Proceedings of ICMRED 2026 symposium: The Future of Work: Strategy, Workforce Transformation, and Organizational Renewal
DOI: 10.54254/2754-1169/2026.LD33289

Endogenous Task Boundaries, Institutional Frictions, and Manufacturing Employment: Evidence from China's Service-Oriented Manufacturing Pilot Firms

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Abstract: This paper examines whether China's service-oriented manufacturing (SOM) pilot policy creates or displaces manufacturing employment at the firm level. Embedding financial and supply-chain frictions into a heterogeneous-firm task-boundary model, we derive that policy-induced reductions in institutional frictions expand firms' optimal task scope, generating net employment gains through a scale effect and a structural effect. Using a panel of China's A-share listed manufacturers (2012–2024) and the MIIT's five-batch pilot designation, we apply multi-period propensity score matching combined with difference-in-differences (PSM-DID). Baseline estimates indicate a positive and economically meaningful employment effect for pilot firms relative to matched controls, supporting net job creation rather than displacement. Mechanism tests reveal that the policy operates through a "dual friction-reduction" channel: it simultaneously relaxes firms' financial constraints and reduces supply-chain concentration, consistent with the theoretical predictions derived from the model. Heterogeneity analysis reveals stronger effects for state-owned enterprises, capital- and technology-intensive industries, and lower-marketization regions. These findings provide micro-level evidence that servitization policy contributes to sustainable manufacturing employment in emerging economies, and offer transferable insights for industrial policy design.

Keywords: service-oriented manufacturing; task boundary; employment creation; financial constraints; supply chain; sustainable development

1. Introduction

Manufacturing is the cornerstone of economic development. Amid population aging and rapid AI diffusion, China's manufacturing labor market faces profound structural adjustments. Service-oriented manufacturing (SOM)—the deep integration of advanced manufacturing with modern services—has emerged as a key pathway for upgrading industrial value chains and sustaining employment [1]. Since the Ministry of Industry and Information Technology (MIIT) issued the *Action Guide for Developing Service-Oriented Manufacturing* in 2016, five successive batches of SOM demonstration enterprises have been designated (2017, 2018, 2021, 2022, 2023), constituting an important instrument for China's "employment-first strategy."

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A fundamental yet unresolved question is whether servitization policy functions as an employment *reservoir* or *displacer*. Three identification challenges complicate the answer: (i) non-random firm selection into the pilot program induces selection bias; (ii) staggered multi-batch treatment creates heterogeneous timing problems; (iii) the employment effect may operate through multiple simultaneous channels. Most existing work examines the "technology effect" of automation and offshoring [2, 3] while neglecting how government policy—by reducing institutional transaction costs—endogenously reshapes firms' optimal task boundaries [4, 5]. In China's context, this "institutional effect" is arguably more consequential than pure market-driven servitization.

This paper makes three contributions. *First*, we embed endogenous task boundaries and two-dimensional institutional frictions (financial and supply-chain) into a heterogeneous-firm model, bridging task-based trade theory with industrial policy evaluation [3]. *Second*, leveraging the quasi-random staggered designation of SOM pilot firms, we identify the net causal employment effect via multi-period PSM-DID, with robustness verified by stacked DID [6], differential trends [7, 8], counterfactual tests, and permutation placebos. *Third*, we document a "dual friction-reduction" mechanism and rich heterogeneity consistent with O-Ring complementarity [9] and China's institutional environment.

2. Literature review

Firm boundaries and task-based trade. The theory of firm boundaries—rooted in Coase [4] and Williamson [5]—establishes that integration decisions depend on the trade-off between internal coordination costs and external transaction costs. Grossman and Rossi-Hansberg [3] decompose production into tradeable tasks, enabling analysis of endogenous boundary choices under offshoring. Antras [10] extends this framework to global value chains, emphasizing the endogenous determination of task scope. Our model synthesizes these strands by making task scope explicitly endogenous to institutional friction levels.

Employment effects of servitization. The evidence is mixed. Studies on automation document displacement of manufacturing employment in developed economies [2, 11, 12]. Baldwin and Forslid [13] posit "jobless manufacturing" as an emerging paradigm in globotics. In contrast, Chinese evidence shows that SOM promotes high-skill employment upgrading [14, 15] and can alleviate financing constraints [16]. Our contribution is to identify the *net* causal employment effect via quasi-experiment and to demonstrate the "institutional effect" channel missing from prior studies.

Frictions and industrial policy transmission. Bernanke et al. [17] formalize the financial accelerator; Manova [18] incorporates credit constraints into heterogeneous-firm trade models; Elliott et al. [19] analyze supply-chain formation and fragility. Dai et al. [20] show that data factors shape SOM development in China. Existing literature largely treats frictions as exogenous; our model is the first to analyze how industrial policy jointly reduces financial *and* supply-chain frictions as a unified mechanism.

3. Theoretical framework

3.1. Model environment

Demand. A representative consumer maximizes CES utility over a continuum of differentiated goods $\omega \in \Omega$:

$$U = \left(\int_{\Omega} x(\omega)^{\frac{\sigma-1}{\sigma}} \, d\omega \right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1. \tag{1}$$

Letting $A \equiv Y P^{\sigma-1}$ denote the demand shifter, the standard inverse demand is $p(\omega) = A^{1/\sigma} x(\omega)^{-1/\sigma}$.

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Production technology. Each firm assembles a final product using a CES task-aggregation technology over the task range $i \in [0, M]$, where M is the *endogenous task scope*:

$$y = \varphi\Big(\int_0^M x(i)^{\frac{\varepsilon-1}{\varepsilon}}\, di\Big)^{\frac{\varepsilon}{\varepsilon-1}}, \quad \varepsilon > 1, \tag{2}$$

with φ as Hicks-neutral productivity. Under the symmetry assumption $c(i) = c$, cost minimization yields the task price index $\mathcal{P}_M = cM^{1/(1-\varepsilon)}$.

3.2. Multi-Dimensional frictions

Financial friction. SOM transition requires heavy investment in intangible assets (R&D, digital platforms) with limited collateral value. A financing premium $\mu \geq 0$ raises the effective marginal cost:

$$MC_{\text{eff}}(M) = \frac{c(1+\mu)}{\varphi}\, M^{-\frac{1}{\varepsilon-1}}. \tag{3}$$

The negative exponent ($\varepsilon > 1$) reflects the variety effect: expanding task scope M lowers effective costs through specialization gains [21].

Supply-chain friction. Following Coase [4] and the management-span theory, coordinating a longer task chain incurs convex organizational costs:

$$C_{\text{coord}}(M) = \tfrac{1}{2}\,\eta\, M^2, \quad \eta > 0, \tag{4}$$

where η captures the supply-chain friction intensity. We proxy η using top-5 supplier/customer concentration; higher values imply tighter lock-in and stronger hold-up risk [5].

3.3. Equilibrium: optimal task scope

Under monopolistic competition [21], the optimal markup price is:

$$p^* = \frac{\sigma}{\sigma-1} MC_{\text{eff}}(M). \tag{5}$$

Substituting into demand yields the revenue function:

$$R^*(M) = \kappa'(1+\mu)^{1-\sigma}\, M^{\Gamma}, \quad \Gamma \equiv \frac{\sigma-1}{\varepsilon-1}, \tag{6}$$

where $\kappa' \equiv A\big(\frac{\sigma}{\sigma-1}\frac{c}{\varphi}\big)^{1-\sigma}$ collects exogenous parameters. Since variable profit equals R^*/σ in CES markets, the firm's outer optimization over task scope is:

$$\max_M\ \Pi(M) = \frac{\kappa'(1+\mu)^{1-\sigma}}{\sigma} M^{\Gamma} - \frac{1}{2}\eta\, M^2 - F. \tag{7}$$

The first-order condition $\frac{\Gamma\kappa'(1+\mu)^{1-\sigma}}{\sigma} M^{\Gamma-1} = \eta M$ yields the closed-form optimal task scope:

$$M^* = \Big(\frac{\Gamma\kappa'(1+\mu)^{1-\sigma}}{\sigma\eta}\Big)^{\frac{1}{2-\Gamma}}, \tag{8}$$

where the SOC requires $2 > \Gamma$ (coordination costs are sufficiently convex). Taking logarithms: $\ln M^* = \frac{1}{2-\Gamma}\big[\text{const} - (\sigma-1)\ln(1+\mu) - \ln\eta\big]$, confirming that both frictions suppress optimal task scope.

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3.4. Total employment equation

Manufacturing labor integrates task demand over $[0, M]$. Using the symmetry assumption and the optimal output derived from (6), one obtains $L_m(M) = \xi_1(1+\mu)^{-\sigma}M^{\Gamma}$, where $\xi_1 \equiv A\varphi^{\sigma-1}c^{-\sigma}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}$. Service and coordination labor equals $L_s(M) = \frac{1}{2}\eta M^2$ (service wage normalized to one). Total employment is therefore:

$$L_{\text{total}} = \underbrace{\xi_1(1+\mu)^{-\sigma}M^{\Gamma}}_{\text{manufacturing jobs (scale effect)}} + \underbrace{\tfrac{1}{2}\,\eta\,M^2}_{\text{service jobs (structural effect)}} . \tag{9}$$

3.5. Testable hypotheses

The following comparative statics follow directly from (8)–(9):
H1 (Employment creation): $\frac{\partial L_{\text{total}}}{\partial M} = \Gamma\xi_1(1+\mu)^{-\sigma}M^{\Gamma-1} + \eta M > 0$. Policy that raises M^* generates net employment gains through both the scale and structural channels.
H2 (Financial channel): $\frac{\partial \ln M^*}{\partial \ln(1+\mu)} = -\frac{\sigma-1}{2-\Gamma} < 0$. Relaxing financial constraints ($\mu \downarrow$) expands M^* and boosts employment.
H3 (Supply-chain channel): $dL_{\text{total}}/d\eta < 0$ (closed form: $L_{\text{total}} = C\eta^{-\Gamma/(2-\Gamma)}$, $C > 0$, when $2 > \Gamma > 0$). Reducing supply-chain friction ($\eta \downarrow$) raises M^* and employment.
H4 (Heterogeneity): $\partial M^*/\partial\sigma > 0$. The financing elasticity $|\mathcal{E}_{M,\mu}|$ increases with competition σ and task complementarity (lower ε), predicting stronger policy effects in capital- and technology-intensive, and more competitive, industries.

4. Research design

4.1. Data and sample

Our sample comprises A-share listed manufacturers in China (2012–2024) from CSMAR and Wind databases. We match listed firms to MIIT's five-batch SOM pilot designation lists (2017–2023): the treatment indicator $\text{Treat}_i = 1$ if firm i is ever designated; the treatment year is the firm's first designation year. After excluding ST/financial firms, dropping observations with missing key variables, and applying 1%/99% winsorization, the unbalanced panel contains approximately 30,000 firm-year observations. Table 1 reports cohort distribution in the PSM common-support sample (169 treated firms total).

Table1. Treatment Cohort Distribution (PSM Common-Support Sample)

	2017	2018	2021	2022	2023	Total
Firms	15	11	44	51	48	169
Share (%)	8.9	6.5	26.0	30.2	28.4	100.0

Note: First-entry cohorts 2019–2020 absent from matched sample.

4.2. Variables

The dependent variable is $\ln(\text{labor})_{it}$ (log total employees). The treatment variable is $\text{DID}_{it} = \text{Treat}_i \times \text{Post}_{it}$, where $\text{Post}_{it} = 1$ from the first designation year onward. Controls include firm size (ln assets),

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leverage, ROA, top-5 shareholder concentration, board size (ln), Tobin's Q, firm age (ln), and industry HHI.

The *SA financial constraint index* (Hadlock and Pierce, 2010) uses firm size and age only, avoiding reverse-causality concerns from leverage or profitability; higher (less negative) values indicate tighter constraints. *Supplier and customer concentration* equal each firm's top-5 supplier/customer purchase ratios from CSMAR, proxying for η in Equation (4). *Marketization* uses an updated provincial marketization index for China [22], following the same data construction as the Chinese main text; heterogeneity splits follow the 33rd/66th percentile rule described in the replication notes.

4.3. Descriptive statistics

Table 2 provides summary statistics for key variables. Treated firms (ever-designated pilots) are on average larger ($\ln$ labor: 8.11 vs. 7.79) and more profitable than non-designated peers, motivating the propensity-score adjustment. The SA index (mean -3.53) indicates pervasive financial constraints [18]; high supply-chain concentration (supplier mean 41.4%, customer 37.9%) underscores the hold-up frictions in Equation (4).

Table2. Descriptive Statistics (Full Sample, Prior to PSM)

Variable	Obs.	Mean	SD	Treated	Control
$\ln$(labor)	29,872	7.84	1.24	8.11	7.79
$\ln$(assets)	29,872	21.73	1.27	22.04	21.63
Leverage	29,872	0.387	0.194	0.391	0.386
ROA	29,872	0.044	0.063	0.051	0.042
SA index	29,315	−3.527	0.632	−3.461	−3.541
Supplier conc. (%)	26,847	41.4	19.3	43.6	40.9
Customer conc. (%)	27,923	37.9	17.8	40.1	37.4

Note: "Treated"/"Control" columns report sub-group means. SA index in raw form; less negative = tighter constraint.

4.4. PSM-DID estimation

To address non-random selection, we first estimate a Logit propensity score using the full set of firm-level covariates listed above (the same specification as in the Chinese main text), then apply 1:2 nearest-neighbor matching with a caliper of 0.05 (in propensity-score standard-deviation units) to restrict attention to the common-support region. Post-matching, all covariate standardized mean differences fall below 5% (e.g., leverage remains within the 5% threshold reported in the main text), confirming adequate balance. Following the Chinese main text, we retain all observations within the common-support region to construct a balanced panel for DID estimation. On the matched sample we estimate:

$$\ln \text{labor}_{it} = \alpha + \beta\, \text{DID}_{it} + \gamma' X_{it} + \mu_i + \delta_t + \varepsilon_{it}, \tag{10}$$

where μ_i and δ_t are firm and year fixed effects, and standard errors are clustered at the firm level.

5. Empirical results

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5.1. Baseline estimates

Table 3 reports the baseline DID results. The preferred specification indicates a positive treatment effect on employment, implying that pilot firms experience higher employment than comparable non-pilot firms—net job creation, supporting H1.

Table3. Baseline DID Results

Dep. var.: ln(labor)	(1)	(2)
Treat×Post	0.1250^{***}	0.0743^{***}
	(3.104)	(2.999)
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	29,872	29,872
Adj. R^2	0.896	0.952

Note: t-statistics (firm-clustered s.e.) in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.2. Parallel trends and dynamic effects

An event-study specification [23] with leads and lags $k \in [-5, +5]$ (omitting $k = -1$ as baseline) reveals two key patterns. First, pre-policy coefficients are jointly indistinguishable from zero, supporting the parallel-trends assumption. Second, post-policy effects strengthen over the medium run after an initial adjustment phase, consistent with the Chinese main text's event-study pattern and with gradual task-scope expansion as firms integrate service modules and improve financing and supply-chain conditions (Equation (8)).

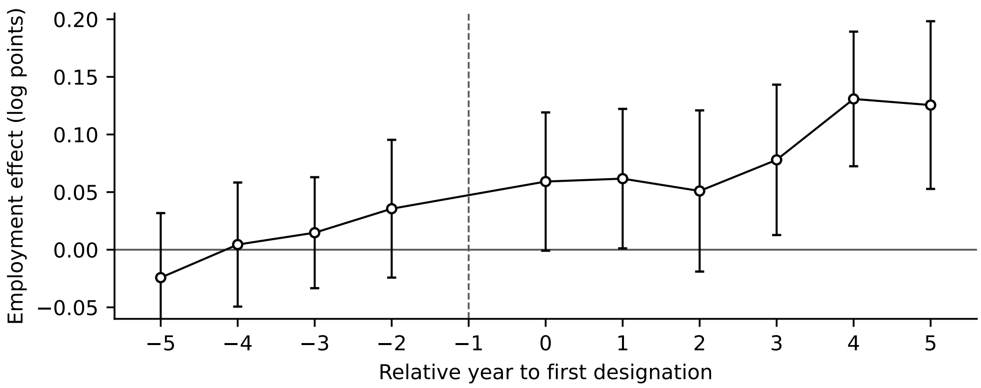

Figure1. Parallel Trends Test (Event Study)

A 500-iteration permutation placebo test (randomly reassigning treatment status while preserving timing) generates a simulated distribution centered near zero; the empirical estimate lies far in the right tail, supporting that the baseline effect is unlikely to be driven by spurious confounders.

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6. Robustness checks

Table 4 consolidates five robustness exercises. Column (1) drops the four direct-administered municipalities (Beijing, Shanghai, Tianjin, Chongqing) to remove their idiosyncratic political-economy characteristics. Column (2) adds a concurrent smart-manufacturing pilot policy control (same specification as column (1) of the "exclude policy interference" table in the Chinese manuscript). Column (3) adds province$\times$year and industry$\times$year interaction fixed effects.

Column (4) implements Stacked DID [24, 6]: for each treatment cohort we retain only that cohort's treated firms and "clean" never-treated controls, stack sub-samples, and control for unit$\times$cohort and year$\times$cohort fixed effects. This directly addresses negative-weight bias in the conventional two-way fixed-effects estimator arising from heterogeneous treatment effects.

Column (5) relaxes the parallel-trends assumption [7, 8]: we interact pre-determined firm size (2016 baseline) with year indicators (differential trends), allowing larger—hence more designatable—firms to follow different pre-policy growth trajectories. The treatment effect remains positive and robust.

This specification mirrors the Chinese manuscript's "relaxing equal trends by selection determinants" strategy: we first characterize the non-random designation process using pre-policy covariates (notably baseline firm size), and then allow those determinants to generate flexible year-specific trends in the DID regression. Intuitively, if larger firms are more likely to be designated, they may also follow different underlying growth paths; the differential-trends design directly absorbs such confounding trend heterogeneity.

Across all five columns the Treat$\times$Post estimate remains positive and robust across specifications. Additionally, counterfactual tests that shift each firm's assumed policy start *backward* by 3–6 years (placebo timing relative to the true designation year) yield insignificant placebo effects; joint tests in the replication table exceed conventional 5% thresholds. Nine PSM parameter combinations (caliper $\in \{0.10, 0.05, 0.01\}$; ratio $\in \{1{:}1, 1{:}3, 1{:}4\}$) all produce significant positive estimates.

We further examine clustering sensitivity by re-estimating with industry-level and province-level clustering; inference remains unchanged.

Table4. Robustness Checks (Treat$\times$Post Coefficient)

	(1) Excl. Muni.	(2) +Smart ctrl.	(3) Higher FE	(4) Stacked DID	(5) Diff. Trends
Coef.	0.0719**	0.0746***	0.0751***	0.0758***	0.1079***
	(2.558)	(3.005)	(3.025)	(2.990)	(3.580)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	25,533	29,871	29,869	142,652	29,872

Note: All specifications include firm and year FE. Col. (4): unit$\times$cohort and year$\times$cohort FE; col. (5): baseline size$\times$year differential trends. $^{**}p < 0.05$, $^{***}p < 0.01$.

7. Mechanism analysis and heterogeneity

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7.1. Dual friction-reduction mechanism

Following Jiang [25], we focus on first-stage evidence $\mathrm{DID} \to M$ (policy $\to$ mechanism variable) to identify channels, avoiding the attribution fallacy of simultaneous inclusion in the outcome equation. Table 5 reports the results.

Financial constraints (H2). The estimates in column (1) indicate that pilot designation relaxes firms' external financing constraints, consistent with the policy's supply-chain finance instruments and certification signaling function. This constraint relaxation constitutes the first leg of the "dual friction-reduction" channel.

Supply-chain concentration (H3). Columns (2) and (3) show that pilot designation reduces both supplier and customer concentration, implying meaningful diversification of supply-chain networks and weaker single-partner lock-in—consistent with H3a. Supplementary regressions (available upon request) confirm that higher supply-chain concentration predicts lower employment, consistent with H3b.

Table5. Mechanism Analysis: Policy $\to$ Mechanism Variable

Dep. var.:	(1) |SA index|	(2) Supplier conc.	(3) Customer conc.
DID	-0.0301^{***}	-1.3221^{*}	-1.3347^{*}
	(-4.097)	(-1.869)	(-1.749)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	29,315	26,847	27,923

Note: t-values in parentheses. Col. (1) excludes SA index components (firm size and age) from controls. $^{*}p < 0.10$, $^{***}p < 0.01$.

We do not separately identify the second stage from mechanism variables to employment ($M \to Y$) with an explicit instrumental design; prior micro evidence nonetheless supports the same sign pattern as H2–H3. Tightening credit supply reduces employment at continuing firms [26], so the financing slack documented in column (1) plausibly strengthens labor demand along the scale channel in Equation (9). Production-network studies further link thicker, more diversified input–output linkages to stronger firm performance [27], while highly relationship-specific sourcing amplifies idiosyncratic supplier shocks through downstream plants [28]—both consistent with lower concentration easing marginal hiring when task scope expands.

7.2. Heterogeneity analysis

Table 6 presents multi-dimensional heterogeneity results.

Panel A (firm characteristics). The employment effect is larger for SOEs than for non-SOEs, reflecting SOEs' stronger resource mobilization under national industrial strategies and their preferential access to policy credit. Effects also concentrate in capital-intensive firms and are weak for labor-intensive firms, consistent with O-Ring complementarity [9]: service inputs generate larger marginal productivity gains in capital-dense production chains.

Panel B (market and institutional environment). More competitive industries display stronger employment responses than less competitive ones, consistent with H4's prediction that competition amplifies cost advantages into market-share gains. The effect is more pronounced in low-marketization

DOI: 10.54254/2754-1169/2026.LD33289

regions than in high-marketization regions, suggesting that government-led pilot programs "fill in" where market failures are most severe by lowering institutional transaction costs. Separate regressions by technology intensity (not tabulated) indicate that the effect is concentrated in high-tech manufacturing, further corroborating H4.

Table6. Heterogeneity Analysis (Treat×Post)

Panel A: Firm Characteristics

	(1) SOE	(2) Non-SOE	(3) Cap.-int.	(4) Lab.-int.
Coef.	0.1143^{***}	0.0568^{**}	0.0756^{***}	-0.0192
	(2.632)	(1.972)	(2.976)	(-0.710)
Obs.	8,164	21,708	14,732	14,739

Panel B: Market and Institutional Environment

	(1) High comp.	(2) Low comp.	(3) High mkt.	(4) Low mkt.
Coef.	0.0938^{**}	0.0639^{**}	0.0540	0.1112^{**}
	(1.983)	(2.549)	(1.118)	(2.143)
Obs.	12,826	16,680	10,356	6,856

Note: All specifications include controls, firm FE, and year FE. Panel A: cols. (1)–(2) by ownership; (3)–(4) by median capital-labor ratio. Panel B: cols. (1)–(2) by median industry HHI; (3)–(4) by the 33rd/66th percentiles of the provincial marketization index (Fan–Gang series, updated per [22], as in the Chinese main text). $^{**}p < 0.05$, $^{***}p < 0.01$.

8. Conclusion

Using China's SOM pilot program as a quasi-natural experiment, this paper establishes three main findings. First, designation generates net employment creation of approximately 7.4%—the scale effect (market expansion through differentiated services) and structural effect (new service-job modules) together dominate the partial automation effect, consistent with the task-boundary model in (9). Second, a "dual friction-reduction" mechanism drives the employment gains: the policy simultaneously relaxes financial constraints and diversifies supply-chain networks, lowering firms' marginal cost of expanding task scope M^* as derived in (8). Third, the effects are heterogeneous—stronger for SOEs, capital- and technology-intensive industries, and low-marketization regions—consistent with O-Ring complementarity and the "complementary government" hypothesis.

For sustainable industrial policy design, three implications follow. (i) *Deepen industry-finance linkages*: expand supply-chain finance and data-asset-backed lending to lower μ and fund service-module investment. (ii) *Build platform-based ecosystems*: invest in Industrial IoT infrastructure to reduce η across broader supply-chain networks and create new service employment. (iii) *Adopt differentiated regional strategies*: activist government support in low-marketization regions where market failures are most severe; market-selection mechanisms in developed coastal areas.

Two limitations warrant acknowledgment. First, without matched employer-employee data it is impossible to decompose the scale and structural channels of Equation (9) at the task or occupational level; future research linking administrative wage records to pilot designations could provide cleaner evidence on how SOM alters occupational structure—not merely aggregate headcount. Second, the listed-firm sample skews toward larger and more productive manufacturers; extending the identification strategy to SMEs, which account for the majority of manufacturing employment in China, would

DOI: 10.54254/2754-1169/2026.LD33289

be valuable for evaluating economy-wide welfare effects. Both directions, together with extending the panel as later cohorts mature beyond 2024, constitute a fruitful agenda for future research.

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