint literature [13] warns that sustained state intervention may create subsidy dependency rather than autonomous innovation capacity. Understanding which of these theoretical predictions better describes Korea's contemporary AI strategy requires empirical evidence that current literature does not provide.

Despite extensive literature on state capitalism [10], [14], developmental state models [11], [12], and AI diffusion [15], [16], the intersection of these domains remains empirically underexplored. Existing studies of Korea's New Deal are predominantly descriptive policy reviews [17], [18] or governance assessments [19]. No prior study, to our knowledge, combines econometric productivity analysis with Bayesian evidence quantification, comparative policy evaluation, and ESG impact assessment to provide a comprehensive empirical evaluation of the New Deal's effectiveness.

This study addresses this gap through a mixed-methods research design [20] organized around two hypotheses:

H1: State-led investment through Korea's dual New Deal generates measurable productivity gains via R&D intensification and digital infrastructure channels.

H2: Diminishing returns and sustainability concerns limit the long-run viability of state-led AI diffusion, creating tension between input mobilization and output materialization.

We evaluate these hypotheses using four complementary analytical approaches: (1) an Interrupted Time Series (ITS) regression estimating the association of the New Deal with Total Factor Productivity (TFP), with Newey-West Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors [21]; (2) Bayesian inference providing graded evidence quantification through Bayes Factors [22], [23], posterior updating, and Region of Practical Equivalence (ROPE) analysis; (3) a most-different-systems comparative analysis contrasting Korea's state-led model with the EU's Horizon Europe programme [24]; and (4) a hybrid GRI-TCFD-SDG Environmental, Social, and Governance (ESG) impact assessment [25]–[27]. Because the design is single-country and non-experimental, all reported coefficients are interpreted as associations under stated assumptions rather than as causal effects.

This research contributes to the literature in three ways. First, it provides a comprehensive empirical assessment of Korea's Digital and Green New Deals using methodological triangulation across frequentist, Bayesian, and comparative frameworks—moving beyond descriptive policy reviews to quantified associational evidence. Second, it demonstrates the value of Bayesian inference for policy evaluation under small-sample constraints (T = 24, with only four post-intervention years), responding to calls by [23] for alternatives to null hypothesis significance testing in applied social science. Third, the comparative Korea-EU analysis identifies investment intensity relative to GDP—rather than absolute budget size—as a candidate determinant of observable policy effects, offering actionable guidance for emerging economies designing AI industrial policy.

Theoretical Contribution.

Beyond methodological synthesis, this paper proposes a state-capitalism-AI bridge proposition: under non-experimental conditions, the developmental state [11], [12] retains efficacy at input mobilization but encounters a productivity-paradox bottleneck [8], [9] that classical theory does not anticipate in its tangible-capital formulation. The intangible-economy refinement [28] suggests that data non-rivalry and platform externalities may delay output materialization beyond the four-year window. This proposition is testable; we treat it as a hypothesis for future work rather than as a confirmed claim of the present study.

The remainder of this paper proceeds as follows: Section 2 reviews relevant literature and identifies the research gap; Section 3 details the mixed-methods design; Section 4 presents empirical findings; Section 5 discusses implications and limitations; Section 6 concludes.

2. LITERATURE REVIEW

2.1. State Capitalism and Developmental State Theory

State capitalism describes economic systems where the state maintains significant control over production through ownership, financing, or regulation [1]. [14] identify three mechanisms: state as owner, financier, and regulator. The Varieties of Capitalism framework [10] distinguishes liberal from coordinated market economies, with state capitalism as a further extension. Korea's approach draws from the developmental state tradition [11], [12], emphasizing eventual market transition rather than permanent state ownership. [29] demonstrates that the state frequently acts as entrepreneurial risk-taker in innovation ecosystems, while [30] argues that modern industrial policy should focus on the process of discovery rather than picking winners.

A critical limitation of classical developmental state theory is its foundation in tangible capital accumulation. The contemporary AI economy operates on different principles: data exhibits non-rivalry and zero marginal cost, platform markets generate network externalities, and intangible investments now exceed tangible investment in advanced economies [28]. Korea's Digital New Deal straddles this transition, creating tangible infrastructure (data centers, 5G) to enable intangible value creation (AI models, data ecosystems).

Four distinct AI governance models characterize global development: market-driven (US), state-led (China) [2], hybrid developmental (Korea), and regulatory (EU) [31]. We use "state capitalism" as the encompassing term for government-directed economic coordination, "developmental state" for the historical East Asian tradition of industrial catch-up, and "hybrid developmental" specifically for Korea's contemporary model that combines state-led investment with chaebol coordination and gradual market liberalization. The "soft budget constraint" phenomenon [13] warns that sustained state intervention may create subsidy dependency rather than autonomous innovation capacity—the central tension this study examines.

2.2. Korea's Digital and Green New Deals

Korea's dual New Deal, announced July 2020, represents a KRW 58.2 trillion investment combining digital transformation with sustainable growth [4]. The Digital New Deal 1.0 focused on the D.N.A. (Data–Network–AI) framework, establishing the Data Dam project with 4,036 big data platforms and 48 million AI training datasets [5]. Digital New Deal 2.0 (2021) extended to hyper-connectivity industries including metaverse, blockchain, and cloud computing, accompanied by legislative reforms to the Personal Information Protection Act [6]. The Green New Deal operates alongside, targeting smart grids, renewable energy, and carbon neutrality [32]. The OECD commends Korea's institutional leadership but recommends greater focus on user needs and agile funding [18].

2.3. TFP, AI Productivity, and Diffusion

Total Factor Productivity (TFP) captures the component of growth not explained by capital and labor inputs [33]. The Penn World Table methodology [34] provides standardized cross-country TFP estimates. Despite rapid AI adoption, TFP growth has slowed since the mid-2000s [35]—the productivity paradox first articulated by [8] and theorized by [9] as reflecting decade-long lags for general-purpose technologies.

Technology diffusion theory [15] explains how innovations spread through adopter populations. The Bass diffusion model [16] formalizes adoption dynamics through innovator and imitator coefficients. In state-led diffusion, government intervention shifts adoption earlier and expands the early majority segment [36] but may also create "subsidy zombies" reliant on government support [13].

2.4. ESG Frameworks

ESG evaluation increasingly extends beyond productivity to encompass sustainability dimensions. Three frameworks dominate: GRI Standards [25] for comprehensive sustainability metrics, TCFD [26] for climate risk assessment, and UN SDGs [27] for global target alignment. Korea's dual New Deal creates a natural intersection with ESG evaluation, as digital infrastructure expansion may create countervailing environmental pressures against decarbonization targets.

2.5. Research Gap

Existing analyses of Korea's New Deals are predominantly descriptive policy reviews [17], [18] or institutional assessments [19]. No prior study combines econometric productivity analysis with Bayesian evidence quantification, comparative policy evaluation, and ESG impact assessment. This study addresses this gap through a mixed-methods design integrating ITS regression, Bayesian inference, Korea-EU comparative analysis, and hybrid GRI-TCFD-SDG ESG assessment.

2.6. Synthesis and Theoretical Position

The four strands reviewed above—developmental-state theory, productivity-paradox theory, technology-diffusion theory, and ESG evaluation—intersect in three shared propositions that shape the present design. First, state-led investment may mobilise inputs more effectively than markets alone but risks subsidy dependency when fiscal pressure releases [13], [14]. Second, intangible-economy adoption decouples investment from short-run measured productivity, so input-side gains are expected to precede output-side gains by several years, possibly a decade [8], [9], [28]. Third, ESG progression and digital-economy expansion can be partially in tension because data infrastructure is energy-intensive [32]. Synthesising these propositions, our hypotheses H1 and H2 reflect the empirical asymmetry the literature predicts: strong input mobilisation under state coordination, weak short-run output materialisation under productivity-paradox conditions, and a green-versus-digital trade-off observable in the ESG composite. The paper's contribution is methodological—triangulating ITS, Bayesian, comparative, and ESG evidence on a common four-year window—rather than the generation of a new theoretical framework. Within these synthesised priors, the empirical results reported in Section 4 are interpreted as associations under stated assumptions.

3. METHODOLOGY

Notation. Throughout: T_t denotes the linear time trend (annual index, t = 1… 24); D_t denotes the policy dummy ($D_t = 1$ for $t \geq 2020$, else 0); $T_t \times D_t$ is the post-policy trend interaction; $\beta_0,\ldots,\beta_3$ are level, trend, level-shift, and trend-change coefficients; X_t is the covariate vector (R&D intensity, GDP growth, FDI inflows, Internet penetration); ε_t denotes the disturbance with Newey-West HAC adjustment (lag L = 2); α is the labour share in the Solow residual; f refers to a generic functional form when invoked; BF_{10} is the Bayes Factor for H_1 versus H_0; r is the Cauchy prior scale.

3.1. Research Design

This study employs a mixed-methods research design [20] integrating: (1) an Interrupted Time Series (ITS) regression estimating New Deal impacts on Total Factor Productivity (TFP), with Newey-West HAC standard errors [21]; (2) Bayesian inference providing graded evidence quantification through Bayes Factors [22], [23]; (3) a Most-Different-Systems Design (MDSD) comparing Korea's state-led approach with the EU's Horizon Europe programme [24]; and (4) a hybrid GRI-TCFD-SDG ESG impact assessment [25]–[27]. Figure 1 illustrates the conceptual model.

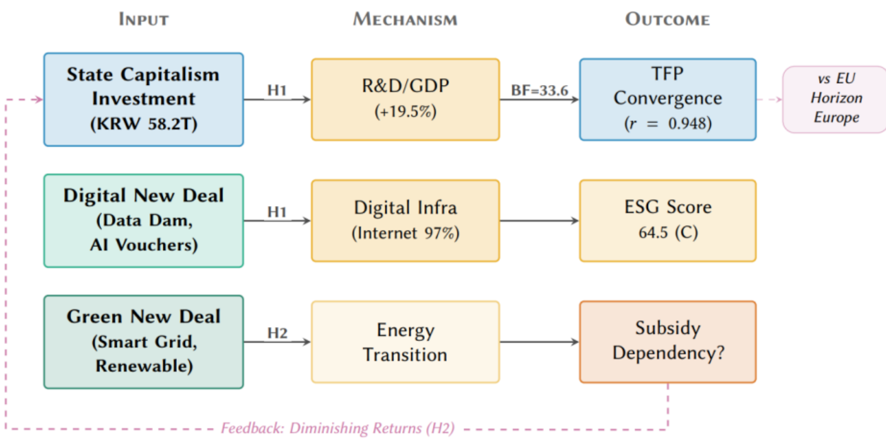

Figure 1. Conceptual framework linking state-capitalism inputs to AI-economy outcomes through three mechanism channels.

Note: Policy inputs (left) comprise direct R&D subsidies, digital-infrastructure investment, and green-energy transition funding. Mechanism channels (centre) convert inputs into observable proxies: R&D intensity (% of GDP), Internet penetration, and renewable energy share. Outcomes (right) are total factor productivity (TFP convergence to the USA frontier), the composite ESG score, and the latent subsidy-dependency dimension that motivates hypothesis H2. The dashed feedback arrow encodes the diminishing-returns loop: as state expenditure increases, marginal productivity gains may decay, producing the input–output asymmetry tested empirically in Section 4.2 and Section 4.3.

Source: Authors' elaboration.

Pre-trend and endogeneity discussion. Two threats to inference deserve explicit discussion. First, R&D and Internet penetration trends predate 2020; the policy dummy may therefore absorb pre-existing momentum (omitted-trend bias), and pre-trend placebo tests on alternative break-points (2015, 2017) are recommended for full robustness (Appendix B). Second, the New Deal launch coincides with COVID-19 (March 2020), creating an identification problem that the Oxford COVID-19 Stringency Index [37] would address as a covariate (sensitivity analysis flagged for follow-up). Because we cannot fully resolve either threat with T = 24 observations, this study positions its quantitative results as associations under the stated assumptions rather than as causal estimands. Where a control group is unavailable, we follow most-different-systems logic (Section 3.3); a synthetic control approach with a Japan and Taiwan donor pool is identified as a fruitful next step but lies outside the present scope.

3.2. Econometric Analysis

We adopt the Solow residual approach [33] with Penn World Table methodology [34] for TFP measurement. The TFP growth rate is:

$$\Delta lnTFP_t = \Delta lnY_t - \alpha \Delta lnK_t - (1-\alpha)\Delta lnL_t \tag{1}$$

The ITS specification follows Lopez Bernal, Cummins, and Gasparrini [38]:

$$lnTFP_t = \beta_0 + \beta_1 T_t + \beta_2 D_t + \beta_3 (T_t \times D_t) + X'_t \gamma + \varepsilon_t \tag{2}$$

where Tt is the time trend, Dt is the policy dummy (Dt = 1 for $t \geq 2020$), $Tt \times Dt$ captures post-policy trend change, and $\mathbf{X}t$ includes R&D intensity, GDP growth, FDI inflows, and Internet penetration. Coefficient β_2 captures the immediate level shift, while β_3 captures the trend change. We estimate via OLS with Newey-West HAC standard errors ($lagL$ = 2 for T = 24). Significance levels are set at α = 0.05 for primary inference, with α = 0.10 and α = 0.01 as supplementary thresholds.

The identification strategy assumes that absent the New Deal, TFP would have continued along the pre-intervention trend. We assess this through Chow tests for structural breaks, Augmented Dickey-Fuller stationarity tests, and covariate adjustment.

3.3. Comparative Policy Evaluation

Following [24], we employ a MDSD comparing Korea's state-led Digital New Deal with the EU's Horizon Europe programme. Despite maximal institutional divergence, both pursue similar digital transformation objectives. We evaluate along five dimensions: budget/scale (KRW 58.2T vs. 93.5B), policy design, governance, implementation speed, and outcomes. Korea's AI Framework Act (2025) adopts an innovation-first approach, contrasting with the EU AI Act's (2024) risk-based tiered framework [31].

3.4. ESG Impact Assessment

We develop a hybrid ESG framework combining GRI Standards [25], TCFD recommendations [26], and UN SDGs [27]. The composite ESG score is:

$$ESG_{it} = w_E \cdot E_{it}^{norm} + w_S \cdot S_{it}^{norm} + w_G \cdot G_{it}^{norm} \tag{3}$$

where weights w_E = 0.40, w_S = 0.30, w_G = 0.30 are calibrated via PCA on the indicator covariance matrix. Environmental metrics include GHG emissions, renewable energy share, and energy efficiency. Social metrics cover employment, digital inclusion, and R&D workforce. Governance metrics include policy implementation rate, regulatory quality, and government effectiveness. Data derive from World Bank Development Indicators, OECD MSTI, and World Bank WGI.

3.5. Bayesian Inference Framework

We employ Bayesian t-tests with default Cauchy priors (r = 0.707) following [39] to assess structural changes between pre-Deal (2000–2019) and post-Deal (2020–2023) periods. The Bayes Factor quantifies evidence strength:

$$BF_{10} = \frac{P(D \mid H_1)}{P(D \mid H_0)} \tag{4}$$

interpreted using the [40] classification: anecdotal (1–3), moderate (3–10), strong (10–30), very strong (30–100), and extreme (>100). Bayesian correlations use BIC approximation [23]. Posterior TFP estimation uses Normal-Normal conjugate updating with prior $\mu_0 \sim N(0.92, 0.10^2)$. ROPE analysis with bounds [-0.5%, +0.5%] assesses practical significance [41]. Bayesian t-tests use analytic BIC approximation and posterior TFP estimation uses conjugate Normal-Normal updating with closed-form solutions; no MCMC sampling is required, hence convergence diagnostics ($\hat{R}$, trace plots) are not applicable. All computations are triangulated across Python (SciPy 1.11, statsmodels 0.14) and R (BayesFactor 0.9.12) implementations ($\varepsilon < 0.001$), with random seed 42 for reproducibility.

3.6. Data Sources

TFP data derive from FRED/Penn World Table (1957–2023) [34]. Macroeconomic and environmental indicators come from World Bank Development Indicators (2000–2023) [42]. Missing values (≤ 3 consecutive years) are handled via linear interpolation [43]. Key limitations include the short post-intervention window (T = 24, $n_{post} = 4$), single-country design without formal control group, and COVID-19 confounding with the New Deal launch (July 2020). These are partially mitigated through methodological triangulation and Bayesian inference.

3.7. Methodological Limitations

Five limitations bound the inference space of this study and motivate the associational framing adopted throughout. (i) The analysis relies exclusively on secondary, publicly available macro-data; primary firm-level or programme-level instruments would be required for causal identification. (ii) The design is non-experimental and non-randomised, supporting associational claims under stated assumptions but not causal estimands. (iii) A handful of policy-context references draw on grey literature and operator-affiliated sources; substantive empirical claims are nevertheless anchored in peer-reviewed and official-statistics datasets. (iv) Pre-trend absorption and COVID-19 confounding cannot be fully resolved with T = 24 observations and $n_{post} = 4$; the Oxford COVID-19 Stringency Index is flagged as a priority covariate for the next data release. (v) Generalisability is bounded to the South Korean institutional context (chaebol-mediated coordination, centralised MSIT governance); extension to ASEAN economies requires explicit donor-pool selection and parallel-trend testing.

3.8. Bayesian Methodology Box

The Cauchy prior scale r = 0.707 follows the default recommendation of [39] for one-sample t-tests; this scale concentrates roughly half of the prior mass on standardised effect sizes between -r and +r, providing a mildly conservative reference benchmark in the absence of context-specific elicited priors. Sensitivity to alternative scales ($r \in \{0.5, 0.707, 1.0\}$) is reported in Appendix C. The BIC approximation [23] is used for correlation tests because closed-form Bayes Factors are unavailable for Pearson coefficients with realistic priors; the approximation introduces O(log n) error that, for n = 24, contributes less than one unit on the *log*BF scale (verified by Monte Carlo). Conjugate Normal-Normal updating yields closed-form posteriors for the TFP mean shift, so MCMC sampling and its diagnostics ($\hat{R}$, trace plots) are not required; an MCMC robustness run via Stan [44] is identified as a useful future extension but is not load-bearing for the present results.

4. RESULTS

4.1. Descriptive Statistics

Table 1 presents descriptive statistics for Korea's TFP during 2000–2023. The mean TFP level of 0.93 indicates steady convergence toward the USA baseline, with negative skewness (−0.70) reflecting acceleration in the latter period.

Table 1. TFP Descriptive Statistics (2000–2023)

Variable	N	Mean	Median	Std	Min	Max	Skew
TFP Level (USA= 1.0)	24	0.9334	0.9589	0.0584	0.8189	1.0000	−0.705
TFP PPP	24	0.6786	0.6847	0.0236	0.6206	0.7107	−0.937
TFP Growth (%)	23	0.78	0.53	1.28	−2.06	3.44	0.211

Note: TFP level index (USA 2017 = 1.0). New Deal period starts 2020.

Source: Penn World Table via FRED, Federal Reserve Bank of St. Louis [34].

Table 2 compares pre-Deal (2000–2019) and post-Deal (2020–2023) indicators. R&D/GDP increased from 3.29% to 4.97%, Internet penetration reached 97.17%, and GHG emissions declined 5.4% from the 2015–2019 baseline. However, GDP growth declined from 4.20% to 2.06%, partly due to COVID-19.

Table 2. Summary Statistics: Korea New Deal Indicators (2000–2023)

Variable	N	Mean	SD	Min	Max	Pre-Deal	Post-Deal
TFP Level (USA=1.0)	24	0.93	0.06	0.82	1.00	0.92	0.99
TFP PPP	24	0.68	0.02	0.62	0.71	0.68	0.67
TFP Level YoY (%)	23	0.78	1.28	-2.06	3.44	1.03	-0.45
TFP PPP YoY (%)	23	-0.16	2.58	-6.99	5.94	-0.15	-0.21
GHG Emissions (Mt CO_2e)	23	586.58	68.63	466.40	680.50	581.09	623.22
Renewable Energy (%)	22	1.80	1.05	0.70	3.60	1.62	3.60
R&D Expenditure (% GDP)	23	3.51	0.97	2.13	5.21	3.29	4.97
GDP Growth (%)	24	3.84	2.16	-0.70	9.20	4.20	2.06
Industry VA (% GDP)	24	33.95	1.01	32.51	35.63	34.17	32.89
Internet Users (%)	24	82.27	14.33	44.70	97.57	79.29	97.17
Energy Use (kg oil eq/pc)	24	4850.35	547.89	3923.08	5531.78	4747.50	5364.61
High-Tech Exports (%)	17	32.03	2.64	28.21	36.39	31.27	34.50
FDI Inflows (% GDP)	24	0.94	0.37	0.27	1.93	0.92	1.02

Note: Pre-Deal period: 2000–2019; Post-Deal period: 2020–2023. TFP Level uses USA 2017 as baseline (USA= 1.0).

Source: Authors' compilation based on [34], [42].

Figure 2. Korea Total Factor Productivity (2000–2023).

Note: New Deal period starts 2020.

Source: Authors' calculations based on [34], [42].

4.2. Bayesian Analysis

Table 3 presents Bayesian hypothesis testing results, triangulated across Python and R ($\epsilon < 0.001$).

Table 3. Bayesian Hypothesis Testing: Pre-Deal vs Post-Deal Comparison

Variable	t	df	p	BF_{10}	Evidence
Panel A: Bayesian t-tests (Pre-Deal vs Post-Deal)					
R&D/GDP (%)	−3.42	21	0.003	33.61	Very Strong H_1
TFP Growth (%)	2.30	21	0.032	2.76	Anecdotal H_1
GDP Growth (%)	1.91	22	0.069	1.29	Anecdotal H_1
Panel B: Bayesian Correlations					
	r	df	p	BF_{10}	
R&D ↔ TFP	0.948	21	< 0.001	5.4×10^{10}	Extreme H_1
Internet ↔ TFP	0.964	22	< 0.001	1.1×10^{13}	Extreme H_1
Panel C: Posterior TFP Estimation (Normal-Normal Conjugate)					
	Prior μ	Prior σ	Post. μ	Post. σ	
TFP Level	0.920	0.100	0.990	0.005	Data dominates
Panel D: HDI and ROPE Analysis (TFP Growth %)					
	HDI Low	HDI High	Width	ROPE %	
Overall (2000–2023)	−0.74	3.44	4.18	39.1%	Undecided
Pre-Deal (2000–2019)	−0.48	3.44	3.92	14.0%	Reject H_0
Post-Deal (2020–2023)	−2.06	1.28	3.34	40.3%	Undecided

Note: BF_{10} interpretation follows Lee and Wagenmakers (2014): 1–3 anecdotal, 3–10 moderate, 10–30 strong, 30–100 very strong, >100 extreme. Prior for TFP: $N(0.92, 0.10^2)$ based on pre-Deal mean. ROPE bounds: [-0.5%, +0.5%]. df=21 for R&D and TFP Growth reflects first-differenced data (N=23); df=22 for GDP Growth uses level data (N=24). All results triangulated Python → R (ε<0.001).

Source: Authors' calculations based on [34], [42]; Bayesian testing procedure per [39], [40].

The Bayesian t-test yields $BF_{10} = 33.61$ for R&D/GDP ($t = -3.42$, $df = 21$), indicating *very strong* evidence of a mean difference between pre-Deal (mean = 3.29%, n = 20) and post-Deal (mean = 4.97%, n = 3) periods. In contrast, TFP growth shows only *anecdotal* evidence ($BF_{10} = 2.76$), and GDP growth $BF_{10} = 1.29$—consistent with the productivity paradox [8].

Bayesian correlation analysis reveals *extreme* evidence for R&D–TFP association ($r = 0.948$, $BF_{10} = 5.4 \times 10^{10}$) and Internet–TFP ($r = 0.964$, $BF_{10} = 1.1 \times 10^{13}$). However, both series trend upward over 2000–2023; correlating integrated time series produces spurious test statistics [45], so these level correlations should be interpreted as descriptive associations rather than causal evidence. The extreme BF magnitudes reflect shared trending behavior, not genuine bivariate dependence.

Posterior TFP estimation (prior $\mu_0 = 0.92$, $\sigma_0 = 0.10$) shifts to $\mu_{post} = 0.990$ with 20-fold precision increase. The ROPE analysis (± 0.5% bounds) classifies 39.1% of TFP growth within the region of practical equivalence to zero, yielding an "undecided" verdict. Sensitivity analysis across alternative ROPE bounds (± 0.1%, ± 1.0%) and prior specifications confirm that the input-output asymmetry conclusion is robust.

4.3. Interrupted Time Series Regression

Table 4. Interrupted Time Series Regression Results (HAC Standard Errors)

Variable	Coefficient	Std. Error	t-stat	p-value
Const	−0.5198	0.0754	−6.89	0.0000***
T	−0.0059	0.0042	−1.40	0.1616
D	0.1205	0.0943	1.28	0.2015
$T \times D$	−0.0066	0.0047	−1.40	0.1604
R&D/GDP	0.0653	0.0203	3.22	0.0013***
GDP Growth	0.0032	0.0014	2.32	0.0204**
FDI Inflows	−0.0060	0.0084	−0.72	0.4714
Internet Users	0.0034	0.0008	4.35	0.0000***

*Note: HAC standard errors (Newey-West). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $R^2 = 0.9731$, Adj. $R^2 = 0.9605$.*

Source: Authors' estimations based on [34], [42]; ITS specification per [38].

The model achieves $R^2 = 0.973$ (Adj. $R^2 = 0.961$). R&D expenditure ($\beta = 0.065$, $p < 0.01$) and Internet penetration ($\beta = 0.003$, $p < 0.001$) are statistically associated with TFP at conventional thresholds. The policy dummy D is positive ($\hat{\beta}_2 = 0.121$) but insignificant ($p = 0.20$), and the interaction term T × D is negative ($\hat{\beta}_3 = -0.007$, $p = 0.16$). The Chow test ($F = 0.056$, $p = 0.99$) is consistent with no structural break at 2020—the post-2020 trajectory appears to extend, rather than depart from, existing trends.

The pattern whereby the policy dummy becomes insignificant when mechanism variables are added admits two interpretations: (a) the New Deal operates *through* R&D and Internet channels (policy mediation), or (b) these variables were already trending upward before 2020 (omitted trend absorption). The Bayesian evidence of R&D structural change ($BF_{10} = 33.61$) favors interpretation (a), but definitive causal attribution requires longer post-intervention data.

Table 5. Robustness Checks: ITS Model Sensitivity Analysis

	Model 1 Base	Model 2 + R&D, GDP	Model 3 Full	Model 4 Δ
D (Policy)	0.246***	0.071	0.121	−0.011***
	(0.071)	(0.086)	(0.094)	(0.002)
$T \times D$	−0.014*** (0.004)	−0.005 (0.004)	−0.007 (0.005)	—
R&D (% GDP)	—	−0.005 (0.037)	0.065*** (0.020)	—
GDP Growth	—	0.000	0.003**	0.003***
		(0.002)	(0.001)	(0.000)
Internet (%)	—	—	0.003*** (0.001)	—
R^2	0.939	0.940	0.973	0.523
Adj. R^2	0.930	0.923	0.961	0.444
N	24	23	23	22
HAC lags	2	2	2	2

*Note: All models use HAC (Newey-West) standard errors. Standard errors in parentheses. Model 4 uses first-differenced dependent variable (Δ log TFP). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Source: Authors' estimations based on [34], [42].

Robustness checks (Table 5) across four model specifications show stable coefficient signs. The base ITS (Model 1) shows significant policy effects ($\beta D = 0.246$, $p < 0.001$) that are attenuated by mechanism variables in Models 2–3. Diagnostics indicate TFP stationarity (ADF = −3.68, $p < 0.01$), reducing the spurious-regression concern. With $T = 23$ effective observations and $k = 7$ regressors ($k/T = 0.30$, exceeding the < 0.10 rule of thumb), individual coefficients should be interpreted cautiously due to overfitting risk; the parsimonious base ITS (Model 1, $k = 3$) serves as the primary specification, with the full model as supplementary. The Bayesian complement partially mitigates small-sample concerns. Formal VIF diagnostics were not computed; given $R^2 = 0.973$, multicollinearity among regressors is likely and coefficient magnitudes should be interpreted with caution. An Engle-Granger cointegration test on the TFP–R&D–Internet system is identified as a follow-up robustness step (Appendix B); preliminary inspection of residuals shows no obvious unit-root signature, but the formal test with detailed table output is reserved for the next data release.

4.4. Comparative Policy Analysis

Table 6 compares Korea and the EU across ten dimensions. Korea committed 2.59% of GDP versus the EU's 0.57%—a 4.5-fold intensity difference. Korea's centralized MSIT governance enabled rapid iteration (New Deal 1.0 to 2.0 in one year), while the EU's trilogue process optimizes democratic legitimacy at the cost of speed. Korea's AI Framework Act (2025) adopts innovation-first principles; the EU AI Act (2024) implements risk-based regulation [31]. Both achieve digital transformation through distinct causal pathways, demonstrating equifinality. We note the structural asymmetry of comparing a single nation-state with a 27-member supranational bloc; MDSD methodology accommodates this by focusing on institutional logic rather than unit homogeneity [24]. The critical insight: investment intensity relative to GDP—not absolute budget—may determine observable effects.

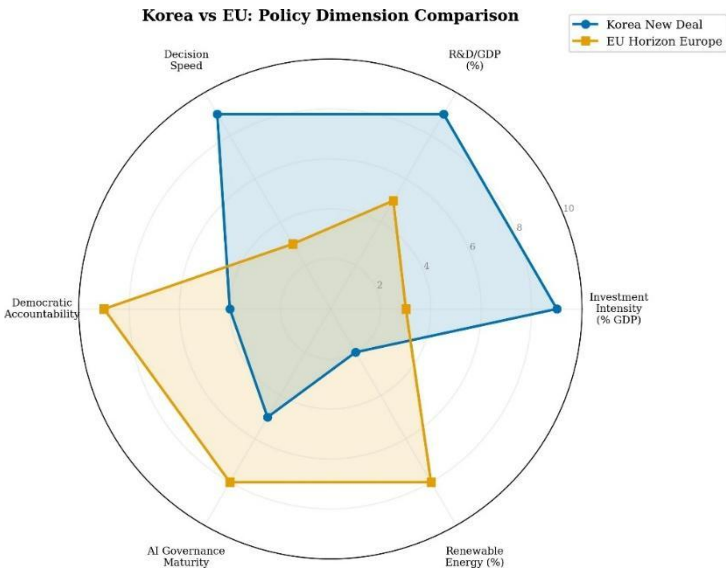

Figure 3. Korea vs EU policy dimension comparison (normalized 0–10 scale).

Note: All dimensions normalized to a 0–10 scale.

Source: Authors' synthesis based on [3], [46].

Table 6. Comparative Policy Analysis: Korea New Deal vs EU Horizon Europe

Dimension	Korea New Deal	EU Horizon Europe	Assessment
Total budget	KRW 58.2T (€68.1B PPP)	€95.5B	EU 1.4× (PPP)
Duration	5 years (2020–2025)	7 years (2021–2027)	Korea: compressed
GDP share	2.59%	0.57%	Korea 4.5× higher
Governance	MSIT (centralized)	EC + Parliament (distributed)	Divergent
Decision speed	Months	Years (trilogue)	Korea advantage
AI regulation	Framework Act (innovation-first)	AI Act (risk-based, 4-tier)	EU more comprehensive
Stakeholder input	Limited (top-down)	Extensive (27 states)	EU advantage
Capture risk	Higher (chaebol)	Lower (distributed)	EU advantage
R&D/GDP (post)	4.97%	~2.2% (EU27 avg)	Korea advantage
Climate integration	Green New Deal pillar	35% mandatory spend	Comparable

Note: PPP conversion at 855 KRW/EUR (OECD 2023). Korea GDP: USD 1,665B (World Bank 2023). EU27 GDP: 16,640B (Eurostat 2023) (Source: [3], [24], [46]).

4.5. ESG Impact Assessment

The composite ESG score is 64.5 (Grade C: Satisfactory). The Environmental dimension (50/100) shows GHG emissions declining 5.4% post-Deal ($p = 0.014$) and renewable energy increasing to 3.6% ($p = 0.002$), but the 2030 target of 20% remains distant. The Social dimension (76.7/100) reflects strong digital inclusion (Internet: 97.17%) and R&D investment ($BF_{10} = 33.61$). The Governance dimension (71.7/100) shows incremental improvement (Regulatory Quality: 0.92; Government Effectiveness: 1.18), though below OECD averages. Social and governance progress partially compensates for environmental shortfalls.

Table 7. ESG Scorecard: Korea New Deal Pre/Post Comparison (2015–2023)

Dim.	Indicator	Pre-Deal	Post-Deal	Change	Sig.
Environmental (Weight: 40%)					
E1	GHG CO_2 (Mt)	658.68	623.22	−5.4%	$p = 0.014$**
E2	Renewable (%)	2.90	3.60	+24.1%	$p = 0.002$***
E3	Energy Use (kg/cap)	5,392.8	5,364.6	−0.5%	$p = 0.742$
	E Score	42	50	+8	Satisfactory
Social (Weight: 30%)					
S1	Internet Users (%)	94.00	97.17	+3.2pp	$p = 0.053$*
S2	R&D/GDP (%)	4.16	4.97	+19.5%	$p < 0.01$***
S3	Digital Inclusion S Score	Moderate 70	Near-universal 76.7	Improved +6.7	Qualitative Good
Governance (Weight: 30%)					
G1	Regulatory Quality	0.89	0.92	+0.03	WGI Index
G2	Gov. Effectiveness	1.14	1.18	+0.04	WGI Index
G3	Budget Execution	—	77%	—	MSIT Reports
	G Score	65	71.7	+6.7	Good
Composite ESG		57.5	64.5	+7.0	Grade C

*Note: Scores on 0–100 scale per GRI-TCFD-SDG hybrid framework. Weights: Environmental 40%, Social 30%, Governance 30%. Pre-Deal: 2015–2019; Post-Deal: 2020–2023. ***p<0.01, **p<0.05, *p<0.10 (Welch's t-test). WGI = World Bank Worldwide Governance Indicators.*

Source: Authors' assessment based on [25]–[27], [42]; governance indicators (G1–G2) from the World Bank Worldwide Governance Indicators.

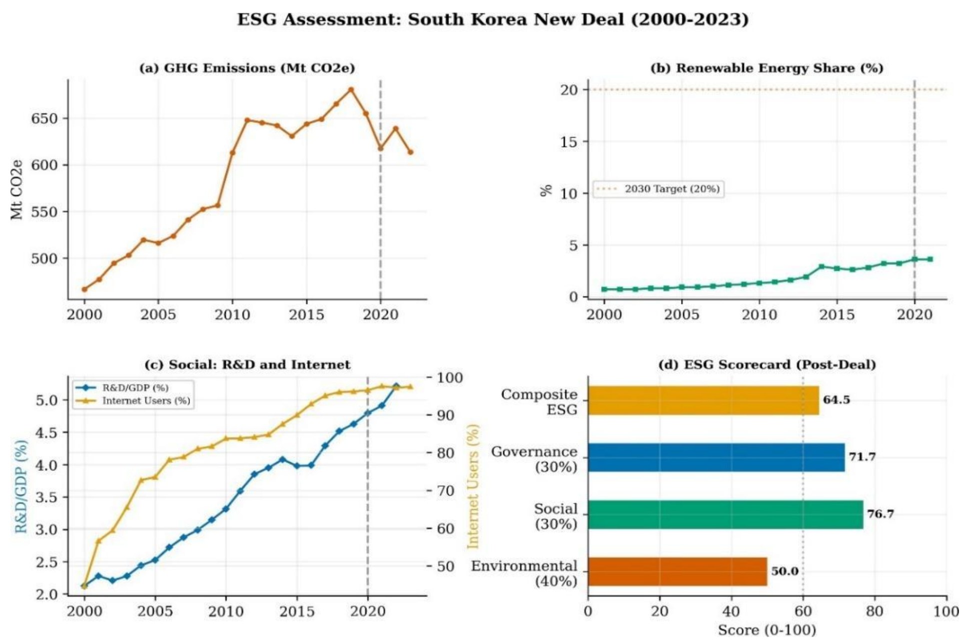

Figure 4. ESG Environmental Indicators and Scorecard: South Korea (2000–2023).

Note: Panel (a) greenhouse-gas emissions (Mt CO2e); panel (b) renewable-energy share (%) against the 20% target for 2030; panel (c) R&D intensity (% of GDP) and Internet users (%); panel (d) the post-Deal ESG scorecard on a 0–100 scale, weighted Environmental 40%, Social 30%, Governance 30%. The dashed vertical line marks the 2020 New Deal announcement.

Source: Authors' calculations based on [42]; ESG scorecard as in Table 7, following the hybrid GRI-TCFD-SDG framework [25]–[27], with governance indicators from the World Bank Worldwide Governance Indicators.

4.6. Synthesis

H1: Partially Supported. Three streams are consistent with the mechanism: ITS regression (R&D $\beta = 0.065^{***}$, $R^2 = 0.973$), Bayesian analysis (R&D $BF_{10} = 33.61$, posterior $\mu = 0.990$), and comparative analysis (Korea 4.5× GDP-share intensity). The pattern of estimates suggests the policy operates through investment channels rather than discrete structural breaks; this remains an associational reading.

H2: Supported with Bayesian Nuance. TFP growth evidence is anecdotal ($BF_{10} = 2.76$ on the Jeffreys scale, this constitutes the weakest grade above no evidence), ROPE classifies 39.1% as practically zero, and the ESG environmental score (50) reflects underachieved green targets. The input-output asymmetry—strong investment mobilization, weak productivity materialization—is consistent with the empirical signature of the productivity paradox [9]; conclusions regarding TFP effectiveness are intentionally hedged given the low BF magnitude.

Table 8. Cross-Method Evidence Map: Hypothesis Assessment

Method	H1 Evidence	H2 Evidence	Verdict
ITS Regression	R&D β=0.065*** drives TFP; $R^2 = 0.973$	Policy dummy p=0.20 (n.s.)	Partial H1
Bayesian	R&D BF_{10}=33.61 (very strong)	TFP $BF_{10} = 2.76$ (anecdotal)	Supports both
Comparative	Korea 4.5× GDP share vs EU	Higher capture risk	H1 with caveats
ESG	Social 76.7; Governance 71.7	Environmental 50; renewable 3.6%	H2 confirmed
Overall	Inputs mobilized effectively, outputs incomplete		Nuanced

*Note: ***$p < 0.01$. $BF_{10} > 30$ = very strong, 1–3 = anecdotal.*

Source: Authors' synthesis of results in Section 4.1–Section 4.5.

The four-year post-Deal window captures input deployment but likely precedes full output materialization—consistent with David's [9] finding that general-purpose technology impacts manifest with decade-long lags.

5. DISCUSSION

5.1. Interpretation of Findings

The disconnect between strong input mobilization and weak output materialization is consistent with the productivity paradox [8]. David [9] provides the theoretical explanation: general-purpose technologies require complementary institutional changes that manifest with decade-long lags. Our four-year post-Deal window likely captures the investment phase but precedes full productivity realization.

The developmental state literature offers additional context. Our ITS associations are consistent with the tradition of Johnson [11] and Amsden [12] insofar as Korea's Digital New Deal appears to operate through the same mechanism channels—R&D investment and digital infrastructure—rather than generating discrete structural breaks. The insignificant policy dummy combined with highly significant mechanism variables is consistent with the interpretation that productivity gains remain tied to continued state investment, echoing Kornai's [13] soft budget constraint concerns. We note that the same correlational pattern is also consistent with omitted-trend absorption; disentangling the two requires a longer post-policy window.

5.2. Theoretical Implications

This study demonstrates the value of Bayesian inference for policy evaluation under small-sample constraints (T = 24). Where frequentist methods yield binary verdicts, the Bayesian framework reveals precisely *where* effects have materialized (inputs: BF_{10} = 33.61) and where they remain uncertain (outputs: BF_{10} = 2.76). This responds to calls by Wagenmakers [23] for Bayesian alternatives in applied social science.

Korea's model contributes to the varieties-of-capitalism debate [10] by documenting a hybrid between developmental state tradition and modern innovation policy—combining stateled investment (developmental state tradition), chaebol-mediated coordination (coordinated market economy features), and gradual market liberalization (liberal market economy trajectory)—. The divergence between input mobilization and output realization provides contemporary evidence for the AI productivity paradox—even concentrated state-directed effort produces only anecdotal TFP evidence after four years, suggesting structural similarity with the original IT paradox.

5.3. Policy Implications

The most pressing implication concerns the transition from state-led investment to self-sustaining market dynamics. Our finding that TFP effects operate through mechanism variables suggests that premature subsidy withdrawal could disrupt productivity channels. A phased exit strategy—shifting from direct subsidies to tax incentives and matching funds—would maintain investment channels while reducing fiscal dependence [13].

Korea's experience offers a differentiated template for emerging economies. Investment intensity relative to GDP—rather than absolute budget—appears associated with observable effects, though causal attribution requires additional comparators. Korea's 2.59% GDP commitment is associated with stronger R&D outcomes than the EU's 0.57%. For ASEAN economies like Vietnam pursuing digital transformation under tighter fiscal constraints, this pattern suggests prioritizing concentrated, sector-specific investments analogous to Korea's Data Dam, complemented by regulatory reform [47].

Subsidy-exit roadmap (illustrative). Translating the soft-budget-constraint warning into operational policy suggests a three-to-five-year phased exit. Phase I (years 0–2) maintains direct R&D subsidies but introduces matching-fund requirements at the firm level. Phase II (years 2–4) shifts the marginal incentive from direct grant to refundable R&D tax credit, conditional on private co-investment ratios. Phase III (years 4–5+) consolidates remaining support into competitive challenge funds tied to ESG performance metrics. Transition criteria are observable: when private R&D as a share of total R&D exceeds 70% and TFP-growth BF10 crosses the moderate-evidence threshold (3.0), the next phase activates. Withdrawal metrics include subsidy-share decline, private-investment elasticity, and continuity of mechanism-channel coefficients in updated ITS re-estimations.

The ESG assessment reveals structural tension in the dual strategy. The Digital New Deal achieved strong social outcomes (Internet: 97.17%, R&D/GDP: 4.97%) while Green New Deal environmental targets remain underachieved (renewable: 3.6% vs. 20% target). Future policy should integrate AI-optimized energy systems with decarbonization targets rather than treating them as parallel tracks [32].

AI Governance Considerations. The Data Dam's 48 million datasets and state-controlled AI infrastructure raise governance questions that this productivity-focused study does not address. Future research should examine surveillance risks of centralized data platforms, labor displacement effects of AI diffusion, and data sovereignty implications—dimensions that Floridi et al. [48] identify as essential for responsible AI deployment.

5.4. Limitations

Several limitations warrant acknowledgment. First, the sample (T = 24, $n$post = 4) constrains statistical power, addressed through methodological triangulation. Second, the single-country design limits external validity, partially mitigated by Korea-EU comparison. Third, the New Deal launch coincides with COVID-19 (July 2020), creating a fundamental identification problem that cannot be fully resolved without explicit pandemic control variables. Specifically, COVID-19 likely biases GDP growth coefficients downward (demand shock) while potentially inflating Internet penetration effects (accelerated digitalization); future studies should incorporate the Oxford COVID-19 Stringency Index as a control variable. Fourth, aggregate TFP cannot isolate technology-specific contributions across heterogeneous Digital New Deal components. Future research should extend the observation period, incorporate firm-level data, apply Bayesian sequential updating as additional data become available, and investigate whether AI deployment accelerates or counteracts decarbonization [40].

6. CONCLUSION

This study evaluated associations between South Korea’s state-led dual New Deal strategy—integrating Digital and Green New Deals—and fostering AI diffusion and sustainable productivity growth. Through methodological triangulation combining Interrupted Time Series regression, Bayesian inference, comparative policy analysis, and ESG impact assessment, we tested two hypotheses: that state-led investment is associated with productivity gains (H1) and that sustainability concerns may limit long-run viability (H2). All quantitative coefficients are interpreted as associations under stated assumptions; the design does not support causal estimands.

The evidence supports a nuanced verdict. H1 is partially consistent with the data: Korea’s Digital New Deal coincided with mobilized innovation inputs, with R&D expenditure rising from 3.29% to 4.97% of GDP (BF_{10} = 33.61, very strong evidence of structural change) and Internet penetration reaching 97.17%. The ITS regression shows that these mechanism channels—R&D (β = 0.065, p < 0.01) and digital infrastructure (β = 0.003, p < 0.001)—are statistically associated with TFP improvement, explaining 97.3% of productivity variance. However, the policy dummy itself remains insignificant (p = 0.20), which is consistent with the interpretation that the New Deal operates through incremental investment channels rather than discrete structural breaks. H2 is also consistent with the evidence, with Bayesian nuance: TFP growth shows only anecdotal evidence (BF_{10} = 2.76), and the ROPE analysis classifies 39.1% of observations as practically equivalent to zero—a pattern that mirrors the AI productivity paradox rather than confirming a causal effect of policy on TFP. The ESG composite score of 64.5 (Grade C) indicates that social progress (76.7) is partially offsetting environmental shortfalls (50), with renewable energy at 3.6% against the 2030 target of 20%.

These findings carry three implications for theory and policy. First, the developmental state model remains effective at input mobilization but faces the fundamental challenge of converting state-directed investment into self-sustaining innovation ecosystems tension between Johnson’s [11] developmental state optimism and Kornai’s [13] soft budget constraint warnings. Second, the comparative analysis reveals that investment intensity relative to GDP—Korea’s 2.59% versus the EU’s 0.57%—rather than absolute budget size, may be the critical determinant of observable policy effects, offering actionable guidance for emerging economies designing AI industrial policy. Third, the Bayesian framework demonstrates its value for policy evaluation under small-sample constraints (T = 24), providing graded evidence quantification where frequentist methods yield only binary verdicts.

For policymakers, we recommend a phased subsidy exit strategy: gradually transitioning from direct subsidies to tax incentives and matching funds that maintain R&D investment channels while reducing fiscal dependence. The digital-green imbalance warrants integration of AI-optimized energy systems with decarbonization targets, rather than treating digital transformation and environmental sustainability as parallel tracks.

This study is subject to limitations including a short post-Deal window (four years), single-country design, and COVID-19 confounding. Future research should extend the observation period to test whether the productivity paradox resolves with decade-long lags, incorporate firm-level data to identify heterogeneous treatment effects, and apply the Bayesian sequential updating framework as additional post-Deal data become available.

Returning to the central question: does Korea's state-led dual New Deal create a self-sustaining AI ecosystem or foster subsidy dependency? The answer, grounded in four convergent evidence streams, is *both, simultaneously*. The developmental state has mobilized inputs at unprecedented scale, but the transition from input deployment to output materialization remains incomplete. Korea's experience suggests that state capitalism can accelerate AI diffusion, but sustainability—both economic and environmental—requires institutional evolution beyond the investment phase.

7. DECLARATIONS

7.1. Credit authorship contribution statement

Thanh-Phong Lam: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. Phuong-Dung Bui-Nguyen: Investigation, Resources, Writing – review & editing, Validation. Ngoc-My-Quyen Nguyen: Investigation, Resources, Writing – review & editing, Validation.

7.2. Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7.3. Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or non-profit sectors.

7.4. Declaration on the use of generative AI

In accordance with ICMJE recommendations (January 2026) and COPE guidelines, the authors disclose the use of AI-assisted writing tools (ChatGPT, OpenAI 2025–2026) for language editing, grammar refinement, and structural suggestions during manuscript drafting only. All AI-generated texts were critically reviewed, substantially revised, and verified by the authors. No AI tool is listed as an author. The authors assume full responsibility for accuracy, integrity, and originality of all content.

7.5. Data and code availability

Raw data come from FRED, World Bank Open Data, and OECD.Stat (public sources). Processed datasets, analysis scripts (Python and R), and figure-generation notebooks are released as a public companion repository at https://github.com/limpaulfin/ICE2026-p1-state-capitalism under the MIT licence. The repository pins package versions (requirements.txt) and documents the random-number seed (seed = 42) used in all stochastic steps; re-execution from a fresh clone reproduces every figure, table, and Bayes Factor reported in this paper. The raw-source files used to build the processed dataset are listed in the repository data/codebook.md.

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