

Capacity-Constrained Regulation and the Location of Electricity-Intensive Investment: Evidence from China's Dual-Control Policy

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Abstract

How does regulation reshape spatial allocation when it binds through local capacity rather than marginal compliance costs? Using panel data for Chinese prefecture-level cities from 2013 to 2024, this study exploits the 2021 high-pressure warning issued under China's Dual Control of Energy Consumption policy as a quasi-natural experiment to examine how tightening energy constraints affect the entry and expansion of intelligent computing centers. We find that tightening energy constraints significantly reduce both new deployment and firm expansion. The negative effect is concentrated in cities with higher marginal deployment capacity prior to the policy shock. Further evidence shows that local generation structure influences the policy effect: stable low-carbon power partially mitigates the adverse effect, while the positive expansion effect associated with variable renewable green energy is largely offset under significant energy constraints. At the spatial level, the policy shock does not simply redirect investment toward less constrained or resource-abundant locations. It mainly generates aggregate contraction, with only limited absorption by non-warning cities and no systematic sorting toward more favorable resource endowments. Overall, these findings show that capacity-constrained regulation can shift spatial adjustment from reallocation to aggregate contraction, highlighting the role of local power-system capacity, supply stability, and adjustment frictions in shaping electricity-intensive investment.

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1 Introduction

A central question in environmental and public economics is how regulation reshapes the spatial allocation of economic activity. A large body of research shows that environmental regulation can alter the geography of production by changing the relative attractiveness of operating across locations. This logic underlies the classic pollution haven hypothesis, as developed in influential studies such as [Levinson \(1996\)](#) and [Becker and Henderson \(2000\)](#), and more broadly informs the literature on spatial reallocation under environmental regulation. The standard view emphasizes cost-based adjustment: when regulation raises the relative cost of operating in one location, firms may reduce local activity or relocate toward places with lower regulatory burdens.

This paper studies a different type of regulatory constraint. In many emerging sectors, regulation does not operate only through marginal compliance costs; it can also bind through local capacity. For electricity-intensive activities, such as data centers and intelligent computing centers, the relevant constraint is whether local power systems can accommodate additional demand reliably and continuously. Recent work on electricity reliability highlights the dependence of economic activity on the quality and continuity of power supply ([Borenstein et al. 2023](#)). Once this capacity margin becomes binding, spatial adjustment may differ sharply from the standard relocation logic. Investment may fail to move smoothly toward less constrained places because alternative locations may lack the grid access, supply stability, demand conditions, or supporting infrastructure needed to absorb displaced activity.

This distinction matters because capacity-constrained regulation changes the relevant margin of adjustment. Under cost-based regulation, firms may respond by bearing higher costs, changing production processes, or relocating to lower-cost regions. Under capacity-based regulation, however, the central issue is whether additional activity can be accommodated at all. A project may remain commercially attractive but still fail to enter or expand if the local power system cannot support additional electricity demand or if policy pressure raises the effective approval threshold. The resulting adjustment may therefore appear as aggregate contraction rather than smooth spatial reallocation ([Hjort and Poulsen 2019](#); [DeStefano et al. 2025](#)).

This setting is particularly relevant for electricity-intensive digital infrastructure. Demand for computing power, cloud services, and artificial intelligence applications is often concentrated in economically advanced regions, while the energy capacity needed to support large-scale facilities may be located elsewhere. This spatial mismatch means that the location of new digital infrastructure depends not only on market demand and operating costs, but also on local power-system capacity, reliability, and room for future expansion. When energy governance becomes tighter, locations with strong digital demand

may not necessarily have sufficient electricity-system support, while potential alternative locations may not be able to absorb displaced investment at scale. Recent research on electricity reliability also shows that the continuity and quality of power supply are central to economic activity, especially where production or service provision depends on stable electricity input (Borenstein et al. 2023).

China provides a useful empirical setting for examining this mechanism. The distribution of digital demand and the provision of power support are sharply uneven across space. The need for computing power, digital services, and downstream applications is concentrated in the eastern region, characterized by higher economic activity and advanced digital usage. In contrast, incremental power supply, renewable energy endowments, and a significant share of the land and resource capacity appropriate for electricity-intensive infrastructure are disproportionately located in western and certain central regions of China. This spatial dispersion results in a structural discrepancy between the demand for digital infrastructure and the availability of energy capacity. With the intensification of energy governance, this tension becomes increasingly significant for investment decisions.

This mechanism became particularly salient with the reinforcement of China’s dual-control regime on energy usage. As the pressure on both energy intensity and overall energy consumption increased, local governments faced stronger incentives to restrict energy-intensive projects, tighten approval criteria, and reevaluate development priorities. The 2021 high-pressure warning under the dual-control regime therefore creates a context in which policy-induced energy restrictions became more apparent and binding. This policy shock may directly influence the approval, expansion, and ongoing operation of electricity-intensive digital infrastructure projects.

Against this background, this study examines how energy constraints affect the spatial allocation of intelligent computing centers. To do so, we construct a panel dataset of Chinese prefecture-level cities from 2013 to 2024 and treat the 2021 high-pressure warning issued under the dual-control policy on energy consumption as a policy shock. Intelligent computing center firms are identified through IDC operating license records, and firm-level observations are subsequently aggregated to the city-year level. The analysis further incorporates prefecture-level data on electricity generation, electricity consumption, and generation by source type in order to better understand local power support conditions and generation structure. It also incorporates information on natural resource endowments to preliminarily examine the probable locational shifts resulting from the observed limited reallocation following the policy shock. The main focus is on how local electricity support conditions influence the entry, expansion, and spatial adjustment of intelligent computing centers as energy constraints intensify.

This paper shows that when regulation operates through binding capacity constraints

rather than marginal compliance costs, the standard reallocation logic can break down. Instead of inducing investment to move smoothly toward less constrained locations, capacity-constrained regulation may compress the feasible margin of expansion and generate aggregate contraction. Empirically, the policy shock significantly reduces both new entry and firm expansion. The negative effect is concentrated in cities with stronger pre-policy deployment capacity, suggesting that the initial adjustment operates through the compression of a previously feasible expansion margin. At the spatial level, we find only limited absorption by non-warning cities and little systematic sorting toward resource-abundant locations. These results suggest that the policy did not simply redirect investment to more favorable destinations; it mainly reduced the overall scale of new deployment.

This paper makes two main contributions. First, it contributes to the literature on environmental regulation and spatial reallocation by distinguishing capacity-constrained regulation from the cost-based regulation emphasized in the pollution haven literature. This distinction helps explain why regulation may generate aggregate contraction rather than smooth spatial reallocation when local capacity becomes binding. Second, the paper develops an energy-capacity mechanism for understanding the location of electricity-intensive investment. The location of digital infrastructure is shaped not only by demand and regulatory costs, but also by the carrying capacity, reliability, and generation structure of local power systems. This mechanism is relevant to a wider set of energy-intensive activities, including data centers, AI computing infrastructure, semiconductor fabs, battery production, and electric-vehicle charging networks.

Related Literature. This paper relates to three strands of literature. First, it relates to the literature on environmental regulation and spatial reallocation. [Greenstone \(2002\)](#) shows how environmental regulation reshapes the spatial distribution of pollution-intensive production. [Ryan \(2012\)](#) further shows that regulatory pressure can materially affect investment decisions in concentrated industries. At the levels of adjustment and reallocation, [Walker \(2011\)](#) and [Walker \(2013\)](#) document significant labor-market and transitional impacts of environmental legislation. Recent evidence from [Cui and Moschini \(2020\)](#) shows that environmental regulation also functions through corporate networks and the longevity of plants. This paper extends that tradition while focusing on an alternative margin of adjustment. For electricity-intensive digital infrastructure, the key constraint is often whether local electricity systems can accommodate substantial and continuous demand under tighter policy pressure. In this sense, the paper extends the concept of regulatory reallocation to a setting in which infrastructure feasibility is central to location selection.

Second, this paper relates to the economics literature on electricity constraints, reliability, and firm performance. Using evidence from China, [Fisher-Vanden et al. \(2015\)](#)

show that electricity shortages reduce firm productivity, while [Allcott et al. \(2016\)](#) document substantial industrial losses from power shortages in India. Firm-level evidence from a single-grid context in [Elliott et al. \(2021\)](#) similarly demonstrates that outages impair firm performance. At a broader level, [Fried and Lagakos \(2023\)](#) develop a general-equilibrium framework regarding electricity and productivity. Related work by [Burgess et al. \(2020\)](#), [Chen et al. \(2025\)](#), and [Kassem \(2024\)](#) further shows that electricity institutions, conservation policies, and electrification significantly influence economic activity and industrial development. This literature shows that power-system conditions have concrete economic implications, yet it has devoted significantly less focus to the interaction between stringent energy policies and local electricity fundamentals in determining the location of new electricity-intensive digital capital. This paper contributes by linking policy-induced energy constraints to the spatial distribution of intelligent computing centers, revealing that local electricity support conditions influence the potential for infrastructure expansion.

Third, this paper contributes to the literature on digital infrastructure and economic development. [Greenstein \(2020\)](#) clarifies the broader economic rationale of internet infrastructure, while [Akerman et al. \(2015\)](#) show that broadband development can have substantial labor-market and productivity effects. Yet this literature has focused primarily on the economic implications of digital access and adoption. There is limited understanding of the factors that influence the location of electricity-intensive digital infrastructure under energy constraints. This paper integrates environmental regulation, power system capacity, and the location of digital infrastructure, linking three bodies of research that have mainly developed separately.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual framework and presents the main propositions. Section 3 describes the institutional setting, data, and empirical strategy. Section 4 presents the main empirical results. Section 5 examines the economic implications of energy-constrained reallocation. Section 6 concludes.

2 Conceptual Framework

This section develops a simple framework to distinguish capacity-constrained regulation from cost-based regulation. The key idea is that regulation may affect location choices not only by changing marginal operating costs, but also by restricting the feasible capacity for additional activity. When the constraint binds through local carrying capacity, the adjustment margin may shift from relocation to contraction. To formalize this mechanism, we first present a compact location-choice model and then derive testable implications

for entry, expansion, heterogeneous effects, and spatial reallocation.

2.1 A Simple Model of Capacity-Constrained Adjustment

To formalize the mechanism, consider a simple location choice problem for an electricity-intensive project. A firm considers locating a project in city i . The project yields gross return A_i , pays normal operating cost c_i , faces regulatory cost r_i , and requires electricity demand e . In a standard cost-based framework, regulation affects location choice mainly by raising r_i . A firm can still enter if the net payoff remains positive, or relocate to another city with lower regulatory costs.

Capacity-based regulation adds a different constraint. Let K_i denote the effective local electricity capacity available for additional electricity-intensive deployment. The payoff from locating in city i can be written as

$$\Pi_i = A_i - c_i - r_i - \lambda_i(e - K_i)^+,$$

where $(e - K_i)^+ = \max\{e - K_i, 0\}$, and $\lambda_i(e - K_i)^+$ captures the shadow cost of local capacity pressure. When $e \leq K_i$, this term is zero. When $e > K_i$, the shadow cost rises because the project exceeds the local capacity margin. Entry occurs if

$$Entry_i = \mathbf{1} \{A_i - c_i - r_i - \lambda_i(e - K_i)^+ > 0\}.$$

Policy tightening reduces the effective capacity available for new deployment. Let

$$K_i = \bar{K}_i - \phi P_i,$$

where \bar{K}_i denotes pre-policy local deployment capacity, P_i measures exposure to high-pressure energy constraints, and $\phi > 0$ captures how strongly the policy compresses available capacity. This formulation highlights the key distinction between cost-based and capacity-based regulation. Cost-based regulation changes the price of operating in a location. Capacity-based regulation changes whether additional activity can be accommodated at all. As P_i increases, K_i falls, the shadow cost of capacity pressure increases, and the probability of entry declines.

This framework also clarifies why capacity-constrained regulation may generate aggregate contraction rather than smooth relocation. In the standard pollution-haven logic, an increase in regulatory cost in city i can shift activity toward another city j with lower regulatory costs. Under capacity-constrained regulation, however, relocation requires that

the alternative city also have sufficient unused capacity:

$$Entry_j = \mathbf{1} \{A_j - c_j - r_j - \lambda_j(e - K_j)^+ > 0\}.$$

If alternative locations lack sufficient capacity, reliable electricity supply, grid access, or complementary infrastructure, the decline in constrained cities will not be fully offset elsewhere. In that case,

$$\Delta Entry_i < 0, \quad \Delta Entry_j \approx 0,$$

and aggregate deployment falls:

$$\sum_i \Delta Entry_i < 0.$$

Thus, when the binding constraint is physical or administrative capacity rather than marginal cost, regulation may compress the aggregate expansion margin instead of inducing smooth spatial relocation.

2.2 High-Pressure Energy Constraints and the New Location of Digital Infrastructure

The conventional pollution haven hypothesis posits that energy-intensive and pollution-intensive firms tend to relocate production to regions with less stringent environmental regulations to reduce compliance expenses. Current research has predominantly concentrated on traditional pollution-intensive manufacturing sectors such as steel, cement, and chemicals (Shen et al. 2017; Wang et al. 2019), highlighting how environmental regulation reshapes firms' location choices and regional industrial division through changes in relative costs across places. With the rapid development of the digital economy and artificial intelligence, however, the focus of regulation is changing. For digital infrastructures such as data centers and intelligent computing centers, local pressure is no longer primarily associated with direct emissions. It is increasingly linked to their dependence on uninterrupted electricity supply, energy-consumption limits, and the capacity of local power systems to support rising demand. As a result, the influence of environmental and energy regulations on their spatial distribution may operate through electricity and capacity constraints, rather than through relative compliance costs alone (Wu et al. 2017).

Intelligent computing centers provide a clear setting for this mechanism. They are significantly more electricity-intensive than conventional digital enterprises, require substantial investment during construction, and continue to consume large quantities of electricity and energy resources during operation. When constraints on energy intensity

and total energy consumption become tighter, local governments encounter stronger evaluation pressure, which may raise scrutiny, resource allocation thresholds, and market entry barriers for new energy-intensive projects. Under these circumstances, high-capacity digital infrastructures are more prone to direct constraints on entry, local expansion, and marginal deployment. In the empirical setting of this paper, the 2021 high-pressure warning under China’s dual-control policy represents a policy-induced compression of the feasible capacity available for new electricity-intensive deployment. This corresponds to the capacity-compression mechanism in the model: tightening energy constraints reduce the local room for accommodating additional projects and therefore weaken the entry and expansion of intelligent computing centers.

Proposition 1. When regulation binds through local capacity rather than marginal compliance costs, it reduces the feasible margin of entry and expansion for capacity-intensive investment.

2.3 Electricity Spatial Mismatch and Heterogeneous Policy Effects

The effect of high-pressure energy constraints should vary with cities’ pre-existing deployment capacity. In the simple framework above, the contraction effect is stronger where the pre-policy feasible margin is larger, because these locations have more previously viable deployment space to be compressed by the policy shock. In the context of electricity-intensive digital infrastructure, this pre-policy deployment capacity depends closely on local electricity supply-demand conditions. For intelligent computing centers, whether a project can be established and continue to expand locally depends on whether the locality retains viable capacity under energy-consumption control and related administrative constraints (Lo 2020), and whether the city has an electricity system capable of supporting continuous operation with sufficient reliability and energy supply conditions (Ayyildiz et al. 2025; Wang et al. 2024).

We use electricity spatial mismatch to capture this dimension. Cities vary significantly in their underlying electricity supply circumstances. Some locations possess stronger local generation capacity and can rely more heavily on local supply to facilitate additional electricity-intensive activities. Others may have strong demand for digital infrastructure while facing limited local generation capacity and increased dependence on imported electricity via cross-regional transmission networks (Ma and Xu 2021). These disparities shape cities’ carrying conditions before the policy shock and determine which locations are more likely to experience a compression of marginal deployment space when high-pressure energy constraints tighten.

Cities with lower electricity mismatch typically have stronger local power support, greater reliance on local generation, and more complete supply-side conditions. Before the policy shock, these cities are more likely to have sufficient capacity to accommodate new intelligent computing centers. When high-pressure energy constraints tighten, the policy compresses precisely this previously feasible margin, making the reduction in entry and expansion more visible. By contrast, cities with higher electricity mismatch tend to have weaker local generation support and greater dependence on imported electricity. New electricity-intensive projects in these places may already face tighter practical constraints before the policy shock. Additional policy tightening can still increase pressure, but the observable decline in new deployment may be less pronounced because the initial feasible margin is already limited. Electricity spatial mismatch therefore shapes how capacity-constrained regulation is manifested across cities.

Proposition 2. The negative impact of high-pressure energy constraints on the new deployment and expansion of intelligent computing centers is more likely to be observed in cities with lower electricity mismatch, where pre-policy deployment capacity is stronger.

2.4 Aggregate Contraction and Limited Spatial Reallocation

Under capacity-constrained regulation, the decline in constrained locations does not automatically translate into an equivalent increase elsewhere. In a cost-based setting, firms may relocate when they can identify destinations with lower regulatory costs. In a capacity-based setting, however, less constrained locations are not automatically viable destinations. They must also have sufficient unused capacity, reliable electricity supply, grid access, and complementary infrastructure. If these conditions are limited or spatially mismatched, the investment compressed in constrained cities cannot be fully absorbed by alternative destinations.

This logic is particularly important for electricity-intensive digital infrastructure. Intelligent computing centers require continuous power support, stable system conditions, and room for future expansion. Even if non-warning cities face weaker policy pressure, they may not be able to absorb displaced deployment at scale if they lack sufficient electricity capacity, supporting infrastructure, or demand-side conditions. The aggregate response is therefore more likely to appear as a decline in total deployment, accompanied only by partial absorption in less constrained cities.

Proposition 3. Capacity-constrained regulation generates aggregate contraction rather than full spatial reallocation when alternative locations lack sufficient unused capacity, reliable supply, or complementary infrastructure.

2.5 Generation Structure, Supply Stability, and the Buffering Mechanism of Policy Pressure

The effect of high-pressure energy constraints on the deployment of intelligent computing centers depends not only on the overall balance between electricity supply and demand in a city, but also on the structure of local power supply. Even when cities exhibit comparable aggregate electricity conditions, differences in reliability, flexibility, and effective system support may result in different levels of resilience under stringent regulatory pressures. For electricity-intensive digital infrastructure such as intelligent computing centers, the relevant question is whether local power systems can deliver reliable and continuous support for substantial and persistent electricity demand. A growing economic literature indicates that electricity reliability, transmission capacity, and the structuring of power systems have important implications for allocative efficiency, firm performance, and the geographic distribution of economic activity ([Hausman 2025](#)).

From the perspective of operational characteristics, intelligent computing centers require highly continuous operation, large and persistent electricity consumption, and minimal tolerance for interruptions. Upon establishment, these projects impose stringent demands on power quality, system stability, and future capacity expansion potential. As high-pressure energy limitations intensify, local governments are expected to evaluate new electricity-intensive projects with greater caution and to distribute limited resources more carefully to areas with greater supply security. In this context, the structure of generation is significant because different sources offer differing levels of reliability and flexibility. Under identical policy pressures, cities with more reliable and dispatchable energy supplies are typically better positioned to facilitate the establishment and growth of electricity-intensive digital infrastructure, consistent with the role of power-system stability emphasized in [Hausman \(2025\)](#).

Among low-carbon sources, hydropower and nuclear power are typically more capable of delivering consistent support and enhanced system flexibility. Hydropower plays an important role in flexible power systems, while nuclear generation is typically characterized by more stable output across time ([Paraschiv 2023](#); [Vagnoni et al. 2024](#)). For cities with stronger pre-existing support from solid low-carbon sources, local power systems may retain greater room for adjustment even under tighter energy constraints. This can reduce the effective pressure faced by the new establishment and expansion of intelligent computing centers.

In contrast, wind and solar energy also contribute to de-carbonization, but their production is more sensitive to weather conditions and temporal fluctuations. As a result, a higher share of variable renewables does not inherently ensure robust support for uninterrupted, high-capacity digital infrastructure. Recent research on reliable wind- and

solar-based systems shows that maintaining sufficiency in these systems is more challenging and requires additional planning and balancing efforts (Ruggles et al. 2024). Under tighter energy constraints, this implies that different low-carbon generation structures may differ substantially in the extent of effective support they offer for new electricity-intensive projects.

From this perspective, generation structure shapes the effective intensity of high-pressure energy constraints at the local level. Under identical policy pressures, cities with stronger support from stable low-carbon electricity are more inclined to maintain opportunities for new deployment and expansion, whereas cities whose supply structure is more volatile may encounter a more pronounced compression of viable deployment space. The local generation structure therefore serves both as an important factor for the location of intelligent computing centers and as a mechanism influencing the policy effect.

Proposition 4. Under high-pressure energy constraints, local generation structure influences the policy response of intelligent computing centers’ deployment and expansion.

3 Institutional Background and Research Design

3.1 Institutional Background

To advance its energy-saving and carbon-reduction goals, China progressively established a dual-control regime centered on two targets: energy intensity and total energy consumption. Unlike general forms of green governance, the distinctive feature of this policy lies in the way it transforms local energy constraints into stringent constraints with explicit assessment pressure and concrete implications for resource allocation. In particular, when local governments experience pressure regarding both energy intensity reduction and overall energy consumption management, they typically implement stricter project approvals, allocate energy-use quotas more rigorously, and enhance energy-saving review procedures in a more conspicuous manner.

In 2021, China’s National Development and Reform Commission issued the Barometer of the *Completion of Dual-Control Targets for Energy Consumption in Each Region during the First Half of 2021*, which classified provincial performance along two dimensions: the target for reducing energy intensity and the target for controlling total energy consumption. For the energy-intensity reduction target, nine provinces were placed under first-level warning: Qinghai, Ningxia, Guangxi, Guangdong, Fujian, Xinjiang, Yunnan, Shaanxi, and Jiangsu. Ten provinces were assigned second-level warn-

ing: Zhejiang, Henan, Gansu, Sichuan, Anhui, Guizhou, Shanxi, Heilongjiang, Liaoning, and Jiangxi. Eleven provinces or municipalities were placed under third-level warning: Shanghai, Chongqing, Beijing, Tianjin, Hunan, Shandong, Jilin, Hainan, Hubei, Hebei, and Inner Mongolia. For the total energy-consumption control target, eight provinces were placed under first-level warning: Qinghai, Ningxia, Guangxi, Guangdong, Fujian, Yunnan, Jiangsu, and Hubei. Five provinces were assigned second-level warning: Xinjiang, Shaanxi, Zhejiang, Sichuan, and Anhui. Seventeen provinces or municipalities were placed under third-level warning: Henan, Gansu, Guizhou, Shanxi, Heilongjiang, Liaoning, Jiangxi, Shanghai, Chongqing, Beijing, Tianjin, Hunan, Shandong, Jilin, Hainan, Hebei, and Inner Mongolia.

The importance of this institutional arrangement lies in the fact that it transformed previously abstract energy constraints into differentiated and visible policy pressure. For electricity-intensive digital infrastructure such as intelligent computing centers, such a policy shock was not merely part of a broad green-governance backdrop, but could also directly affect the criteria for project approval, expansion, and ongoing operation. In this sense, the 2021 high-pressure warning issued under the dual-control regime offers an ideal institutional setting for assessing the impact of binding energy constraints on the spatial allocation of digital infrastructure.

3.2 Identification Strategy

3.2.1 Baseline Model

This study leverages the 2021 high-pressure warning issued under China’s dual-control policy on energy consumption to develop a prefecture-level policy shock framework. The baseline treatment group comprises prefecture-level cities located in provinces that were simultaneously placed under the Level I warning for energy intensity and the Level I warning for total energy consumption. According to the *Barometer of the Completion of Dual-Control Targets for Energy Consumption in Different Regions during the First Half of 2021*, these provinces include Qinghai, Ningxia, Guangxi, Guangdong, Fujian, Yunnan, and Jiangsu. Prefecture-level cities in all other provinces serve as the control group.

Because the *Barometer of the Completion of Dual-Control Targets for Energy Consumption in Different Regions during the First Half of 2021* was released in August 2021, while this study relies on annual data, the year 2021 contains observations from both before and after the policy announcement. This complicates the clear distinction between pre-policy and post-policy annual effects. To avoid mixing short-run adjustments within the transition year with the policy shock itself, this study defines 2022 and subsequent

years as the post-policy period, 2013 to 2020 as the pre-policy period, and excludes the 2021 sample from the analysis.

For estimation, we employ the Synthetic Difference-in-Differences (SDID) method to identify the average effect of high-pressure energy constraints. Relative to the conventional difference-in-differences approach, SDID preserves the basic identification logic of DID while introducing both unit weights and time weights, so that the treatment and control groups can be better aligned in terms of pre-policy levels and trends. This helps reduce bias arising from systematic differences before the policy shock. Since the treatment group in this study is characterized by clear regional selectivity, and provinces subject to the high-pressure warning may differ substantially from other regions in economic development, fiscal capacity, and industrial foundations, SDID is better suited to producing a more robust estimate of the average treatment effect. The estimand can be written as:

$$\hat{\tau}^{SDID} = \left(\sum_{i \in \mathcal{T}} \hat{\omega}_i \sum_{t \in \mathcal{P}} \hat{\lambda}_t Y_{it} - \sum_{i \in \mathcal{C}} \hat{\omega}_i \sum_{t \in \mathcal{P}} \hat{\lambda}_t Y_{it} \right) - \left(\sum_{i \in \mathcal{T}} \hat{\omega}_i \sum_{t \in \mathcal{B}} \hat{\lambda}_t Y_{it} - \sum_{i \in \mathcal{C}} \hat{\omega}_i \sum_{t \in \mathcal{B}} \hat{\lambda}_t Y_{it} \right) \quad (1)$$

where \mathcal{T} and \mathcal{C} denote the sets of treated and control cities, respectively, and \mathcal{P} and \mathcal{B} denote the post-policy and pre-policy periods. $\hat{\omega}_i$ is the unit weight, and $\hat{\lambda}_t$ is the time weight. Both sets of weights are optimized using pre-treatment observations so that the weighted control group can approximate the dynamic path of the treated group as closely as possible before the policy takes effect. In this study, prefecture-level cities in provinces that were simultaneously subject to the Level I warning for energy intensity and the Level I warning for total energy consumption are defined as the treatment group, while all other cities form the control group. The post-policy period is designated as 2022 and beyond, and the pre-policy period is specified as 2013 to 2020.

The baseline dependent variable is the annual net increase in the number of intelligent computing center firms in city i during year t . In addition, this study uses the log growth in the number of firms as a supplementary measure to verify the robustness of the findings.

3.2.2 Heterogeneity Analysis

After determining the average effect of high-pressure energy constraints, this study further investigates whether the policy shock varies among cities with distinct pre-existing electricity supply-demand structures. Because intelligent computing centers are a type of electricity-intensive digital infrastructure, their entry and expansion depend significantly on the actual carrying capacity of local power systems. The extent of pre-existing electricity spatial mismatch is expected to shape how the policy shock is manifested across cities.

To capture electricity spatial mismatch, this study uses the electricity gap ratio (*GapRatio*), defined as:

$$GapRatio_{it} = \frac{Cons_{it} - Gen_{it}}{Cons_{it}} \quad (2)$$

where $Cons_{it}$ denotes electricity consumption in city i in year t , and Gen_{it} denotes electricity generation in city i in year t . A higher value of this indicator implies that local generation covers a smaller share of local electricity demand, that the city relies more heavily on external electricity sources, and that electricity spatial mismatch is more severe.

The empirical analysis is performed by subgroup estimation. Specifically, cities are categorized into high-mismatch and low-mismatch groups according to the median level of pre-existing electricity spatial mismatch, and the effect of high-pressure energy constraints on the new deployment and expansion of intelligent computing centers is estimated separately for each group. The study compares the magnitude of the policy effect among groups to determine how high-pressure energy restrictions vary under different local electricity supply-demand conditions.

3.2.3 Extended Analysis

After identifying the average effect of high-pressure energy constraints and its heterogeneous manifestation under different levels of electricity mismatch, this study further examines whether local generation structure affects the way the policy shock shapes the location of intelligent computing centers.

The analysis focuses on two representative categories of power sources: stable low-carbon power and variable renewable green power. The former captures low-carbon electricity support with stronger continuity and dispatchability, whereas the latter reflects green generation structures whose output is more sensitive to fluctuations in natural conditions. In the empirical analysis, the share of stable low-carbon power and the share of variable green power are used as representative indicators to measure the relative importance of these two types of sources in local generation structure. Consequently, the following fixed-effects model is estimated to test the moderating influence of various power-source types:

$$\begin{aligned} Y_{it} = & \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Post_t \times PowerType_{it}) \\ & + \beta_3(Treat_i \times Post_t \times PowerType_{it}) + \delta Controls_{it} \\ & + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (3)$$

where Y_{it} denotes, respectively, the annual net increase in intelligent computing center firms and the log growth in the number of firms. $PowerType_{it}$ refers, respectively, to the

share of stable low-carbon power and the share of variable green power.

3.3 Data

Dependent variables The core dependent variable in this study is the number of intelligent computing center firms at the prefecture-city level. Firms are identified based on whether they hold an IDC (Internet Data Center) operating license. Specifically, the study systematically collects IDC licensing information from the fixed batch announcements of the *List of Granted Value-Added Telecommunications Business Operating Licenses* and the associated query system in the Integrated Management Information System for the Telecommunications Business Market on the Ministry of Industry and Information Technology’s government service platform. IDC operating licenses are used as the basis for identification because, under the *Guidelines for the Approval of Telecommunications Business Operating Licenses* issued by the Ministry of Industry and Information Technology, firms applying for IDC business are required to complete evaluations and reviews covering the physical server room operation security system, website filing system, resource management system, and information security management system before approval. Holding an IDC operating license therefore provides a reasonably good indication that a firm actually possesses and operates computing infrastructure resources.

After cleaning the raw license records, the study identifies firms whose business category includes “Internet Data Center Services” according to the *Classified Catalog of Telecommunications Services (2022 Edition)*. This business falls under the first category of value-added telecommunications services and carries the business code B11. We then use the company name, license number, service coverage, and other information attached to the license to match each firm to its Unified Social Credit Code and to identify the year of license issuance and related business attributes. Finally, the identified IDC firms are aggregated to the prefecture-city-by-year level according to firms’ registered locations, yielding the number of intelligent computing center firms in each prefecture-level city in each year.

On this basis, since the study focuses on how high-pressure energy constraints affect the new deployment and expansion of intelligent computing centers, it further constructs a set of incremental indicators, including the annual net increase in the number of firms, the logarithmic growth in the number of firms, and whether new entry occurs in a given year.

Explanatory variable The core explanatory variable in this study is the 2021 high-pressure warning under the dual-control policy on energy consumption. The identification is based on the *Barometer of the Completion of Dual-Control Targets for Energy*

Consumption in Different Regions during the First Half of 2021 issued by the National Development and Reform Commission. According to this document, Qinghai, Ningxia, Guangxi, Guangdong, Fujian, Yunnan, and Jiangsu were simultaneously placed under the Level I warning for energy intensity and the Level I warning for total energy consumption. The study therefore defines prefecture-level cities in these provinces as the treatment group, while prefecture-level cities in all other provinces serve as the control group.

Since this policy document was released in August 2021, while the analysis uses annual data, the year 2021 includes observations from both before and after the policy announcement, making it difficult to identify the complete post-policy effect. The study therefore designates 2022 and after as the post-policy period, the years 2013 to 2020 as the pre-policy period, and omits the 2021 sample. In the baseline identification, the study employs the SDID method to estimate the average treatment effect of high-pressure energy constraints.

Moderating variables To characterize local electricity supply-demand conditions and the extent of mismatch, this paper constructs prefecture-level data on electricity generation and electricity consumption. The construction of prefecture-level electricity generation data proceeds in two steps. First, the paper compiles plant-level information for Chinese power plants based on data released by the World Resources Institute (WRI). Second, using ArcGIS 10.8 and the geographic coordinates of power plants, each plant is assigned to its corresponding prefecture-level city. Based on this information, the share of installed capacity in each prefecture-level city relative to total installed capacity in its province is calculated. These shares are then used to allocate provincial-level installed capacity and electricity generation to prefecture-level cities, thereby producing city-level total generation data and, further, disaggregated generation by source, including thermal power, hydropower, wind power, solar power, and nuclear power.

Provincial electricity generation and electricity consumption data are both obtained from the National Bureau of Statistics. Because official statistics do not systematically report electricity consumption at the prefecture-city level, this paper further uses prefecture-level nighttime light data to construct allocation weights for electricity consumption, which are then used to distribute provincial electricity consumption across the prefecture-level cities under each province. This process produces electricity usage data at the city level. In contrast to utilizing population or gross regional product as allocation weights, nighttime lights more accurately represent the intensity of local economic activity and corresponding electricity consumption, making them more appropriate for the spatial disaggregation of electricity usage at the prefecture-city level.

Control variables To control as far as possible for variations in local economic conditions, market size, and industrial structure that may affect the location of digital infrastructure, this paper also collects a set of prefecture-level macroeconomic variables, including GDP per capita (in logarithm), fiscal revenue (in logarithm), total retail sales of consumer goods (in logarithm), and the share of the tertiary sector. These data are obtained from the EPS database. Together with the firm identification data and the prefecture-level electricity supply-demand data described above, these variables form a panel dataset of Chinese prefecture-level cities spanning 2013 to 2024. Descriptive statistics are reported in Table 1.

[**Insert Table 1 Here**]

4 Empirical Results

This section tests the main empirical implications derived from the capacity-constrained regulation framework. Section 4.1 examines Proposition 1 by estimating whether the policy shock reduces the entry and expansion of intelligent computing centers. Section 4.2 examines Proposition 2 by testing whether the effect is stronger in cities with greater pre-policy deployment capacity, proxied by lower electricity mismatch. Section 4.3 examines Proposition 4 by assessing whether local generation structure moderates the strength of the policy effect. Proposition 3, which concerns aggregate contraction and limited spatial reallocation, is examined in Section 5.

4.1 Baseline Effects of Energy Constraints

4.1.1 Effects on Entry and Expansion

Table 2 presents the baseline estimates of the effect of high-pressure energy constraints on the entry and expansion of intelligent computing center firms. These estimates correspond to Proposition 1, which predicts that when regulation binds through local capacity, it reduces the feasible margin of entry and expansion for capacity-intensive investment. The results show that high-pressure energy constraints significantly weaken the ability of affected cities to facilitate new intelligent computing center deployment.

[**Insert Table 2 Here**]

Column (1) shows that high-pressure energy constraints significantly reduced the annual net increase in intelligent computing center firms in treated cities after the policy shock, with the estimated decline amounting to about 119% of the sample average annual

net increase. This result supports Proposition 1 and points to a substantial compression in the local margin for new deployment. In terms of the simple framework, the policy shock can be interpreted as a reduction in effective local capacity K_i , which raises the shadow cost of capacity pressure and lowers the likelihood of new deployment. The pattern is consistent with the economic characteristics of intelligent computing centers. As a form of electricity-intensive digital infrastructure, their deployment depends on reliable power supply, adequate approval space, and room for subsequent expansion, all of which become more constrained under tighter energy governance.

Column (2) further shows that high-pressure energy constraints significantly slowed the expansion of intelligent computing center firms in treated cities after the policy shock. The estimated effect implies a decline in firm growth of about 3%, indicating that the policy shock affected not only annual net entry but also the overall pace of expansion. Taken together, the results in Columns (1) and (2) suggest that tighter energy governance compressed both new deployment at the margin and the broader expansion dynamics of intelligent computing centers. A plausible explanation is that stricter energy constraints raised the practical threshold for accommodating additional electricity-intensive projects, making local expansion more difficult even when demand for digital infrastructure remained strong.

Figure 1 provides a graphical illustration of the dynamic paths of the treated group and the synthetic control group before and after the policy under the SDID framework. Before the policy intervention, the trajectories of the treated and control groups are broadly similar, especially in terms of direction and fluctuation during the pre-policy period. This shows that the counterfactual path constructed by SDID fits the pre-policy evolution of the treated group reasonably well. The shaded area representing time weights is also concentrated mainly in the pre-policy period, indicating that identification relies primarily on pre-treatment fit. After the policy takes effect, the treated group's trajectory falls clearly below that of the control group, with a more pronounced decline in 2023. This pattern is consistent with the negative estimates reported in Table 2. The graphical evidence therefore reinforces the perspective that, when high-pressure energy constraints tightened, the expansion path of intelligent computing centers in affected cities shifted downward relative to the counterfactual trajectory.

[**Insert Figure 1 Here**]

Taken together, the results in Table 2 and Figure 1 show that tighter energy constraints significantly weakened the ability of affected cities to accommodate new intelligent computing center deployment. The consistency between the regression estimates and the SDID trends further suggests that the policy shock led to a clear downward shift in the expansion path of intelligent computing centers in treated cities.

4.1.2 Robustness Checks

Placebo test We conduct a placebo test to further examine whether the baseline results could be driven by random noise or other unobserved factors in the sample. Specifically, while keeping the sample structure and estimation method unchanged, the treatment group is repeatedly reassigned at random, and the resulting false treatment effects are re-estimated to obtain the empirical distribution of placebo ATT estimates. If the baseline result merely reflects random fluctuation, the true estimate should lie near the center of this distribution. In contrast, if the actual policy shock has indeed produced a systematic effect on the location of intelligent computing centers, the true estimate should fall in the tail of the placebo distribution, distinctly separated from the majority of random estimates.

Figure 2 reports the results of the placebo test. The solid line illustrates the kernel density distribution of the placebo ATT estimates, whereas the vertical dashed line marks the true treatment effect estimated in the baseline regression. Most placebo estimates obtained from random reassignment cluster near zero, while the true estimate lies clearly in the left tail of the distribution and is well separated from the main mass of the placebo estimates. This result shows that, under random assignment of the treatment group, it is difficult to obtain a negative effect of comparable magnitude and direction to the baseline result.

[**Insert Figure 2 Here**]

This result suggests that the negative policy effect identified above is unlikely to be driven by incidental sample assignment, nor is it likely to reflect common shocks unrelated to the policy timing. Instead, the inhibitory effect of high-pressure energy constraints on the entry and expansion of intelligent computing centers is targeted and systematic, and the baseline estimates remain robust under random reassignment. The placebo test therefore provides additional support for the credibility of the core identification result, namely that the 2021 high-pressure warning under the dual-control policy on energy consumption did alter the relative conditions under which affected cities could facilitate investment in electricity-intensive digital infrastructure.

Alternative sample windows Given that the baseline results may be sensitive to the choice of sample period, this study further tests the robustness of the main findings by adjusting the estimation window. Specifically, two alternative sample windows are constructed. Window A retains the 2016–2024 sample while excluding the policy implementation year 2021. Window B further shifts the starting year to 2017 and likewise excludes 2021. This adjustment serves two purposes. First, it shortens the pre-policy pe-

riod and thereby reduces the potential influence of earlier observations on the estimates. Second, it excludes the year of policy implementation in order to limit possible contamination from transmission lags, differences in implementation timing, and short-run adjustment noise.

Table 3 reports the estimation results based on the alternative sample windows. Columns (1) and (2) correspond to Window A. When the dependent variable is the annual net increase in intelligent computing center firms, the estimated coefficient on the treatment effect is -0.0430 and is statistically significant at the 5% level. When the dependent variable is the log change in the number of firms, the estimated coefficient is -0.0265 and is statistically significant at the 10% level. Columns (3) and (4) correspond to Window B. The results show that after shortening the pre-policy period, the estimated treatment effect remains significantly negative. When the dependent variable is the annual net increase in intelligent computing center firms, the estimated coefficient is -0.0521 and is statistically significant at the 10% level. When the dependent variable is the log change in the number of firms, the estimated coefficient is -0.0290 and is statistically significant at the 5% level.

[**Insert Table 3 Here**]

Overall, the core treatment effect remains consistent in sign and statistically significant across different dependent-variable measures, regardless of whether a relatively broader alternative window is used or the pre-policy observation period is further shortened. This demonstrates that the negative policy effect identified above does not depend on a particular choice of sample window. Even after excluding the policy implementation year and shifting the starting year of the sample, the inhibitory effect of high-pressure energy constraints on the entry and expansion of intelligent computing centers remains stable.

Alternative policy timing To further rule out the possibility that the baseline results are driven by other contemporaneous shocks or underlying trend changes, this study conducts an alternative policy timing test. Specifically, while maintaining the sample range, variable definitions, and estimation method, the policy implementation year is falsely re-assigned to 2018, 2019, and 2020, and the SDID model is re-estimated accordingly. If the negative policy effect identified above were in fact driven by pre-existing trend differences between the treatment and control groups or by some unobserved common shocks, then comparably significant results should also appear under these false policy years. Conversely, if the baseline result truly corresponds to the actual policy shock, the estimated coefficients should be statistically insignificant when the policy timing is shifted forward.

Table 4 presents the results of this test. When the policy year is falsely designated as 2018, 2019, and 2020, the estimated coefficients are -0.000575 , -0.00448 , and -0.0570 ,

respectively, none of which reaches conventional levels of statistical significance. These results show that there is no stable or identifiable anticipatory effect prior to the actual policy shock.

[**Insert Table 4 Here**]

4.2 Results of Heterogeneity Analysis

Building on the average effect above, we next examine Proposition 2. The capacity-constrained regulation framework predicts that the contraction effect should be stronger where the pre-policy feasible deployment margin was larger. In the empirical setting, we use lower electricity mismatch as a proxy for stronger pre-policy deployment capacity, because these cities have stronger local power support and greater ability to accommodate additional electricity-intensive projects before the policy shock. In accordance with the setup in Section 3.2.2, the sample is divided into a low-mismatch group and a high-mismatch group based on the cities' pre-existing electricity gap ratio, and the SDID method is applied separately to each group.

Table 5 reports the subgroup estimation results. In low-mismatch cities, stringent energy constraints significantly reduced the annual net increase in intelligent computing center firms after the policy shock. The estimated decline of 0.0609 indicates a marked compression in the local margin for new deployment. In high-mismatch cities, the estimated effect is also negative, but it does not reach conventional levels of statistical significance, suggesting that the policy shock did not yield a robust observable contraction in this group.

[**Insert Table 5 Here**]

This result demonstrates that the effect of high-pressure energy constraints is concentrated mainly in low-mismatch cities. Low-mismatch cities usually have stronger local electricity carrying capacity and more complete supply-side support, and therefore tend to lie closer to the practical margin for new deployment and expansion before the policy takes effect. As a result, once high-pressure energy constraints tighten, the policy shock is more likely to manifest itself directly in the form of reduced entry and slower expansion. This pattern is consistent with the capacity-constrained regulation framework. The policy shock has the strongest observable effect where the pre-policy feasible deployment margin was larger, because this is the margin that can be directly compressed by tighter energy governance. By comparison, high-mismatch cities tend to have weaker underlying electricity carrying conditions and more limited room for new deployment, so the observable contraction is relatively weaker.

4.3 Results of Extended Analysis

Table 6 examines Proposition 4, which predicts that local power-system characteristics should moderate the effect of capacity-constrained regulation. If reliable and dispatchable generation preserves a larger feasible deployment margin under tighter constraints, the adverse policy effect should be weaker in cities with stronger stable low-carbon power support. Column (1) presents the result for the share of stable low-carbon power. The estimated coefficient on $\text{Treat} \times \text{Post} \times \text{Stable share}$ is positive, suggesting that the negative effect of high-pressure energy constraints is relatively weaker in cities with a higher share of stable low-carbon power. Nonetheless, this interaction term fails to reach conventional levels of statistical significance, indicating that the buffering role of stable low-carbon power is present but not statistically significant.

[**Insert Table 6 Here**]

Column (2) shows that a higher share of variable green power is associated with stronger expansion of intelligent computing center firms in non-treated cities following the policy shock. However, this relationship becomes much weaker in treated cities facing high-pressure energy constraints. In magnitude, the positive association diminishes by about 86% in treated cities, indicating that the majority of the expansion-supporting role of variable green power is eroded once cities are exposed to tighter energy governance. This suggests that, while variable green power may support expansion in relatively unconstrained environments, it does not provide the same level of effective support under tighter policy pressure as stable low-carbon power.

Taken together, these findings support Proposition 4. Generation structure affects the effective deployment margin under high-pressure energy constraints. Stable and dispatchable low-carbon electricity appears more capable of preserving feasible deployment space, whereas variable green power provides more limited effective support once capacity constraints become binding.

5 Economic Implications of Energy-Constrained Reallocation

The results in Section 4 show that high-pressure energy constraints significantly reduce the entry and expansion of intelligent computing center firms, with effects that vary systematically with local electricity conditions and generation structure. This section turns to Proposition 3, which predicts that capacity-constrained regulation may generate aggregate contraction rather than full spatial reallocation when alternative locations lack

sufficient unused capacity, reliable supply, or complementary infrastructure. Empirically, we examine this prediction from three perspectives. First, we assess whether the city-level contraction translates into aggregate contraction or is accompanied by cross-regional reallocation. Second, we evaluate whether any reallocation is reflected in the relative absorption of activity by non-warning cities. Third, we test whether such reallocation, if present, is systematically aligned with underlying resource endowments. Together, these analyses characterize whether the policy shock redirected deployment across space or mainly compressed the overall margin of new deployment.

5.1 Aggregate Contraction versus Spatial Reallocation

High-pressure energy constraints significantly inhibit the entry and expansion of intelligent computing centers. However, the average treatment effect at the city level alone does not reveal whether this shock mainly takes the form of aggregate contraction at the national level or is also accompanied by a redistribution of new deployment toward other regions. To answer this question, we examine the year-to-year change in intelligent computing center deployment at both the national aggregate level and the grouped aggregate level before and after the policy shock.

Figure 3 reports the annual changes in total new entry and total net increase at the national level. The figure shows that, regardless of whether measured by new establishments or by net increase, the national deployment of intelligent computing centers reached a transitory peak around 2021, followed by a significant fall in 2022 and 2023. Despite observable recovery in 2024, the overall level remains below the pre-policy peak. This pattern suggests that when high-pressure energy constraints tightened, the initial observable response was a pronounced slowdown in aggregate deployment, with the nationwide rate of expansion showing a distinct contraction.

[**Insert Figure 3 Here**]

Building on this observation, Figure 4 further compares the annual changes in new entries and net increases between treated and non-treated cities. The results show that new deployment weakened in both groups following the policy shock, with a notably larger decline in treated cities. In terms of new entry, treated cities experienced a faster post-2021 decline, with the contraction becoming especially sharp in 2023. A similar pattern is observed for net increase. In contrast, although non-treated cities were also affected by the broader nationwide slowdown, the magnitude of decline was relatively smaller, and signs of recovery were evident by 2024.

[**Insert Figure 4 Here**]

These aggregate trends suggest that the post-policy adjustment in intelligent computing center deployment was first expressed through a contraction in overall new deployment, with the contraction concentrated more heavily in treated cities. At the same time, the smaller decline in non-treated cities points to a possible shift in the relative geographic distribution of new deployment. This aggregate evidence therefore suggests that the policy shock was associated primarily with aggregate contraction, while also raising the possibility that part of the affected deployment was relatively absorbed by non-treated cities.

5.2 Relative Absorption in Non-Warning Cities

The aggregate evidence above suggests that non-warning cities did not experience a contraction of the same magnitude as warning cities after the policy tightening. Aggregate patterns alone, however, cannot determine whether this relative difference reflects a systematic recipient effect. To examine this issue more directly, we compare the change in intelligent computing center deployment between warning and non-warning cities before and after the policy intervention.

Table 7 reports the corresponding estimates. The results show that, following the policy shock, non-treated cities performed relatively better than warning cities in terms of the net increase, firm growth, and new entry of intelligent computing centers. Specifically, non-treated cities experienced a stronger net increase, about 3% faster firm growth, and a roughly 3 percentage-point higher probability of new entry after the policy shock.

[**Insert Table 7 Here**]

These results suggest that non-warning cities displayed stronger relative resilience after the tightening of high-pressure energy constraints. In relative terms, they absorbed part of the deployment that was compressed in warning cities. At the same time, this recipient effect should be understood as limited. It reflects weaker contraction and faster recovery in non-warning cities relative to warning cities, rather than a broad-based relocation of activity across space.

Overall, the evidence is consistent with partial reallocation toward non-warning cities, but not with a full spatial replacement of the contraction in warning cities. This finding further suggests that, although energy constraints have begun to shape the spatial allocation of electricity-intensive digital infrastructure, the resulting adjustment remains incomplete and constrained. Whether this limited reallocation moved more strongly toward locations with more favorable underlying resource endowments is examined in the next section.

5.3 Limited Evidence of Sorting by Resource Endowments

Given the limited relative absorption observed in non-warning cities, the next question is whether the remaining post-policy deployment was systematically directed toward locations with stronger resource endowments. Beyond actual electricity transmission capacity, natural resource endowments shape the long-run potential for local energy supply. This subsection therefore examines whether post-policy deployment was more likely to occur in places with more favorable underlying resource conditions.

Precipitation, wind patterns, and solar radiation all affect the long-run potential for energy supply in a given location. If spatial reallocation proceeded smoothly, the new deployment that occurred after the policy shock would be more likely to concentrate in areas with superior resource conditions. This subsection therefore examines whether the limited reallocation was systematically directed toward locations with more favorable natural resource endowments.

Specifically, the analysis uses precipitation, wind potential, and solar radiation as indicators of resource endowments, capturing the natural conditions for hydropower, wind power, and photovoltaic generation across regions. The relevant data are drawn from the National Tibetan Plateau Data Center. To reflect each city’s relatively stable resource base before the policy shock, we construct pre-policy natural resource endowment measures using averages over the 2016–2020 period. For the outcome variables, we use two measures: the cumulative number of new entries over 2022–2024, and an indicator for whether at least one new entry occurred during 2022–2024. To focus on the destination of constrained reallocation, the sample is restricted to non-warning cities, allowing us to examine whether stronger resource endowments are associated with more favorable post-policy deployment within this group.

[**Insert Table 8 Here**]

Table 8 reports the corresponding regression results. Overall, regardless of whether the dependent variable is cumulative new entry or the occurrence of any new entry, the resource-endowment variables, including precipitation, wind potential, and solar radiation, do not show robust statistical significance. This suggests that, although some spatial adjustment occurred after high-pressure energy constraints tightened, the limited post-policy deployment did not systematically shift toward locations with more favorable resource endowments.

This finding suggests that post-policy deployment was not systematically sorted along underlying resource advantages. Instead, the geography of adjustment is shaped by a broader combination of grid access, supply stability, supporting infrastructure, and local

implementation capacity. As a result, favorable resource endowments alone were insufficient to generate a clear post-policy pattern of destination choice. This absence of sorting is economically meaningful, as it contrasts with standard models in which relocation follows comparative advantage.

Taken together, these results show that the standard reallocation mechanism is limited under capacity-constrained regulation. When local capacity becomes binding, regulation can directly compress the feasible expansion margin, leaving only partial absorption elsewhere rather than smooth relocation across space.

6 Conclusion

This paper examines how spatial allocation changes when regulation binds through local capacity rather than marginal compliance costs. We study this question in the context of electricity-intensive digital infrastructure, using the 2021 high-pressure warning under China’s Dual Control of Energy Consumption policy as a quasi-natural experiment. The baseline estimates show that the policy shock significantly reduced the annual net increase in intelligent computing center firms by approximately 119% of the sample average and slowed firm growth by roughly 3%.

The results show that this adverse effect is concentrated in low-mismatch cities, where local electricity support was stronger and the potential for additional deployment was greater before the policy shock. As energy constraints intensified, it was precisely this feasible expansion margin that became compressed. At the spatial level, the adjustment is mainly driven by aggregate contraction rather than efficient reallocation. Although non-warning cities exhibit some relative absorption, the magnitude is insufficient to offset the decline in warning cities, and we find little evidence that post-policy deployment systematically shifted toward areas with stronger resource endowments.

The implications extend beyond the Chinese dual-control setting. As data centers, AI computing clusters, semiconductor fabs, battery plants, and electric-vehicle charging networks expand, local electricity systems increasingly become a binding condition for investment. Policies that regulate energy use therefore need to consider not only aggregate energy targets, but also the spatial distribution of capacity, grid access, and supply reliability. Without coordination between energy governance and infrastructure planning, capacity-based regulation may suppress new investment more than it reallocates activity efficiently across space.

Several directions for future research remain. First, it is important to evaluate the efficiency implications of energy-constrained reallocation, in particular whether the observed contraction and limited sorting reflect welfare-reducing misallocation or constraints that

prevent efficient spatial adjustment. Second, it is useful to examine how policy design, such as interregional electricity coordination, transmission investment, and power-market design, can mitigate these constraints and facilitate more effective allocation. Finally, extending the analysis to firm- or project-level responses, including investment scale, expansion timing, and facility utilization, would provide deeper insight into the micro-level adjustment mechanisms.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

AI-assisted tools, including ChatGPT and Grammarly, were used to edit the manuscript for clarity and language. These tools did not generate scientific content or contribute to data analysis, interpretation, or conclusions. All content was reviewed and verified by the authors, who retain full responsibility for the manuscript.

Data Statement

This study combines proprietary and publicly available data sources. Proprietary datasets, including the EPS database, the CSMAR database, and other licensed databases, were accessed under institutional agreements and are subject to access restrictions; as such, the authors are not permitted to redistribute these data. All publicly available data sources are described in detail within the paper. Replication code is available from the authors upon request.

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Tables and Figures

Figures

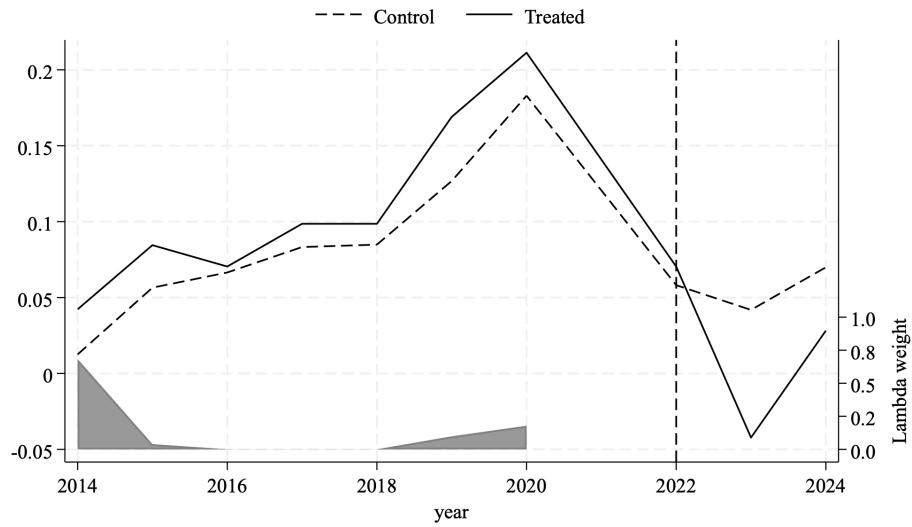


Figure 1: SDID Trends for Treated and Synthetic Control Groups

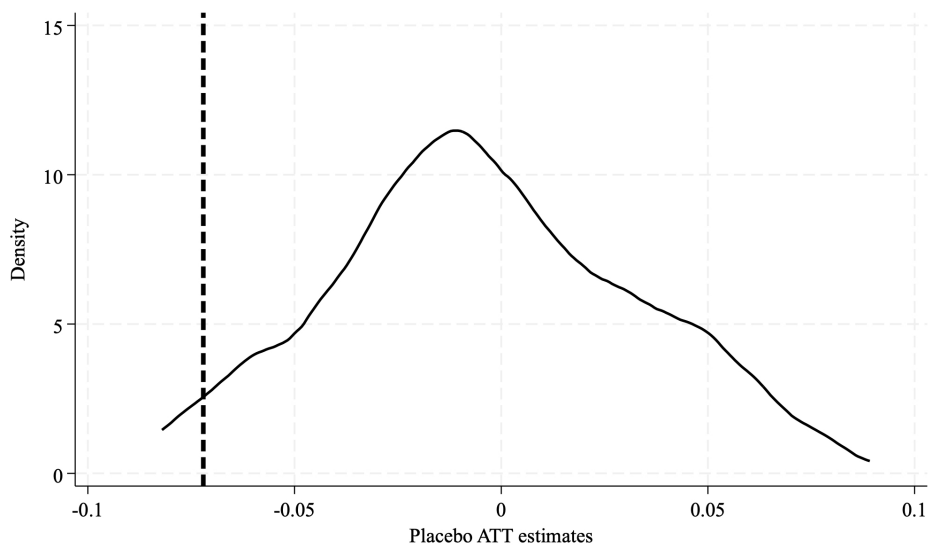


Figure 2: Placebo Test of the Estimated ATT under the SDID Framework

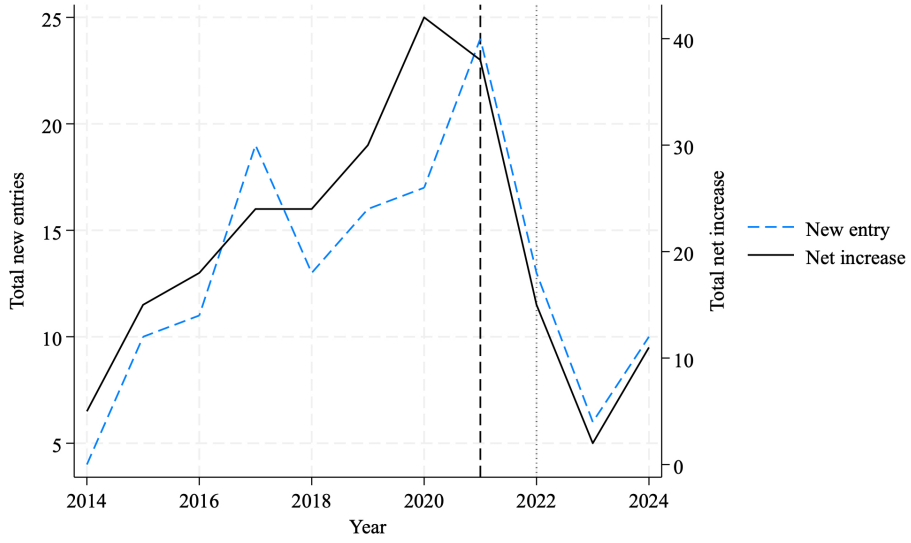


Figure 3: National Trends in New Entry and Net Increase of Intelligent Computing Centers

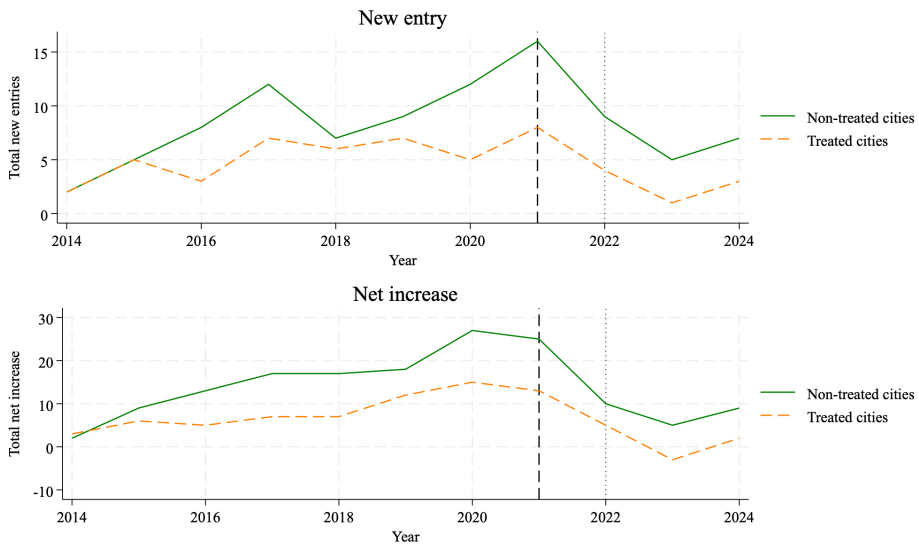


Figure 4: Trends in New Entry and Net Increase in Treated and Non-treated Cities

Tables

Table 1: Descriptive Statistics of Key Variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Annual net increase in ICC firms	3,696	0.0606	0.4758	-1.0000	12.0000
Log change in ICC firms	3,696	0.0158	0.1079	-0.6931	1.0986
New entry of ICC firms	3,696	0.0387	0.1929	0.0000	1.0000
Power supply-demand gap ratio	3,870	-0.3848	2.2439	-51.5416	0.9904
Log GDP per capita	3,371	10.9151	0.5523	9.0368	12.5614
Log fiscal revenue	3,391	14.1418	1.0869	10.9521	18.2432
Log retail sales of consumer goods	3,383	15.7611	1.0858	12.2674	19.0367
Share of tertiary industry	3,110	45.5922	9.6388	16.4400	85.2700

Table 2: Baseline SDID Estimates

VARIABLES	(1)	(2)
	Baseline SDID controls	Robustness log change
Treat \times Post	-0.0721** (0.0358)	-0.0329*** (0.0123)
Observations	2,850	2,850
Controls	Yes	Yes
Unit weighting	Yes	Yes
Time weighting	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Robustness Checks Using Alternative Sample Windows

VARIABLES	(1)	(2)	(3)	(4)
	Window A	Window A	Window B	Window B
	Net increase	Log change	Net increase	Log change
Treat \times Post	-0.0430** (0.0194)	-0.0265* (0.0147)	-0.0521* (0.0311)	-0.0290** (0.0119)
Observations	2,280	2,280	1,995	1,995
Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Robustness Checks Using Alternative Policy Timing

VARIABLES	(1)	(2)	(3)
	Placebo_2018	Placebo_2019	Placebo_2020
Treat \times Post ₂₀₁₈	-0.000575 (0.0304)		
Treat \times Post ₂₀₁₉		-0.00448 (0.0335)	
Treat \times Post ₂₀₂₀			-0.0570 (0.0404)
Observations	2,850	2,850	2,850
Controls	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Heterogeneous Policy Effects by Electricity Mismatch

VARIABLES	(1)	(2)
	Low mismatch	High mismatch
Treat \times Post	-0.0609** (0.0292)	-0.106 (0.0953)
Observations	1,430	1,420
Controls	Yes	Yes
Unit weighting	Yes	Yes
Time weighting	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Stable versus Variable Low-Carbon Power Shares under High-Pressure Energy Constraints

VARIABLES	(1)	(2)
	Stable share	Variable share
Post \times Stable share	0.0047 (0.0107)	
Treat \times Post	-0.0656 (0.0683)	-0.0663 (0.0543)
Treat \times Post \times Stable share	0.0169 (0.0820)	
Post \times Variable share		0.1652** (0.0770)
Treat \times Post \times Variable share		-0.1416** (0.0711)
Constant	-1.8975** (0.8652)	-0.9309* (0.5470)
Observations	2,536	2,536
R-squared	0.5338	0.5373
Controls	Yes	Yes
Prefecture FE	Yes	Yes
Year FE	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Relative Absorption in Non-treated Cities after the Policy Shock

VARIABLES	(1)	(2)	(3)
	Net increase	Log change	New entry
Post \times Recipient effect	0.0682* (0.0373)	0.0285*** (0.0106)	0.0298* (0.0163)
Constant	-0.8578 (0.8607)	-0.1695 (0.2432)	-0.3204 (0.3765)
Observations	2,536	2,536	2,536
R-squared	0.5366	0.1719	0.3785
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Natural Resource Endowments and Limited Reallocation

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Cum. entry	Cum. entry	Cum. entry	Any entry	Any entry	Any entry
Endowment	Precip.	Wind	Solar	Precip.	Wind	Solar
Precipitation endowment	-0.0002 (0.0006)			0.0053 (0.0058)		
Wind endowment		-0.0170 (0.0455)			-0.1530 (0.5139)	
Solar radiation endowment			-0.0020 (0.0014)			-0.0158 (0.0215)
Constant	-2.1134*** (0.6596)	-2.1081*** (0.6572)	-1.7900*** (0.6512)	-21.7061*** (8.3868)	-21.6015** (8.4067)	-18.7606** (8.7895)
Observations	214	214	214	214	214	214
R-squared	0.2533	0.2537	0.2595			
Model	OLS	OLS	OLS	Logit	Logit	Logit
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.