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# From AI Policy to Corporate Strategic Change: Evidence on Firm-Size Heterogeneity from China's AI Pilot Zones

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**Abstract**

Artificial intelligence (AI) pilot-zone policies aim to expand firms' technological opportunities, yet their relationship with changes in internal resource allocation remains unclear. Using 15,989 firm-year observations from 2377 nonfinancial Chinese A-share listed firms during 2016–2024, this study employs the Callaway–Sant'Anna staggered difference-in-differences framework to examine corporate strategic change (SC). SC is measured as an equally weighted index of standardized absolute annual changes in six accounting-based resource-allocation ratios, capturing adjustment magnitude rather than direction or performance. The pooled average treatment effect is −0.0162, with a 95% confidence interval from −0.0634 to 0.0310 and a normal-approximation minimum detectable effect of 0.0675 at 5% significance and 80% power, providing insufficient evidence of a detectable average effect. In contrast, the formal Small–Large difference in estimated effects is −0.0993, with a *p*-value of 0.0113. A joint test rejects equality of the six dimension-specific Small–Large contrasts, with plant and equipment newness showing the clearest difference after multiple-testing correction. Pre-treatment diagnostics vary across policy cohorts, and sensitivity analyses warrant caution in interpreting the estimates. These findings distinguish resource-allocation changes from technology adoption and business outcomes, providing an organizational perspective on heterogeneous firm responses relevant to sustainable digital transformation.

**Keywords:** artificial intelligence policy; corporate strategic change; firm-size heterogeneity; strategic flexibility; staggered difference-in-differences; sustainable digital transformation

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## 1. Introduction

The emergence of new technologies creates opportunities for firms while raising questions about how they adjust their existing operations and resource-allocation arrangements. However, expanding technological opportunities does not necessarily lead firms to alter their established resource commitments. Firms may respond to technological change by adjusting their R&D, production, and operating activities, or they may adopt new technologies within existing resource configurations. These responses need not involve resource-allocation changes in similar magnitude. Firms' responses to technological change may therefore be reflected not only in innovation, technology adoption, and operating performance but also in observable movements in their resource-allocation indicators. In recent years, China has sought to promote AI development and industrial applications

through the establishment of National New Generation Artificial Intelligence Innovation and Development Pilot Zones, supported by innovation platforms, application demonstrations, and institutional initiatives [1,2]. This policy initiative provides a setting for examining firms' resource-allocation responses to emerging technological opportunities. It also raises an empirical question: Does AI pilot-zone designation correspond to a detectable change in the magnitude of firms' annual resource-allocation adjustments?

Existing research has examined the firm-level consequences of AI-oriented industrial policies, including intelligent upgrading, investment efficiency, labor allocation, corporate competitiveness, and technological innovation [3–8]. Related studies have also highlighted the roles of resource management and capability development in firms' policy responses [7]. Although the literature has advanced our understanding of the economic consequences of AI policies, changes in particular corporate activities or outcomes do not directly reveal the magnitude of movements in firms' internal resource-allocation indicators. Improvements in innovation or operational efficiency may arise from more effective utilization of existing resources or may accompany changes in R&D expenditure, productive capital, and operating activities. Conversely, substantial movements in resource-allocation indicators do not necessarily imply better innovation outcomes or operating performance. The magnitude of annual changes in resource-allocation indicators across corporate activities therefore constitutes a distinct empirical outcome. Examining this outcome offers a complementary perspective on firms' internal operations under AI-oriented industrial policy.

Firms' responses to emerging technological opportunities may extend beyond individual business activities and involve changes in operating expenditures, R&D expenditure, productive capital, and financing arrangements. These activities form part of firms' existing resource-allocation structures, and annual movements in the corresponding accounting indicators provide an observable measure of changes in firms' resource-allocation profiles. Drawing on the corporate strategic-change literature [9–13], this study constructs a composite strategic-change (SC) index by separately standardizing the absolute annual changes in six accounting-based resource-allocation ratios and aggregating them with equal weights. The index captures the magnitude of observable movements in resource-allocation indicators. Importantly, changes in accounting ratios do not directly establish deliberate managerial adjustments, nor do they indicate the direction of resource investment or the effectiveness of strategic transformation. Moreover, indicators associated with different corporate activities may not change uniformly. Firms with similar composite SC values may exhibit different patterns in R&D, productive capital, or financing. Examining the composite index alone may therefore obscure differences across its underlying resource-allocation dimensions.

Firm size may further shape how firms respond to the technological opportunities associated with AI-oriented industrial policy. It is related not only to firms' existing resource endowments but also to their organizational structures, established commitments, and coordination requirements. Larger firms may draw on greater financial resources, technological capabilities, and specialized personnel to undertake resource-intensive adjustments, but established operating arrangements and organizational coordination costs may also constrain their responses. Smaller firms may be more flexible in revising operating priorities, yet limited resources may restrict their capacity to undertake substantial adjustments. Resource advantages and organizational constraints may therefore exert competing influences, making the direction of differences in estimated policy-related effects between firm-size groups theoretically ambiguous. Furthermore, R&D activities, productive capital allocation, operating expenditures, and financing arrangements differ in their resource requirements and adjustment conditions. The relative importance of size-related advantages and constraints may consequently vary across these activities. The analysis therefore considers both the

difference in estimated policy-related effects on composite SC between smaller and larger firms and whether this difference varies across resource-allocation dimensions.

To address these questions, this study examines China's National New Generation Artificial Intelligence Innovation and Development Pilot-Zone program, exploiting the staggered designation of pilot zones between 2019 and 2021. The analysis uses an unbalanced panel of nonfinancial A-share listed firms in China from 2016 to 2024, comprising 2377 firms and 15,989 firm-year observations. We employ the staggered difference-in-differences framework developed by Callaway and Sant'Anna [14]. Policy exposure is assigned according to each firm's fixed pre-policy registered city and the year of its pilot-zone designation, with firms in never-treated cities serving as the comparison group. This measure captures geographic policy exposure rather than firms' actual participation in AI projects or receipt of specific policy support. The analysis first estimates the overall average treatment effect on composite SC, then compares estimated effects between firms classified by their pre-policy size. A joint test across six resource-allocation dimensions further examines whether estimated firm-size heterogeneity varies across corporate activities.

The empirical results reveal three related patterns. First, the estimated average treatment effect on composite SC for the full sample is $-0.0162$, with a $p$-value of 0.5005. The estimate is not statistically significant, providing insufficient evidence of a detectable overall average effect without establishing that the underlying effect is zero. Second, the baseline Small–Large contrast in estimated treatment effects is $-0.0993$, with a $p$-value of 0.0113, indicating a statistically significant difference between firm-size groups. Third, a joint test across the six resource-allocation dimensions rejects the null hypothesis that the estimated Small–Large contrasts are equal. Among individual dimensions, plant and equipment newness provides the clearest statistical evidence of a between-group difference after adjustment for multiple testing. These results suggest that the pooled average estimate may obscure firm-size heterogeneity, while composite SC may conceal differences across resource-allocation activities. Nevertheless, pre-treatment diagnostics and sensitivity analyses warrant caution in interpreting the estimated firm-size differences causally. Accordingly, the findings should be understood as statistical evidence of firm-size and cross-dimensional variation within the current estimation framework rather than as fully identified heterogeneous causal policy effects.

This study contributes to the existing literature in two related ways. First, building on research concerning technological innovation, intelligent upgrading, resource utilization efficiency, and corporate performance, it examines annual movements in firms' resource-allocation indicators as a distinct empirical outcome. By distinguishing external technological opportunities, observable changes in internal resource allocation, and subsequent business outcomes, the study offers a complementary perspective on corporate responses to AI-oriented industrial policy. Second, it connects firm-size heterogeneity with the multidimensional nature of resource-allocation activities. Beyond comparing estimated policy-related effects on composite SC across firm-size groups, the analysis examines whether the estimated firm-size contrasts vary across individual dimensions. This approach offers a more detailed perspective on firm-level heterogeneity and highlights the value of examining individual components alongside composite measures of strategic change. Although resource capabilities, organizational inertia, and adjustment costs provide potential explanations for the observed patterns, their underlying mechanisms are not directly identified. The study thus complements existing research by treating observable resource-allocation movements as a distinct empirical outcome and by examining firm-size heterogeneity across the underlying dimensions of corporate strategic change. These questions are also relevant to research on sustainable digital transformation, as firms may need to reconcile emerging technological opportunities with existing resource commitments and

organizational constraints. The analysis offers evidence on one observable aspect of firms' responses—changes in resource-allocation indicators—without treating their magnitude as a measure of transformation success.

## 2. Literature Review and Hypothesis Development

Advances in artificial intelligence (AI) are changing the technological environment in which firms operate and allocate resources. However, new technological opportunities do not necessarily lead firms to revise their existing activities. Whether firms can use policy-related opportunities, and whether these opportunities translate into observable resource-allocation changes, depends on their existing resources, organizational structures, and prior commitments. Moreover, resource-allocation activities differ in their requirements for financing, technological knowledge, and organizational coordination. The advantages and constraints associated with firm size may therefore matter differently across activities. Drawing on the relevant literature, this section first examines the relationship between AI pilot-zone policy and corporate strategic change, then develops a research question and hypotheses concerning firm-size heterogeneity and its variation across resource-allocation dimensions.

### *2.1. AI Pilot Policy and Corporate Strategic Change*

As AI becomes increasingly integrated into business operations, the external conditions under which firms acquire and use technological resources are changing. To promote AI innovation and industrial applications, China introduced the New Generation Artificial Intelligence Development Plan and subsequently issued guidelines for the construction of National New Generation Artificial Intelligence Innovation and Development Pilot Zones [1,2]. The pilot-zone program is designed to promote technological innovation, application demonstrations, and institutional experimentation through geographically targeted initiatives. Rather than requiring firms to undertake uniform changes in their operations, the program seeks to improve the environment for technology adoption through innovation platforms, digital infrastructure, talent support, and financial services. These measures may reduce the costs of accessing technological knowledge and complementary resources, creating opportunities for firms to reorganize existing activities. Related studies show that digital infrastructure and government data governance can facilitate digital innovation and firm upgrading [15,16]. Although these studies examine different institutional arrangements, they highlight the importance of external technological and institutional conditions in shaping how firms use technological resources.

Whether external policy support translates into changes in internal resource allocation, however, depends on firms' organizational decisions. Oliver [17] argues that organizations are not passive recipients of institutional influences but can respond strategically according to their circumstances. From a resource-management perspective, Sirmon et al. [18] emphasize that acquiring resources does not automatically generate competitive advantage; firms must structure, bundle, and leverage their resources to develop organizational capabilities. From this perspective, the technological and institutional opportunities created by AI pilot zones may lead to adjustments in business activities through firms' internal resource-management processes and organizational decisions. Corporate responses therefore depend not only on the availability of external support but also on existing resource endowments and operational commitments.

Corporate strategic change provides a useful perspective for examining these organizational responses. Rajagopalan and Spreitzer [9] conceptualize strategic change as adjustments to existing strategic arrangements, emphasizing the roles of organizational decisions, internal conditions, and the external environment. Rather than being confined to

a single business activity, strategic change may involve adjustments across multiple areas of resource allocation and organizational operations. Previous studies have used annual movements in accounting-based indicators of resource allocation to assess the magnitude of strategic change [10,11,13]. Importantly, the magnitude of strategic change is distinct from its effectiveness. Zhang and Rajagopalan [10] show that greater strategic change does not necessarily lead to better firm performance. Accordingly, this study focuses on standardized absolute annual changes across multiple resource-allocation dimensions, rather than the direction of adjustment, the quality of strategic decisions, or the extent of AI adoption. This distinction allows corporate strategic change to be examined as an outcome separate from technological upgrading and operating efficiency.

Existing research has examined the firm-level consequences of China's AI pilot-zone policy from several perspectives. Studies have investigated its effects on intelligent upgrading, inefficient investment, and labor investment efficiency [3–5], while others have examined manufacturing resilience, firm competitiveness, and innovation disparities [6–8]. The literature provides important evidence on how AI policy affects particular technological activities and business outcomes. However, changes in technological upgrading, investment efficiency, or competitiveness do not necessarily indicate changes in the overall magnitude of firms' resource-allocation adjustments. For example, a firm may improve the efficiency of its production processes without substantially changing its expenditure ratios or capital structure. Conversely, considerable movements in resource-allocation indicators do not necessarily imply successful technological upgrading. This study complements existing research by examining whether AI pilot-zone policy is associated with changes in the magnitude of annual resource-allocation adjustments across multiple dimensions.

From a resource-allocation perspective, AI pilot-zone policy may generate different corporate responses. On the one hand, new opportunities for technological application may lead firms to reassess the expected returns and costs of their existing activities, prompting changes in operating expenditures, R&D resources, productive capital, or financing arrangements. Such adjustments may increase the magnitude of annual changes in resource allocation. On the other hand, firms may respond by gradually incorporating new technologies, improving the use of existing resources, or maintaining relatively stable operating arrangements. Because these responses need not produce similar movements in resource-allocation indicators, the average effect of AI pilot-zone policy on corporate strategic change is theoretically ambiguous. We therefore pose the following research question:

**RQ1.** Is there a statistically detectable average effect of AI pilot-zone policy on corporate strategic change?

### *2.2. Firm Size and Heterogeneous Strategic Responses*

Firms' ability to take advantage of the opportunities created by AI pilot-zone policy depends partly on their existing resource endowments. AI adoption and related operational adjustments often require financing, specialized personnel, technological knowledge, and organizational coordination. Firm size is often associated with differences in access to these resources. Larger firms generally have greater financial and technological resources, which may enable them to undertake adjustments that require substantial investment. Bentley and Kehoe [19] highlight the importance of financial slack and human capital in the context of strategic change. McElheran et al. [20] document differences in AI adoption across firms of different sizes, while related research identifies organizational conditions and existing technological capabilities as important considerations in AI implementation [21]. These studies suggest that firms' initial resource positions may shape their ability to respond to new technological opportunities. However, greater resource availability does not necessarily lead to larger strategic adjustments.

At the same time, larger firms may face greater organizational constraints when reallocating resources. Hannan and Freeman [22] argue that organizational structures and routines developed to ensure reliability and stability can also create structural inertia that makes organizational change more difficult. As firms grow, managerial hierarchies, interdependent business activities, and existing resource commitments may become more complex. Adjusting a particular activity may therefore require coordination across multiple departments and changes to established investment arrangements. These conditions can increase adjustment costs and encourage firms to maintain relatively stable resource configurations. Nevertheless, structural inertia does not imply that larger firms are necessarily less capable of change. Their greater financial and organizational resources may also help them absorb the costs of complex adjustments. Firm size may therefore enhance adjustment capacity while simultaneously increasing organizational constraints.

Smaller firms also face competing advantages and constraints. Their relatively simple organizational structures and less complex coordination processes may allow them to revise business priorities and adjust resource allocations more quickly. Research on small-firm strategy and strategic flexibility provides relevant perspectives on organizational responses to changing environments [23,24]. However, limited financial, human, and technological resources may constrain the scope and continuity of such adjustments. Strategic flexibility concerns a firm's capacity to revise existing decisions and adapt to environmental changes [25,26], whereas this study examines realized annual movements in resource-allocation indicators. The ability to make decisions quickly does not necessarily translate into extensive resource-allocation changes. Likewise, organizational complexity does not prevent firms with sufficient resources from undertaking substantial adjustments.

These differences in resource capacity and organizational constraints may lead to heterogeneous responses to AI pilot-zone policy. Although the policy may improve access to technological knowledge, talent, and complementary resources, firms of different sizes may differ in their capacity to mobilize these resources and in the costs of reorganizing existing activities. Larger firms may undertake more extensive adjustments by drawing on their resource advantages, but established organizational commitments may also limit their responses. Smaller firms may be more flexible in revising business priorities while facing greater constraints on resource-intensive adjustments. These differences may affect not only firms' existing levels of strategic change but also their adjustments relative to what would have occurred without the policy. Because the relative importance of resource advantages and organizational constraints is theoretically ambiguous, we do not predict the direction of the difference between size groups. We therefore propose the following hypothesis:

**H1.** *The estimated policy-related effect on corporate strategic change differs between smaller and larger firms.*

### *2.3. Resource-Allocation Dimensions and Firm-Size Heterogeneity*

Corporate strategic change involves resource-allocation activities that differ in financial requirements, specialized knowledge, organizational coordination, and adjustment costs. Consequently, the resource advantages and organizational constraints associated with firm size may not operate uniformly across these activities. Resource-management theory emphasizes that firms' responses to external opportunities depend on how they structure, bundle, and leverage available resources [18]. Although AI pilot-zone policy may improve the external conditions for technological innovation and application, its relationship with firms' internal resource-allocation adjustments may depend on the characteristics of the activities involved.

Operating resource allocation involves expenditures associated with market development and organizational administration. Selling expenses and non-R&D administrative expenses may respond to changing business conditions, but established personnel arrangements, management procedures, and business relationships can constrain their adjustment. Anderson et al. [27] document asymmetric changes in selling, general, and administrative costs in response to sales fluctuations, highlighting the importance of existing commitments and adjustment costs. Because firms differ in organizational complexity and coordination requirements, estimated policy-related effects on operating-expenditure indicators may also vary with firm size.

R&D resource allocation depends more heavily on specialized knowledge, human capital, and sustained investment. Greater financial and technological resources may enable firms to undertake substantial R&D adjustments, while established research projects and specialized teams may increase the costs of redirecting existing activities. Previous research highlights the importance of technological capabilities and organizational conditions in firms' responses to AI-related opportunities [8,20,21]. The balance between resource capacity and adjustment constraints may therefore differ between R&D and routine operating activities, potentially generating distinct patterns of firm-size heterogeneity.

Productive capital allocation generally involves substantial financial commitments, existing asset structures, and adjustment costs. Changes in equipment and production facilities may require significant investment, technological adaptation, and coordination across production activities. Cooper and Haltiwanger [28] demonstrate that capital adjustment involves different forms of adjustment costs and may occur discontinuously, while Gilchrist et al. [29] emphasize the influence of financial frictions and uncertainty on investment dynamics. Firm size may consequently shape productive capital adjustments through differences in financing capacity, existing asset commitments, and organizational coordination. Capital intensity and plant and equipment newness capture different aspects of productive capital configurations, and their estimated policy-related effects need not exhibit identical firm-size patterns.

Financing arrangements differ from operating and productive capital allocation because they are shaped by funding needs, credit conditions, debt constraints, and existing capital structures. Firm size may influence access to external financing and firms' capacity to adjust financial commitments. Research on financial frictions highlights the relationship between financing conditions and investment dynamics [29], while evidence on supply chain finance suggests that its relationship with corporate strategic change varies across firms at different life-cycle stages [12]. Financing-related adjustments may therefore display patterns of firm-size heterogeneity distinct from those associated with operating expenditures, R&D, and productive capital.

Taken together, resource-allocation activities differ in their requirements for financing, technological knowledge, organizational coordination, and adjustment costs. These differences may alter the relative importance of size-related resource advantages and organizational constraints, potentially leading to variation in estimated policy-related effects across the six dimensions of corporate strategic change. The six indicators capture the magnitude of observable annual movements in accounting-based resource-allocation ratios rather than deliberate managerial adjustments or their effectiveness. Based on these theoretical considerations, we propose the following hypothesis:

**H2.** *Firm-size heterogeneity in the estimated policy-related effects on corporate strategic change varies across resource-allocation dimensions.*

## 3. Research Design

### *3.1. Empirical Strategy and Identification*

To examine the relationship between artificial intelligence (AI) pilot-zone policy and corporate strategic change, this study exploits the staggered designation of China's National New Generation Artificial Intelligence Innovation and Development Pilot Zones between 2019 and 2021. We employ the group–time difference-in-differences (DID) framework developed by Callaway and Sant'Anna [14]. This approach accommodates treatment-effect heterogeneity across policy cohorts and over time, avoiding potentially inappropriate comparisons associated with conventional two-way fixed-effects estimators under staggered treatment adoption [30].

Corporate strategic change (SC) is the dependent variable. Each firm is assigned to a policy cohort based on its fixed pre-policy registered city, with the year of the city's first pilot-zone designation determining the firm's treatment year. Let $G_i = g$ denote the year in which firm $i$ first becomes exposed to the policy, and let $G_i = \infty$ indicate that the firm is never treated during the sample period. The policy treatment variable is defined as

$$AIP_{it} = \begin{cases} 1, & G_i \leq t \\ 0, & G_i > t \end{cases} \tag{1}$$

Here, $AIP_{it}$ indicates whether firm $i$ is exposed to the AI pilot-zone policy in year $t$. Firms in never-treated cities serve as the comparison group, while variation in treatment timing across policy cohorts provides the basis for estimating group–time treatment effects.

The group–time average treatment effect is defined as

$$ATT(g, t) = E[SC_{it}(g) - SC_{it}(0) \mid G_i = g], \quad t \geq g \tag{2}$$

where $SC_{it}(g)$ and $SC_{it}(0)$ denote the potential outcomes under treatment and no treatment, respectively. We estimate group–time effects using a doubly robust procedure that combines outcome regression and propensity-score estimation. The estimation employs varying base periods and pairwise balancing within each two-period DID comparison. Pre-treatment comparisons use adjacent periods, while post-treatment comparisons use the period immediately preceding policy adoption as the reference. Firms are required to have valid observations in the two periods relevant to each comparison, without being observed continuously throughout the sample period. This procedure accommodates the unbalanced firm panel. The resulting post-treatment group–time effects are aggregated to obtain the overall average treatment effect, which addresses RQ1.

To examine firm-size heterogeneity, we classify firms into Small and Large groups using predetermined firm-size information. For each firm, the baseline year is defined as the most recent year no later than 2017 in which firm size, firm age, return on assets, and operating cash flow are jointly observed. Firm size is measured as the natural logarithm of total assets, winsorized at the 1st and 99th percentiles. The median baseline firm size is calculated across the 2377 distinct firms in the final estimation sample, with each firm counted once. Firms below the median are classified as Small, while those at or above the median are classified as Large. Group membership remains fixed throughout the sample period. Treatment effects are estimated separately for the two groups, and their difference is defined as

$$\Delta ATT = ATT_{\text{Small}} - ATT_{\text{Large}} \tag{3}$$

The formal test of H1 evaluates whether this between-group contrast differs significantly from zero. Because firms of different sizes may be exposed to common city-level shocks, we use influence-function-based inference to account for the covariance between

subgroup estimates. Standard errors are clustered at the city level. Firm size is excluded from the covariates in the subgroup estimations because it determines group membership.

To investigate whether firm-size heterogeneity varies across resource-allocation dimensions, we extend the comparison to the six components of SC. For each dimension $k$, we estimate the policy-related effects for smaller and larger firms and calculate the corresponding contrast, $\Delta_k = ATT_{\text{Small},k} - ATT_{\text{Large},k}$. We then conduct a joint Wald test of the null hypothesis $H_0 : \Delta_1 = \Delta_2 = \cdots = \Delta_6$.

The joint covariance matrix of the six estimated contrasts is constructed from city-aligned, cluster-aggregated influence functions and incorporated into the Wald test. This procedure examines whether estimated firm-size differences are equal across resource-allocation dimensions, rather than whether individual dimension-specific effects are statistically significant. We also report the six individual Small–Large contrasts and apply the Holm procedure to account for multiple comparisons.

The causal interpretation of these estimates relies on the absence of anticipation effects, conditional parallel trends, and sufficient overlap between treated and comparison firms. We present dynamic estimates over an event-time window extending from three years before to three years after policy adoption. Pre-treatment patterns are assessed using a joint test of three aggregated event-time Small–Large contrasts and separate cohort-specific joint tests of pre-treatment Small–Large contrasts. We further examine the sensitivity of the findings through alternative sample restrictions, city-level estimates, placebo assignments, and alternative estimation methods. These analyses assess the stability of the estimated differences and the extent to which the identifying assumptions are supported by the data.

### *3.2. Variable Measurement*

#### 3.2.1. Dependent Variable: Corporate Strategic Change

Corporate strategic change (SC) is the dependent variable. Drawing on the multidimensional approach to strategic change developed in previous research [9–13], we measure observable adjustments in firms' resource-allocation configurations using six accounting-based indicators: selling-expense intensity, R&D intensity, capital intensity, plant and equipment newness, non-R&D administrative-expense intensity, and financial leverage. These indicators capture different aspects of firms' operating expenditures, technological development, productive capital, fixed-asset structure, internal administration, and financing arrangements.

Following the measurement approach in the strategic-change literature, we construct SC from the absolute annual changes in six accounting-based resource-allocation ratios. Each ratio is first winsorized at the 1st and 99th percentiles, after which its absolute year-to-year change is calculated. The resulting changes are standardized separately for each dimension using the corresponding mean and standard deviation derived from valid observations in the historical measurement panel covering 2009–2024, prior to the final estimation-sample restrictions. The composite SC index is then constructed as the equally weighted average of the six standardized components. Among the six underlying indicators, non-R&D administrative-expense intensity requires additional reconstruction to account for the change in financial-statement presentation introduced in 2018. The definitions and construction of the other five indicators remain unchanged. The composite SC index is formally expressed as follows:

$$SC_{it} = \frac{1}{6}\sum_{k=1}^{6} Z_{kit} \tag{4}$$

The standardized annual change in dimension k is defined as follows:

$$Z_{kit} = \frac{\left| X^{w}_{kit} - X^{w}_{ki,t-1} \right| - \mu_k}{\sigma_k} \quad (5)$$

Here, $X^{w}_{kit}$ denotes the winsorized value of resource-allocation indicator $k$ for firm $i$ in year $t$. The parameters $\mu_k$ and $\sigma_k$ represent the mean and standard deviation of the corresponding absolute annual changes in the standardization reference sample. The six components are standardized separately before aggregation.

A higher SC value indicates a greater magnitude of annual movements in the underlying resource-allocation ratios relative to their standardization benchmarks. Because the index is constructed from absolute changes, it does not identify the direction of adjustment. Moreover, movements in accounting ratios may reflect changes in operating scale, asset depreciation, financing conditions, or other accounting-related factors rather than deliberate managerial decisions. SC therefore measures the magnitude of observable changes in resource-allocation indicators, not strategic flexibility, the quality of strategic decisions, or their performance consequences.

To address the change in financial-statement presentation introduced in 2018 [31], we reconstruct non-R&D administrative-expense intensity (X5) to improve its comparability over time. Before 2018, identifiable R&D expenditures included in reported administrative expenses are deducted where reliable supporting records are available. From 2018 onward, we use reported administrative expenses, as R&D expenditures are presented separately under the revised reporting format. The resulting non-R&D administrative expenses are divided by operating revenue. This reconstructed indicator is incorporated into the six-dimensional SC index used throughout the empirical analysis. Table 1 presents the definitions and measurements of the six resource-allocation dimensions and other variables.

**Table 1.** Variable definitions and measurement.

| Variable | Symbol | Definition and Measurement |
|---|---|---|
| Corporate strategic change | SC | Equally weighted average of six standardized absolute annual changes in resource-allocation indicators |
| Selling-expense intensity | X1 | Selling expenses divided by operating revenue |
| R&D intensity | X2 | R&D expenditure divided by operating revenue |
| Capital intensity | X3 | Net fixed assets divided by the number of employees |
| Plant and equipment newness | X4 | Net fixed assets divided by gross fixed assets |
| Non-R&D administrative-expense intensity | X5 | Administrative expenses excluding R&D expenditures, divided by operating revenue |
| Financial leverage | X6 | Interest-bearing debt divided by owners' equity |
| AI pilot-zone policy exposure | AIP | Equals one from the year in which the firm's fixed reference city receives pilot-zone designation and zero otherwise |
| Firm size | SIZE | Natural logarithm of total assets |
| Firm age | AGE | Natural logarithm of one plus the number of years since listing |
| Return on assets | ROA | Net profit divided by total assets |
| Operating cash flow | OCF | Net cash flow from operating activities divided by total assets |

#### 3.2.2. Core Explanatory Variable: AI Pilot-Zone Policy

The core explanatory variable is AI pilot-zone policy exposure (AIP). Treatment status is assigned according to the first pilot-zone designation year of each firm's fixed pre-policy registered city. Specifically, the geographic reference is the firm's most recently observed registered city no later than 2018, which remains fixed throughout the sample period.

AIP equals one from the year in which the reference city receives pilot-zone designation and remains one thereafter. It equals zero before designation and throughout the sample period for firms in never-treated cities. This definition follows the staggered DID framework described in Section 3.1.

The variable captures geographic exposure to the pilot-zone policy environment rather than firms' actual participation in specific programs or their utilization of policy support. This distinction is relevant when interpreting the estimated policy-related effects.

#### 3.2.3. Firm Size and Control Variables

Firm size (SIZE) is measured as the natural logarithm of total assets, with the variable winsorized at the 1st and 99th percentiles. To ensure that firm-size classification relies on predetermined information, we identify each firm's baseline year as the most recent year no later than 2017 in which SIZE, firm age, return on assets, and operating cash flow are jointly observed. The corresponding baseline SIZE value is used to determine firm-size group membership, which remains fixed throughout the sample period. The median-based classification procedure is described in Section 3.1.

Following previous research, we include firm age (AGE), return on assets (ROA), and operating cash flow (OCF) as control variables. AGE is measured as the natural logarithm of one plus the number of years since listing. ROA is calculated as net profit divided by total assets, while OCF is measured as net cash flow from operating activities divided by total assets.

All control variables are fixed at their values in the firm's predetermined baseline year, ensuring that the covariates are measured before policy implementation. SIZE is included as a covariate in the full-sample estimation but excluded from the size-specific estimations because it determines firm-size group membership.

### *3.3. Data and Sample Construction*

This study uses an unbalanced panel of nonfinancial firms listed on China's Shanghai and Shenzhen A-share markets from 2016 to 2024. Firm-level financial information, R&D expenditure, employment, and registered-address records are primarily obtained from the CSMAR and Wind databases. Information on the designation and implementation of AI pilot zones is compiled from official policy documents issued by the State Council and the Ministry of Science and Technology. These data are matched using firm identifiers, observation years, and registered-city information.

To ensure data quality, we exclude financial firms and firm-year observations classified as ST, *ST, or PT, as well as observations with missing information required to construct the main variables, predetermined covariates, or geographic treatment assignments. Because SC measures year-to-year changes, its construction also requires consecutive annual observations with complete information across the six strategic dimensions. Although the estimation period begins in 2016, the six underlying resource-allocation indicators from 2015 are used to calculate SC for 2016. After applying these criteria, the final sample comprises 2377 firms and 15,989 firm-year observations.

Policy exposure is assigned using each firm's most recently observed registered city no later than 2018. This reference city remains fixed throughout the study period. County-level cities are assigned to their administratively responsible prefecture-level cities to maintain a

consistent geographic classification for policy matching and city-level clustering. Firms are then assigned to the 2019, 2020, or 2021 treatment cohort according to the year in which their reference city first entered the pilot-zone program. Firms in cities that were never designated during the sample period constitute the comparison group.

The AI pilot-zone program was implemented in three cohorts between 2019 and 2021. Within the 2016–2024 observation period, the 2019, 2020, and 2021 cohorts have up to three, four, and five pre-treatment calendar years, respectively, followed by six, five, and four years from treatment adoption onward. Given the relatively limited pre-treatment observation windows, we assess the identifying assumptions using pre-treatment dynamics and group–time diagnostics, as reported in Section 4.2.

The final sample covers 242 cities, including 17 treated cities and 225 never-treated cities. The three treatment cohorts comprise 712, 210, and 165 firms, respectively, while the comparison group contains 1290 firms. Table 2 reports the distribution of firms and firm-year observations across policy cohorts. Based on pre-policy firm size, the Small group consists of 1182 firms and 7488 firm-year observations, whereas the Large group includes 1195 firms and 8501 firm-year observations. Descriptive statistics for the main variables are presented in Table 3.

**Table 2.** Staggered rollout of the AI pilot-zone program.

| Treatment Year | Cities | Number of Cities | Number of Firms | Firm-Year Observations |
|---|---|---|---|---|
| 2019 | Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei | 6 | 712 | 4755 |
| 2020 | Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, Wuhan | 6 | 210 | 1382 |
| 2021 | Suzhou, Changsha, Zhengzhou, Shenyang, Harbin | 5 | 165 | 1106 |
| Never treated | Other cities outside the three treatment cohorts | 225 | 1290 | 8746 |
| Total | — | 242 | 2377 | 15,989 |

Notes: Treatment cohorts are determined by firms' fixed pre-policy reference cities. The number of firms refers to distinct firms within each cohort, whereas firm-year observations represent valid observations during 2016–2024. City counts are based on the harmonized prefecture-level geographic classification. The baseline treatment definition includes 17 prefecture-level pilot cities. Deqing County was separately designated as a county-level pilot zone; its designation is not extended to Huzhou prefecture as a whole.

**Table 3.** Descriptive statistics.

| Variable | N | Mean | SD | Median | Min. | Max. |
|---|---|---|---|---|---|---|
| SC | 15,989 | −0.024 | 0.495 | −0.163 | −0.602 | 6.770 |
| AIP | 15,989 | 0.304 | 0.460 | 0.000 | 0.000 | 1.000 |
| SIZE | 15,989 | 22.304 | 1.249 | 22.161 | 20.104 | 26.386 |
| AGE | 15,989 | 1.957 | 0.952 | 2.079 | 0.000 | 3.332 |
| ROA | 15,989 | 0.044 | 0.048 | 0.041 | −0.221 | 0.186 |
| OCF | 15,989 | 0.037 | 0.064 | 0.036 | −0.136 | 0.230 |

Notes: SC denotes corporate strategic change, and AIP indicates AI pilot-zone policy exposure. SIZE, AGE, ROA, and OCF represent firm size, firm age, return on assets, and operating cash flow, respectively. The control variables are fixed at their predetermined values observed no later than 2017. All statistics are calculated using the final estimation sample.

## 4. Empirical Results

### *4.1. Baseline Estimates and Firm-Size Heterogeneity*

Table 4 presents the baseline estimation results. For the full sample, the average treatment effect on the treated (ATT) is −0.0162, with a *p*-value of 0.5005 and a 95% confidence interval ranging from −0.0634 to 0.0310. The estimate is not statistically significant, providing insufficient evidence of a detectable average effect of AI pilot-zone policy on

corporate strategic change. However, this result should not be interpreted as evidence that the underlying average effect is zero. To assess estimation precision, we calculate the minimum detectable effect (MDE) using a normal approximation based on the estimated standard error. At a two-sided significance level of 5% and statistical power of 80%, the MDE is approximately 0.0675, indicating limited sensitivity to policy effects smaller than this magnitude.

**Table 4.** Baseline average treatment effects.

| Statistic | Full Sample | Smaller Firms | Larger Firms | Small–Large |
|---|---|---|---|---|
| Average ATT | −0.0162 | −0.0691 | 0.0302 | −0.0993 |
| Standard error | 0.0241 | 0.0329 | 0.0278 | 0.0392 |
| *p*-value | 0.5005 | 0.0356 | 0.2768 | 0.0113 |
| 95% CI | [−0.0634, 0.0310] | — | — | [−0.1761, −0.0224] |
| Minimum detectable effect (80% power) | 0.0675 | — | — | — |
| Firm-year observations | 15,989 | 7488 | 8501 | — |
| Firms | 2377 | 1182 | 1195 | — |
| 2019 cohort firms | 712 | 341 | 371 | — |
| 2020 cohort firms | 210 | 106 | 104 | — |
| 2021 cohort firms | 165 | 90 | 75 | — |
| Never-treated firms | 1290 | 645 | 645 | — |
| City clusters | 242 | 181 | 198 | 242 |
| Treated cities | 17 | 17 | 17 | 17 |

Notes: This table reports average treatment effects on the treated (ATTs) estimated using the Callaway–Sant'Anna staggered difference-in-differences framework. Treatment status is assigned according to firms' fixed pre-policy registered cities. Never-treated firms serve as the comparison group. The estimates employ a doubly robust procedure with varying pre-treatment base periods and pair-balanced comparisons. Covariates are predetermined using observations no later than 2017. Firm size is included in the full-sample specification but excluded from the size-specific estimations. Standard errors are clustered at the city level. The Small–Large contrast is formally estimated using city-aligned influence functions that account for covariance between subgroup estimates. The minimum detectable effect is calculated using a two-sided 5% significance level and 80% statistical power under a normal approximation. Pre-treatment diagnostics and their implications for interpreting the estimates are discussed in Section 4.2. Cohort-specific firm counts refer to distinct firms in the underlying estimation samples rather than the effective numbers contributing to individual group–time treatment-effect estimates.

We next examine whether the estimated policy effects differ between smaller and larger firms, classified according to their pre-policy size. As shown in Table 4, the ATT for smaller firms is −0.0691, with a *p*-value of 0.0356, indicating statistical significance at the 5% level. In contrast, the ATT for larger firms is 0.0302, with a *p*-value of 0.2768, and is not statistically significant. The formal Small–Large contrast is −0.0993, with a *p*-value of 0.0113, indicating a statistically significant difference between the two groups. The estimated policy-related effect on SC is therefore lower for smaller firms than for larger firms. The coexistence of an insignificant pooled ATT and a significant between-group contrast suggests that the aggregate estimate may obscure firm-size heterogeneity. This finding is consistent with H1, which predicts differences in estimated policy effects between firm-size groups without specifying their direction.

These results should be interpreted in light of the construction of the SC index. SC is measured as the equally weighted average of standardized absolute annual changes in six accounting-based resource-allocation indicators. It captures the magnitude of observed movements in these indicators rather than the direction of resource investment or firms' capacity for strategic adjustment. A negative ATT represents a lower estimated SC outcome relative to the counterfactual without policy exposure; it does not necessarily imply a reduction in actual resource investment. Accordingly, the lower ATT for smaller firms

should not be interpreted as evidence that AI pilot-zone policy inhibits their strategic transformation. The identifying assumptions and stability of the estimated firm-size contrast are examined further through dynamic estimates and sensitivity analyses.

### *4.2. Dynamic Effects and Identification Diagnostics*

Figure 1 presents the dynamic estimates relative to the timing of policy implementation. Over the post-treatment window spanning the implementation year through the third subsequent year, the aggregated average effect for the full sample is −0.0330 and is not statistically significant, consistent with the baseline findings. The corresponding effect for smaller firms is −0.0756 and is significant at the 1% level, while the estimate for larger firms is 0.0068 and is statistically insignificant. The formal Small–Large contrast is −0.0824, with a *p*-value of 0.0132, indicating a significant difference at the 5% level. The negative firm-size contrast observed in the baseline estimates is therefore also present in the post-treatment event-time window.

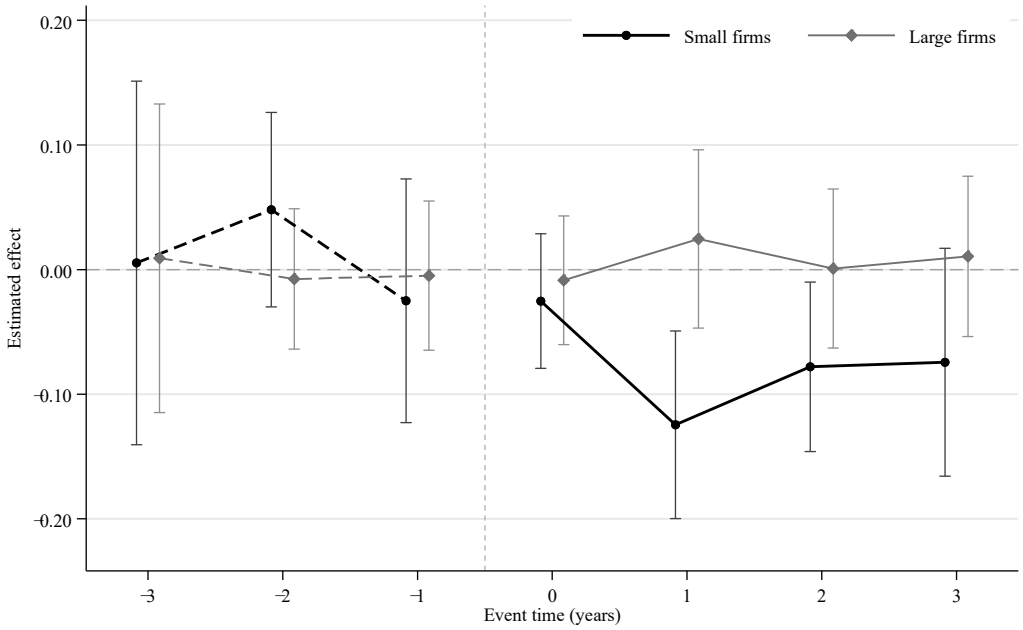



**Figure 1.** Dynamic estimates of corporate strategic change by firm size. Notes: Error bars represent 95% pointwise confidence intervals based on normal-approximation inference with city-clustered standard errors. Pre-treatment estimates are varying-base-period pseudo-effects, whereas post-treatment estimates are event-time average treatment effects on the treated. The two periods are displayed separately.

Table 5 reports the pre-treatment diagnostics for the formal Small–Large contrasts. The joint test of three aggregated pre-treatment event-time effects yields a *p*-value of 0.7325, indicating that the null hypothesis cannot be rejected. Cohort-specific tests yield *p*-values of 0.7149, 0.0891, and 0.0336 for the 2019, 2020, and 2021 cohorts, respectively. Thus, the null hypothesis is rejected at the 5% level only for the 2021 cohort. These results indicate that the pre-treatment evidence is sensitive to cohort-level disaggregation. Although the aggregated test does not detect significant pre-treatment differences, it does not conclusively establish parallel trends. The estimated firm-size contrasts should therefore be interpreted with appropriate caution.

**Table 5.** Pre-treatment diagnostics of firm-size differences.

| Test | Number of Restrictions | *p*-Value | Result at 5% |
|---|---|---|---|
| Aggregated pre-treatment event-time effects | 3 | 0.73249 | Not rejected |
| 2019 cohort-specific joint test | 2 | 0.7149 | Not rejected |
| 2020 cohort-specific joint test | 3 | 0.0891 | Not rejected |
| 2021 cohort-specific joint test | 4 | 0.0336 | Rejected |

Notes: This table reports joint tests of pre-treatment differences between smaller and larger firms. The aggregated test examines three pre-treatment event-time contrasts, while the cohort-specific tests examine the available pre-treatment contrasts within each policy cohort. The number of restrictions indicates the number of coefficients tested jointly. Inference accounts for city-level clustering and the covariance between subgroup estimates. Rejection decisions are based on the 5% significance level.

### *4.3. Robustness and Sensitivity Analyses*

We assess the robustness of the baseline findings by examining alternative sample restrictions, placebo policy assignments, pre-policy strategic-change characteristics, and alternative estimation methods. Table 6 summarizes the main results across alternative specifications, allowing a comparison of the estimated firm-size differences under different sample restrictions and estimation approaches.

**Table 6.** Robustness and sensitivity analyses of firm-size heterogeneity.

| Specification | Small–Large | *p*-Value |
|---|---|---|
| Baseline | −0.0993 | 0.0113 |
| Excluding pre-policy city movers | −0.0909 | <0.05 |
| Excluding city movers throughout the sample | −0.1050 | 0.0123 |
| Complete pre-policy SC history | −0.0749 | 0.1635 |
| City-level DDD | −0.0770 | 0.0908 |
| Sun–Abraham estimator | −0.0707 | 0.0070 |

Notes: This table reports the estimated Small–Large differences in corporate strategic change under alternative sample restrictions and estimation methods. The baseline specification uses the Callaway–Sant'Anna staggered difference-in-differences estimator, with standard errors clustered at the city level. The geographic and pre-policy SC restrictions assess the sensitivity of the estimates to sample composition. The city-level triple-difference (DDD) specification assigns equal weight to policy cohorts and differs from the baseline model in its level of analysis and weighting structure. The Sun–Abraham estimate covers the post-treatment event-time window from implementation through the third subsequent year, with inference based on 399 valid stratified city-bootstrap replications and a normal approximation. All reported *p*-values are two-sided. Additional sensitivity analyses and placebo tests are discussed in the text.

Changes in firms' city assignments may affect the identification of policy treatment status. An audit of registered-address histories for firms in the final estimation sample identified 43 firms with observed registered-city changes during 2009–2018 and 99 firms with such changes during 2009–2024. To assess their influence, we re-estimate the model under alternative geographic sample restrictions. After excluding firms with observed changes in city assignment before policy implementation, the Small–Large treatment-effect difference is −0.0909 and remains significant at the 5% level.

We also conduct city-level placebo tests to assess the sensitivity of the estimates to the assignment of pilot cities. Holding the number of treated cities in each policy cohort constant, we construct placebo treatment assignments using stratified and unrestricted reassignment schemes. As summarized in Table A2, both reassignment schemes yield 499 valid simulations. The two-sided studentized empirical *p*-value is 0.056 under stratified reassignment and 0.046 under unrestricted reassignment. The difference between these results indicates that statistical significance is somewhat sensitive to the reassignment scheme. Moreover, pilot cities were not randomly selected, and the simulations are conditional on

the availability of valid sample support. These placebo tests therefore cannot fully rule out potential influences associated with policy location selection.

To assess sensitivity to pre-policy strategic change, we first restrict the sample to firms with complete pre-policy SC records, retaining 1316 firms and 10,709 firm-year observations. The estimated Small–Large contrast is −0.0749, with a *p*-value of 0.1635, com-pared with the baseline estimate of −0.0993 and a *p*-value of 0.0113. We then introduce an additional control for pre-policy SC while keeping the restricted sample unchanged. The resulting contrast remains negative at −0.0697, with a *p*-value of 0.2508. Table A3 presents these two specifications side by side, showing that both estimates are based on the same restricted sample of 1316 firms and 10,709 firm-year observations. Although the estimates are consistently negative, statistical significance is not maintained under the sample restriction. These findings indicate sensitivity to sample composition, while the additional pre-policy SC control produces only a modest change in the point estimate within the same sample.

We further examine the results at the city level using a triple-difference specification. This approach focuses on the difference in average strategic change between smaller and larger firms within cities and assigns equal weight to policy cohorts. The estimated Small–Large contrast is −0.0770, with a *p*-value of 0.0908 under conventional city-clustered inference. A wild cluster bootstrap yields a *p*-value of 0.0666. The negative point estimate does not reach the 5% significance level under either inference procedure. Because the city-level specification differs from the firm-level staggered difference-in-differences design in its estimand and weighting structure, these results provide supplementary evidence rather than a direct replication of the baseline ATT.

As an alternative estimation approach, we employ the Sun–Abraham interaction-weighted event-study estimator [32]. Averaging equally over post-treatment event times 0–3 yields a Small–Large contrast of −0.0707, with a standard error of 0.0262 based on 399 valid stratified city-bootstrap replications and a normal-approximation *p*-value of 0.0070. Table A1 presents the baseline Callaway–Sant'Anna and Sun–Abraham estimates side by side, including their respective post-treatment estimands, standard errors, and *p*-values. Although this estimate is negative and statistically significant at the 1% level, it is not a direct replication of the baseline Callaway–Sant'Anna contrast because the two estimators employ different post-treatment aggregation windows and weighting structures. Moreover, the joint test of pre-treatment effects for smaller firms remains significant at the 1% level under the Sun–Abraham specification. Thus, the alternative estimate is consistent with the negative direction of the baseline contrast but does not resolve the concerns raised by the pre-treatment diagnostics.

Taken together, the sensitivity analyses yield consistently negative firm-size con-trasts, although their statistical significance varies across specifications. Excluding firms with observable geographic changes produces results broadly consistent with the baseline findings. The Sun–Abraham estimator also yields a negative and statistically significant contrast, albeit under a different post-treatment aggregation window and weighting structure. In contrast, the restricted sample with complete pre-policy SC records does not yield a significant difference, and the city-level analysis provides weaker statistical support. The estimated firm-size difference is therefore observed across multiple specifications, while its statistical significance remains sensitive to sample composition and the method of inference.

### *4.4. Dimension Decomposition*

Table 7 presents the treatment-effect estimates and formal firm-size comparisons for the six components of the SC index. To account for the risk of false positives arising from multiple comparisons, we apply the Holm procedure to adjust the *p*-values of the

six between-group tests. We also conduct a joint test to examine whether the estimated firm-size differences are equal across resource-allocation dimensions.

**Table 7.** Dimension decomposition of strategic change.

| Dimension | Small ATT | Large ATT | Small–Large | SE | *p*-Value | Holm *p* |
|---|---|---|---|---|---|---|
| Selling-expense intensity | −0.0441 | 0.1009 | −0.1450 | 0.0778 | 0.0624 | 0.2495 |
| R&D intensity | 0.0167 | −0.0141 | 0.0308 | 0.0695 | 0.6574 | 1.0000 |
| Capital intensity | −0.0420 | −0.0578 | 0.0158 | 0.0843 | 0.8517 | 1.0000 |
| Plant and equipment newness | −0.2819 | 0.0547 | −0.3366 | 0.0805 | <0.001 | <0.001 |
| Non-R&D administrative intensity | 0.0019 | 0.0090 | −0.0071 | 0.1040 | 0.9453 | 1.0000 |
| Financial leverage | −0.0651 | 0.0884 | −0.1535 | 0.0658 | 0.0197 | 0.0984 |

Joint equality test: Wald = 21.2681; df = 5; $p$ = 0.000721. Notes: The table reports dimension-specific treatment effects and formal Small–Large contrasts. Standard errors account for city-level clustering and between-group covariance. Holm-adjusted $p$-values correct for six comparisons. The joint Wald test evaluates equality of the six contrasts. The joint Wald test uses a covariance matrix constructed from city-aligned, cluster-aggregated influence functions. All six dimensions are estimated using the same complete underlying sample of 15,989 firm-year observations from 2377 firms. For each dimension, the Small subsample contains 7488 firm-year observations from 1182 firms, including 537 firms assigned to treated cities. The Large subsample contains 8501 firm-year observations from 1195 firms, including 550 firms assigned to treated cities. These counts describe the underlying estimation samples rather than the effective numbers of observations contributing to individual group–time treatment-effect estimates, which may vary with treatment timing and pair-balanced comparisons.

The dimension-specific estimates reveal the most pronounced firm-size difference in plant and equipment newness. The Small–Large treatment-effect contrast for this dimension is −0.3366, with an unadjusted $p$-value of 0.00003. The Holm-adjusted $p$-value remains significant at the 1% level, at 0.00017. Compared with larger firms, smaller firms exhibit a substantially lower estimated treatment effect on the magnitude of annual adjustments in plant and equipment newness. The differences are less pronounced across the remaining resource-allocation dimensions. For financial leverage, the Small–Large contrast is −0.1535, with an unadjusted $p$-value of 0.0197, but the Holm-adjusted $p$-value increases to 0.0984, exceeding the 5% significance threshold. The contrast for selling-expense intensity is −0.1450, with an unadjusted $p$-value of 0.0624, and is also insignificant after adjustment. The corresponding contrasts for R&D intensity, capital intensity, and non-R&D administrative-expense intensity are 0.0308, 0.0158, and −0.0071, respectively, none of which is statistically significant. Plant and equipment newness is therefore the only dimension for which the firm-size difference remains significant after correcting for multiple comparisons.

Although the dimension-specific estimates indicate a particularly pronounced contrast in plant and equipment newness, significance in an individual dimension does not, by itself, establish differences across dimensions. We therefore conduct a joint test of equality across the six firm-size contrasts. The test yields a Wald statistic of 21.2681 with five degrees of freedom and a $p$-value of 0.0007, rejecting the null hypothesis that the six contrasts are equal. The joint test therefore supports H2, indicating that the estimated firm-size contrasts are not uniform across resource-allocation dimensions. A supplementary comparison between the plant and equipment newness contrast and the average contrast across the other five dimensions yields a difference of −0.2848, with a $p$-value of 0.0003. This additional comparison further illustrates the pronounced difference associated with plant and equipment newness, although it does not establish that this dimension differs significantly from every other dimension individually.

Overall, the decomposition indicates that firm-size differences in estimated policy-related effects on strategic change are not uniform across resource-allocation dimensions.

The joint test rejects equality across the six dimension-specific contrasts, while plant and equipment newness exhibits particularly pronounced statistical evidence of a negative firm-size difference. These findings support H2 and provide a more detailed view of the heterogeneity observed in the aggregate SC index.

## 5. Discussion

### *5.1. Interpreting Average Effects and Firm-Size Heterogeneity*

The pooled estimation does not detect a statistically significant average effect of AI pilot-zone designation on corporate strategic change. Interpreting this finding requires distinguishing the technological opportunities created by the policy from observable adjustments in firms' internal resource allocation. AI pilot zones are designed to improve the external conditions for technological innovation and application, but firms differ in their ability to translate these opportunities into operational adjustments. Strategic response and resource-management perspectives suggest that firms' responses to external opportunities depend on their internal conditions and capacity to deploy resources [17,18]. Firms may respond by reallocating resources or by changing how existing resources are used. In this study, strategic change is measured through standardized absolute annual changes in six accounting-based resource-allocation ratios. This measure captures the magnitude of observed movements in these indicators rather than technology adoption or operating performance. Given this measurement scope and the precision of the estimates, the pooled results provide insufficient statistical evidence that the average policy effect differs from zero. They do not establish the absence of organizational adjustments or a zero underlying policy effect.

The firm-size analysis reveals a different pattern from the pooled estimate. The Small–Large contrast in estimated policy effects is −0.0993 and is statistically significant at the 5% level in the baseline specification. The pooled average effect and the between-group contrast address distinct statistical questions: the former tests whether the average estimated effect differs from zero, whereas the latter tests whether the estimated effects are equal across firm-size groups. A statistically insignificant pooled estimate therefore does not rule out differences between smaller and larger firms. The negative contrast persists across several sensitivity specifications, although its statistical significance is not uniform. Restricting the sample to firms with complete pre-policy strategic-change records produces an insignificant between-group difference, while alternative city-level estimates provide weaker statistical support. The pooled SC estimate may therefore obscure differences across firm-size groups, but the statistical strength of the estimated contrast remains sensitive to sample composition and estimation choices.

Resource capabilities and organizational adjustment constraints offer competing theoretical perspectives on these estimated differences. Larger firms generally have greater access to financial resources, technological knowledge, and specialized personnel, which may facilitate adjustments requiring substantial resource commitments. Established business relationships, complex organizational structures, and existing commitments may nevertheless increase coordination and adjustment costs. Structural inertia theory highlights the constraints associated with organizational stability [22], while research on organizational slack provides a complementary perspective on the role of resource availability in strategic adjustment [19]. Smaller firms may face lower internal coordination requirements, but limited financing and specialized resources can restrict the scope of their adjustments. Strategic flexibility and the observed magnitude of resource-allocation changes are thus distinct concepts [25,26]. The negative Small–Large contrast indicates a lower estimated SC effect for smaller firms relative to larger firms; it does not establish corresponding changes in investment, technology adoption, or strategic transformation. The estimates also do not

identify the relative contributions of resource capabilities and organizational constraints. Because SC is constructed from absolute annual changes in accounting ratios, differences in the underlying year-to-year variability of these ratios across firm-size groups may also contribute to the estimated contrast. The present analysis does not separately assess this possibility. Examining whether this contrast varies across resource-allocation activities provides a more detailed perspective on the heterogeneity underlying composite SC.

### *5.2. Cross-Dimensional Variation in Firm-Size Heterogeneity*

The estimated firm-size differences also vary across resource-allocation dimensions. Although the composite SC index summarizes the overall magnitude of movements in resource-allocation indicators, it does not fully capture differences across the underlying activities. The joint Wald test of equality across the six dimension-specific Small–Large contrasts yields a statistic of 21.2681 and a $p$-value of 0.000721, rejecting the null hypothesis that all six contrasts are equal. Within the current estimation framework, firm-size differences in estimated policy effects are therefore not identical across resource-allocation dimensions. This result does not imply that every pair of dimensions differs significantly. Rather, the dimensional analysis provides a more detailed view of how estimated firm-size heterogeneity varies across the activities represented in the composite measure.

Plant and equipment newness provides the clearest statistical evidence of a firm-size difference among the six dimensions. Its estimated Small–Large contrast is $-0.3366$, with a Holm-adjusted $p$-value of 0.00017. By comparison, the contrast for capital intensity is 0.0158 and is not statistically significant. Although both indicators concern productive capital, they capture different aspects of firms' asset configurations. Plant and equipment newness is measured as net fixed assets divided by gross fixed assets, and changes in this ratio may reflect depreciation, asset additions, or disposals. Capital intensity is measured as net fixed assets per employee and is also affected by changes in employment. Because the analysis examines absolute annual changes in these ratios, their estimates should not be interpreted as alternative measures of the same capital-adjustment activity. Research on capital-adjustment costs and financial frictions provides a basis for understanding the constraints associated with existing asset commitments, financing conditions, and organizational coordination [28,29]. Nevertheless, the estimated difference in plant and equipment newness does not directly identify deliberate equipment replacement or fixed-asset investment. Nor does the difference in statistical significance between the two indicators establish that their firm-size contrasts differ significantly from each other.

The cross-dimensional pattern can also be considered in relation to the different requirements of resource-allocation activities. Operating expenditures, R&D, productive capital, and financing arrangements place different demands on financial resources, specialized knowledge, and organizational coordination. The relative importance of firm-size advantages and existing organizational constraints may consequently vary across these activities. This interpretation is consistent with the theoretical discussion of resource capabilities, organizational inertia, and adjustment costs developed in Section 2, although the present estimates do not identify their underlying mechanisms. Apart from plant and equipment newness, none of the other five dimensions exhibits a firm-size contrast that remains significant at the 5% level after Holm adjustment. Overall, the joint test provides statistical evidence that estimated firm-size heterogeneity varies across resource-allocation dimensions, while the dimension-specific results clarify where this variation is most apparent.

### *5.3. Theoretical Implications*

Existing studies of China's AI pilot zones have examined firm-level outcomes such as technological upgrading, investment efficiency, innovation, and labor allocation [3–8]. Research on digital infrastructure and government data governance has also examined the relationships between external digital environments and corporate innovation and upgrading [15,16]. Related research on market-based environmental regulation shows that corporate social responsibility can condition firms' green-innovation responses to policy incentives [33], highlighting a policy setting and outcome distinct from the resource-allocation movements examined here. Yi et al. [7] further investigate how AI pilot zones relate to corporate competitiveness through resource structuring and capability leveraging. Building on the literature, the present study extends the analysis to annual changes in firms' internal resource-allocation indicators, focusing on the relationship between external technological opportunities and observable changes in resource allocation. By measuring strategic change through standardized absolute annual changes in six accounting-based indicators, the study distinguishes the magnitude of resource-allocation adjustments from technology adoption and operating performance. Unlike studies focusing on resource capability development or specific corporate outcomes, this analysis treats observable resource-allocation adjustments as a distinct empirical outcome. It thereby provides a complementary perspective on the relationship between external policy opportunities and firms' internal operations.

A second theoretical implication concerns the relationship between firm size and the multidimensional nature of strategic change. Firm size is associated with both resource mobilization capabilities and constraints arising from existing commitments and organizational coordination. Because resource-allocation activities differ in their financial, knowledge, and organizational requirements, the relative importance of these conditions may also vary across activities. Drawing on competing perspectives concerning resource advantages and adjustment constraints, this study combines firm-size comparisons of composite SC with a joint examination of six resource-allocation dimensions. The estimates indicate that the dimension-specific firm-size contrasts are not identical and that capital-related indicators exhibit different statistical patterns. Although the composite SC index summarizes the overall magnitude of resource-allocation changes, it may obscure differences in estimated firm-size effects across individual activities. For research on AI-related industrial policy, this approach adds a perspective that jointly considers organizational characteristics and the nature of resource-allocation activities. For the strategic-change literature, it highlights the value of examining individual resource-allocation dimensions alongside composite measures to obtain a more detailed understanding of observed strategic change. Resource management, organizational inertia, and capital-adjustment cost theories offer potential explanations for these differences, but their underlying mechanisms require further empirical examination. The study thus complements existing research by distinguishing observable resource-allocation adjustments from other corporate outcomes and by examining firm-size heterogeneity across the components of strategic change.

These implications are also relevant to sustainable digital transformation. Access to emerging technologies does not, by itself, indicate how firms adapt existing resource commitments or whether they can sustain transformation-related activities over time. Different resource-allocation activities may involve different adjustment costs, degrees of reversibility, and requirements for financial and organizational resources. The estimated firm-size and cross-dimensional differences therefore draw attention to organizational conditions that may matter when technological opportunities are translated into resource-allocation responses. However, the SC index records annual movements in accounting ratios; it does not establish deliberate investment, the persistence of resource commitments, or economic, so-

cial, or environmental sustainability outcomes. The study thus provides an organizational perspective that future research can connect to longer-term digital transformation.

### *5.4. Limitations and Future Research*

Several limitations qualify the interpretation of our findings. Although the aggregated pre-treatment test does not reject the null hypothesis of zero Small–Large differences, the cohort-specific test for the 2021 cohort rejects the null at the 5% significance level. In addition, the statistical significance of the baseline firm-size contrast varies across sample restrictions and alternative city-level specifications. These findings limit the strength of causal interpretations. Furthermore, policy exposure is assigned according to firms' fixed pre-policy registered cities rather than their actual participation in pilot-zone programs or receipt of specific policy support. The analysis includes only 17 treated cities, and pilot-zone locations were not randomly selected, placing additional constraints on causal interpretation and generalizability.

Further limitations concern the measurement of strategic change and the identification of underlying mechanisms. The SC index captures the magnitude of annual movements in accounting-based resource-allocation ratios rather than deliberate managerial decisions, actual technology adoption, or improvements in firm performance. Moreover, although resource capabilities, financial conditions, and organizational constraints provide theoretical explanations for the observed firm-size differences, their specific mechanisms are not directly identified. Future research could incorporate firm-level policy participation records, detailed information on policy instruments, capital investment and technology adoption, and measures of financial and organizational resources to examine these mechanisms more directly.

## 6. Conclusions and Policy Implications

### *6.1. Conclusions*

This study examines the relationship between China's National New Generation Artificial Intelligence Innovation and Development Pilot-Zone policy and corporate strategic change. Using 15,989 firm-year observations from 2377 nonfinancial A-share listed firms over 2016–2024, we employ a staggered difference-in-differences approach to estimate policy-related effects. Corporate strategic change is measured by a composite index, SC, constructed as the equally weighted average of standardized absolute annual changes in six accounting-based resource-allocation ratios. The index captures the magnitude of observable movements in firms' resource-allocation indicators. The pooled average treatment effect is estimated at $-0.0162$, with a $p$-value of 0.5005. This estimate is not statistically distinguishable from zero, but it does not establish that the underlying average effect is zero. Because SC measures changes in resource-allocation indicators rather than technology adoption, innovation output, or operating performance, the pooled estimate cannot directly establish the policy's effectiveness in these other areas.

Beyond the pooled estimate, the firm-size and dimensional analyses provide more differentiated evidence. In the baseline specification, the estimated Small–Large contrast in composite SC is $-0.0993$ and is statistically significant at the 5% level. A joint test across the six resource-allocation dimensions further rejects the null hypothesis that the dimension-specific Small–Large contrasts are equal, indicating that estimated firm-size heterogeneity is not uniform across resource-allocation dimensions. Among the individual dimensions, plant and equipment newness provides the clearest statistical evidence of a between-group difference after adjustment for multiple testing. Taken together, these findings show that the pooled average estimate does not fully capture the differences between firm-size groups, while the composite SC index may conceal variation in these

differences across its underlying dimensions. Pre-treatment diagnostics and sensitivity analyses nevertheless warrant caution in interpreting the estimates. By distinguishing pooled average effects, firm-size heterogeneity, and its variation across resource-allocation dimensions, this study provides a more detailed empirical account of how estimated policy-related differences in corporate resource-allocation changes vary across firm sizes and activities. From the perspective of sustainable digital transformation, these patterns point to the value of examining resource commitments and organizational constraints alongside technological opportunities. They provide a basis for future research on how observable resource-allocation responses relate to the durability and outcomes of firms' digital transformation.

### *6.2. Policy Implications*

The evaluation of AI pilot-zone policy should distinguish among geographic policy exposure, firms' actual use of policy resources, observable resource-allocation changes, and final business outcomes. Geographic exposure, assigned according to firms' pre-policy registered cities in this study, does not establish whether individual firms have accessed or utilized specific forms of policy support. Similarly, changes in resource-allocation indicators do not directly establish improvements in technology adoption or operating performance. Policy evaluation should therefore assess whether support measures reach firms and how they are utilized, while examining technological applications, innovation activities, and business performance in relation to specific policy objectives. Annual movements in resource-allocation indicators can provide supplementary information on internal operational adjustments, but the magnitude of such movements should not be treated as a direct measure of policy success. Distinguishing resource utilization, corporate activities, and their outcomes would help avoid equating geographic policy exposure with actual benefits or relying on a single resource-allocation indicator to assess policy effectiveness.

Policy implementation should also account for differences in firms' conditions for accessing and utilizing policy resources. The baseline specification yields a statistically significant contrast between firm-size groups, suggesting that organizational differences merit attention in policy implementation and evaluation. Firms differ in their technological capabilities, financial resources, specialized personnel, and internal coordination capabilities, which may shape their ability to obtain and use available support. Implementation efforts could therefore place greater emphasis on identifying the obstacles firms face in accessing policy programs, obtaining technical services, accessing specialized talent, and coordinating resources. Support services and resource provision could then be better aligned with firms' operating conditions and technological needs. Importantly, the Small and Large groups in this study are defined by relative pre-policy firm size within a sample of listed companies and should not be equated with administrative classifications of small and medium-sized enterprises. Policy support should not be allocated mechanically according to these empirical categories. Greater attention to firms' actual resource conditions and policy needs would provide a more appropriate basis for aligning policy implementation with organizational and operational characteristics.

Policy monitoring and feedback should further strengthen the interpretation of resource-allocation indicators alongside firms' actual business activities. The cross-dimensional analysis indicates that estimated firm-size differences vary across resource-allocation indicators, while movements in accounting ratios do not necessarily correspond directly to specific managerial decisions. Policy monitoring could therefore combine financial indicators with records of actual investment, technology adoption, and operational adjustments. Plant and equipment newness provides a relevant example. Changes in this ratio may arise from depreciation, asset acquisitions, or disposals, making it difficult to infer deliberate equipment replacement

or technological upgrading from the ratio alone. Where asset-related indicators exhibit substantial movements, information on capital expenditure, equipment purchases, technological renovation projects, and asset disposals could help clarify the underlying activities. Changes in R&D intensity, operating-expenditure ratios, and financial leverage should likewise be assessed alongside relevant project information, financing records, and operational data, rather than being treated as direct evidence of resource-allocation decisions. Incorporating such information into policy monitoring and feedback would improve the interpretation of firms' resource-allocation responses and provide a more informed basis for refining the implementation and evaluation of AI pilot-zone policy.

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## Appendix A. Supplementary Robustness and Sensitivity Analyses

**Table A1.** Alternative estimator diagnostics for firm-size heterogeneity.

| Estimator | Post-Treatment Estimand | Small–Large | SE | *p*-Value |
|---|---|---|---|---|
| Callaway–Sant'Anna (baseline) | Overall post-treatment ATT contrast | −0.0993 | 0.0392 | 0.0113 |
| Sun–Abraham | Equal-weight average, event times 0–3 | −0.0707 | 0.0262 | 0.0070 |

Notes: The baseline Small–Large contrast uses the Callaway–Sant'Anna staggered difference-in-differences estimator and the overall post-treatment ATT. Its standard error is based on city-aligned influence functions that account for covariance between subgroup estimates. The Sun–Abraham interaction-weighted contrast is the equally weighted average across event times 0–3; its standard error is based on 399 valid stratified city-bootstrap replications, and its *p*-value uses a normal approximation. The estimators use different aggregation windows and weighting structures, so the estimates should be read as a sensitivity comparison.

**Table A2.** City-level placebo reassignment diagnostics.

| Assignment Procedure | Valid Replications | Studentized Empirical *p*-Value | Result at 5% |
|---|---|---|---|
| Stratified reassignment | 499 | 0.056 | Not rejected |
| Unrestricted reassignment | 499 | 0.046 | Rejected |

Notes: This table reports two-sided studentized empirical *p*-values for the formal Small–Large contrast under city-level placebo reassignment. Each procedure uses 499 valid simulations while preserving the number of treated cities in each policy cohort. The reported significance decisions apply a 5% threshold. Because actual pilot-zone designation was not randomized, these tests provide supplementary sensitivity evidence rather than replacing the baseline city-clustered inference.

**Table A3.** Sensitivity of firm-size heterogeneity to pre-policy SC.

| Specification | Firms | Firm-Year Observations | Small–Large | *p*-Value |
|---|---|---|---|---|
| Restricted historical sample | 1316 | 10,709 | −0.0749 | 0.1635 |
| With pre-policy SC control | 1316 | 10,709 | −0.0697 | 0.2508 |

Notes: Both specifications use the same restricted sample of firms with complete pre-policy SC records. The first specification retains the predetermined baseline covariates, while the second additionally controls for pre-policy SC. The reported coefficients are formal Small–Large treatment-effect contrasts. Neither estimate is statistically significant at the 5% level.

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