Growth at the Margin: Political Incentives and Firm Behavior in China

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Abstract

This paper examines how China's annual GDP growth targets—an essential feature of its economic governance—shape incentives for city leaders and influence firm-level output and resource allocation. Using survival models, bunching analysis, and a threshold-based strategy, I find that a one-unit increase in a city leader's performance score—defined as the gap between actual and target GDP growth—raises the probability of promotion by 9–10%. The analysis also reveals a significant clustering of performance scores just above the growth threshold, with observations at that margin occurring 1.5 to 2 times more frequently than would be expected in the absence of such incentives. At the firm level, politically driven pressures produce positive discontinuities in GDP-related indicators, such as inventory accumulation, sales and output. This effect is more pronounced when cities are close to meeting their annual targets or face heightened pressure due to underperformance in the earlier quarters of the year. Using detailed firm-level data on energy consumption and pollution emissions as proxies for real output, the evidence suggests that much of the observed firm-level discontinuity reflects actual economic activity, not just statistical manipulation. These findings suggest that growth incentives alter firm-level output and resource allocation through politically motivated production responses.

1 Introduction

Since the onset of economic reforms in 1978, China has experienced unprecedented economic growth, with GDP expanding more than fortyfold over the past four decades. A cornerstone of this transformation has been the manufacturing sector, which has played a critical role in driving economic expansion.[1] Scholars frequently attribute this success to China's distinctive model of economic governance, characterized by the use of growth targets to align macroeconomic performance with national priorities (Prasad and Rajan, 2006). Central to this framework is a performance-based cadre evaluation system, which closely ties local officials' career advancement to their ability to achieve economic growth within their jurisdictions, with regional GDP growth serving as a primary benchmark for promotion decisions (Chen et al., 2018; Li and Zhou, 2005). However, growing concerns have emerged over the consequences of the country's growth strategy, especially its tendency to generate significant resource misallocation, rising debt burdens, and enduring deficiencies in domestic demand (Hsieh and Klenow, 2009; Chen et al., 2022). Compounding these concerns is growing apprehension among scholars and policymakers over China's overcapacity and export-led growth model, which threatens to disrupt global supply-demand dynamics (Kenderdine and Ling, 2018; Tan and Conran, 2022; Xu and Liu, 2018).[2] Motivated by the critical question of why overcapacity and overproduction have become pervasive, this paper examines the discretionary effects of local officials' incentives on regional development within China's unique governance framework.

In this paper, I make three key contributions to understanding how growth-target incentives shape political behavior and economic outcomes in China. First, I employ a discrete-time survival analysis using detailed data on the career trajectories of city-level officials to examine how meeting GDP growth targets affects their promotion prospects. Second, I construct a novel city-level panel dataset covering nearly two decades of annual growth targets for over 300 cities. Leveraging this dataset, I conduct a bunching analysis to assess how officials respond to growth-related pressures, as reflected in the distribution of performance scores—defined as the difference between actual and target GDP growth rates. The results show a strong link between target attainment and promotion outcomes:

[1] By 2020, China accounted for 20% of global manufacturing exports, cementing its status as the world's leading manufacturing powerhouse. This dominance is further reflected in the industrial manufacturing sector's contribution to the national economy, which accounted for approximately 27% to 33% of GDP in 2022.

[2] U.S. Treasury Secretary Janet Yellen, for instance, has warned that China's practices, including excessive production and exports, could pose significant threats to global market stability.

a one-unit increase in performance score raises the probability of promotion by 9–10%, and officials who meet or exceed targets tend to be promoted approximately 1.5 years earlier one average than those who fall short. I also find substantial bunching in performance scores at the growth threshold, with 50% to 100% more observations than expected under a counterfactual distribution without incentives.[3] One interpretation is that officials respond to promotion incentives by intensifying their efforts, either by mobilizing administrative resources or exerting pressure on local firms—an important mechanism I examine in this paper.

I make a third contribution by examining how political incentives cascade from local officials to firms. Using a threshold-based empirical strategy, I investigate whether pressures to meet growth targets translate into real economic responses among local manufacturing firms—a sector central to China's economy and closely intertwined with local governments. To conduct this analysis, I construct a rich panel dataset by merging the China Industrial Enterprise Database (CIED) with the China Industrial Enterprise Pollution Database (CIEPD), resulting in over 300,000 firm-year observations across more than 20 manufacturing industries. This merged dataset allows me to track both financial indicators and physical metrics such as energy consumption and pollutant emissions—two proxies far less vulnerable to manipulation. By linking firm-level outcomes with city-level target fulfillment, I uncover sharp discontinuities in output, energy use, and pollution precisely at the point where cities just meet their growth targets. These synchronized spikes indicate that a large share of the observed firm response stems from real production activity—even excessive production leading to inventory buildup—rather than mere statistical inflation. Although I cannot fully rule out the possibility of data manipulation, the use of output proxies indicates that over 80% of the observed effect reflects real economic activity. These findings reinforce the broader narrative that China's target-driven governance system generates tangible, micro-level economic effects.

This paper contributes to the literature on institutional target setting and government performance management, a field long debated for its benefits and unintended consequences. Targets can provide clear goals, enhance accountability, and align performance with organizational priorities (Hood, 1991; Li et al., 2019). However, they also introduce risks such as gaming—manipulating data to superficially meet benchmarks (Christopher and Hood, 2006; Zeng and Zhou, 2024)—and tunnel vision, which incentivizes narrow focus on quan-

[3]These findings contrast with previous literature suggesting that, following China's economic reforms, growth targets serve merely as guidelines rather than binding goals (Li et al., 2019).

tifiable indicators at the expense of broader objectives (Bevan and Hood, 2006). While target-based systems promote data-driven decision-making (Smith, 1995), they may also reduce institutional adaptability (Radnor and McGuire, 2004) and demotivate actors when goals are poorly designed (Van Thiel and Leeuw, 2002).[4]

In the context of China, despite a growing body of research on the macroeconomic effects of growth targets (Zhao and Cheng, 2023; Gong et al., 2025), the mechanisms at the micro level remain insufficiently explored. Specifically, scant empirical work has investigated how promotion incentives tied to growth targets influence local officials' behavior and, in turn, affect firm-level outcomes.[5] Although several studies have raised concerns about the reliability of China's macroeconomic data (Zeng and Zhou, 2024; Firth et al., 2011; Chen et al., 2019),[6] suggesting that performance targets may drive strategic reporting or data manipulation just to hit or barely exceed assigned goals (Martinez, 2022), less attention has been paid to the core question addressed here—to what extent, and through which mechanisms, do growth targets translate into real economic activity? This paper demonstrates that political incentives at the local level can provoke real shifts in firm behavior, not merely superficial adjustments to official statistics.

This paper also contributes to the literature on political incentives and bureaucratic governance in hierarchical authoritarian regimes. Within China's administrative structure, the attainment of economic and political benchmarks remains a key determinant of promotion outcomes for local officials (Li and Zhou, 2005; Chen et al., 2018; Yao and Zhang, 2015). At the same time, informal institutions such as guanxi—unobservable personal networks—continue to shape bureaucratic behavior and influence both decision-making and resource allocation (Gold et al., 2002; Jiang and Zhang, 2020; Jia et al., 2015). While these

[4] Scholars emphasize that effective implementation depends on context-sensitive targets, often combined with qualitative or participatory evaluation tools (Moynihan, 2008; Pollitt and Bouckaert, 2011).

[5] Existing studies offer mixed evidence: some suggest these incentives boost innovation and administrative efficiency (Sun et al., 2023; Dai et al., 2021), while others associate them with resource misallocation and environmental harm (Liu et al., 2020).

[6] Some examples of inflated Chinese national or regional accounts have been reported: In 2017, the governor of Liaoning province publicly admitted to fabricating fiscal revenue and GDP figures by over 20% during the years 2011 to 2014. A report from *Xinhua Net*, a prominent state-run media outlet, quoted local officials who disclosed an "unspoken rule" within the system: "Local officials claimed that they could meet any targets set by higher authorities, regardless of difficulty, and that no target would remain unmet." In 2016, Tianjin's Binhai New Area revised its reported GDP from over 1 trillion yuan to 665.4 billion yuan, a nearly 30% reduction. This adjustment was attributed to revised statistical methods and the removal of inflated data. (*Sina News*) Shandong Province announced a revised GDP for 2018 at 6.6649 trillion yuan, a 12.8% decrease (982.1 billion yuan less) from the preliminary figure, following the fourth national economic census. The revision addressed issues such as duplicate reporting and inflated figures by adhering to stricter standards.

dynamics may promote coordination or efficiency in certain contexts, they also contribute to corruption risks and institutional opacity (Pei, 2007; Wang and Zheng, 2020). Empirical research on grassroots officials in China remains limited, largely due to the opacity of personnel systems and the lack of disaggregated data. By compiling detailed career trajectories for over 1,600 city-level party secretaries, this paper provides rare grassroots evidence on the functioning of China's meritocratic apparatus. This paper reinforces the critical role that observable economic performance metrics play in determining promotion outcomes for Chinese officials. Leveraging the structural parallels between China's hierarchical administrative system and corporate governance—where higher-level authorities function analogously to a centralized board of directors—I model promotion dynamics using survival analysis, treating city officials as de facto heads of subsidiary units. Drawing on methods from labor economics, I further connect different cities through officials who rotate across jurisdictions, enabling the identification of individual-level contributions to target achievement while controlling for city-level unobservables.

Finally, this paper contributes to the literature on state-firm relations in China, a field with mixed findings on the extent of government influence over firms. Some studies argue that government interventions primarily target state-owned enterprises (SOEs), with minimal impact on private firms (Naughton, 2007; Lin and Milhaupt, 2013; Mueller et al., 2023). Others highlight substantial government influence over both SOEs and private firms through financial support, regulatory oversight, and political networks (Pearson, 2015; Huang, 2008; Piotroski et al., 2015). This influence also includes indirect mechanisms, such as fostering relationships between officials and business leaders, which shape decision-making across various enterprises (Nee, 1992; Jia et al., 2021; Feldman et al., 2021). The findings of this paper support the broader view, aligning with research that highlights significant government influence over the entire spectrum of Chinese firms. This paper also offers an important insight into the persistent overcapacity and excess supply observed in Chinese firms (Shen and Chen, 2017; Dong and Sun, 2022), suggesting that such patterns may stem from long-term resource misallocation driven by opportunistic government incentives.

The structure of the paper is organized as follows: Section 2 provides an overview of the institutional background. Section 3 introduces the data. Sections 4 and 5 focus on officials and firms, respectively, detailing the empirical strategies and presenting the corresponding results. Section 6 explores output proxies, and Section 7 concludes.

2 Background

2.1 Target Management and Cadre Evaluation

The establishment of economic growth targets in China is deeply rooted in the country's historical and institutional evolution. Introduced in the 1950s as part of the Soviet-style planned economy, these targets initially functioned as mandatory elements of central planning. While the market-oriented reforms of the late 1970s dismantled much of the traditional planning framework, growth targets persisted as essential governance tools. Their continued relevance lies in their dual function: aligning local government objectives with national economic priorities and serving as performance benchmarks for local officials.[7]

The process of setting annual growth targets in China reflects the country's centralized administrative structure, following a hierarchical, top-down approach (Li et al., 2019). The central government sets national growth objectives, which are then cascaded to provincial and prefectural levels. Each tier of government formulates its own targets, often amplifying those of the higher level to demonstrate ambition and commitment.[8]

This target-setting process involves extensive negotiation and deliberation among officials, often taking months to finalize.[9][10] Although these targets are not legally binding, they carry significant weight as they encapsulate governmental priorities and provide a strategic framework for policy implementation. Figure 1 illustrates the trends in annual economic growth targets across different levels of government. It reveals a strong correlation between actual GDP growth and official targets, suggesting that target setting has served

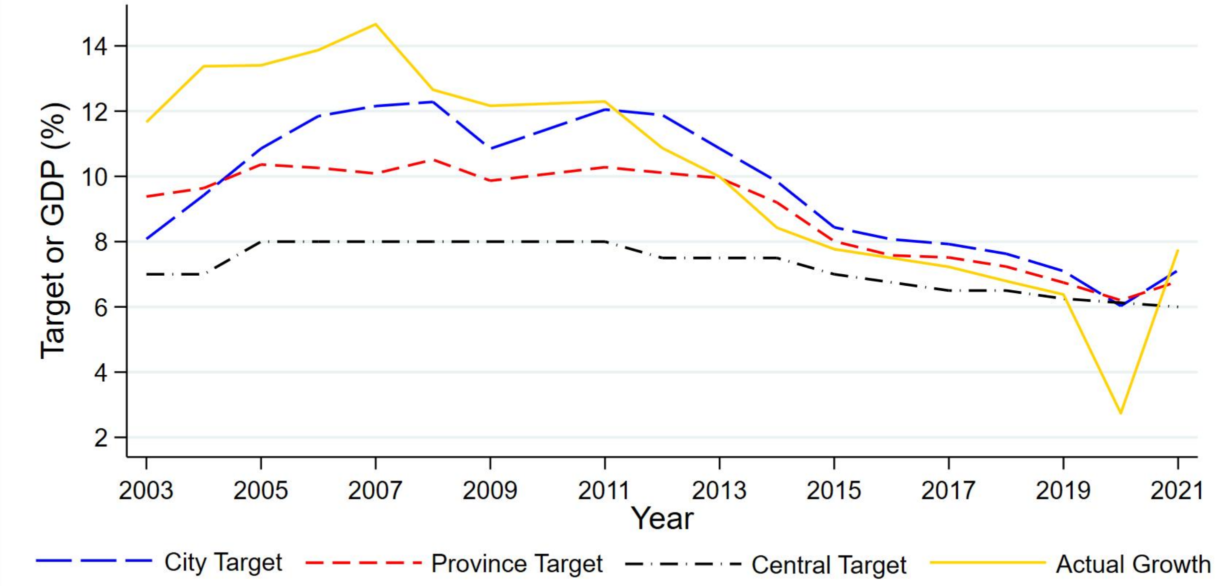
[7]The link between economic outcomes and career advancement became particularly pronounced after Deng Xiaoping's 1992 Southern Tour, which ushered in an era of aggressive market reforms and rapid growth.

[8]For example, provincial growth targets frequently exceed national benchmarks by 10–30%, while prefectural targets typically surpass provincial ones by an additional 2–3 percentage points.

[9]In China, there is extensive bidirectional political communication between higher and lower levels of government (Chen et al., 2021). Before drafting local government work reports, higher-level governments hold economic work conferences to convey future policy intentions and engage in discussions about regional development within their jurisdictions. Following these meetings, governments at various levels begin drafting their respective work reports. During this process, workgroups from each government conduct in-depth research and gather relevant materials from subordinate organizations. Once an initial draft is prepared, feedback sessions are held where higher-level governments review the draft reports and provide feedback to ensure the reports are accurate and objective. Simultaneously, lower-level governments gain deeper insight into the policy directions of their superiors by analyzing the feedback and draft content. After multiple rounds of discussions, revisions, and consultations, the finalized government work report is submitted to the People's Congress for approval.

[10]A city's past economic performance plays a critical role in shaping its current growth target. This relationship is illustrated in Figure A1.

Figure 1: Time Trend of Economic Growth Targets And Overweights



Notes: This figure presents the weighted averages of city-level and provincial annual growth targets over the past 20 years, along with the national growth target and the actual (constant prices) GDP growth rate. The weights are based on each city's or province's respective GDP share. The figure reveals a strong alignment between growth targets and actual performance, particularly in earlier years when actual growth frequently exceeded targets. Since 2013, however, both targets and actual growth have become less ambitious, consistent with findings in the literature suggesting a reduced emphasis on economic performance in official evaluations after this period (Holz, 2014; Chen et al., 2018). The figure also clearly demonstrates the "top-down amplification effect" discussed earlier.

as an effective motivational tool. Moreover, lower-level governments have consistently set growth targets that are at least as ambitious as those of higher-level authorities, reflecting the top-down transmission of pressure embedded in the incentive system.

The cadre evaluation system institutionalizes the importance of growth targets by linking career advancement to quantifiable economic outcomes. Under the CCP's performance-based promotion framework, officials are assessed on a range of criteria, including political loyalty, ideological commitment, administrative capacity, and—crucially—economic achievements (Li and Zhou, 2005; Wang and Zheng, 2020). Regulatory documents such as the *Provisional Regulations on the Assessment of Party and Government Leading Cadres (1998)* codify this performance evaluation process. While qualitative assessments (e.g., leadership style or party discipline) remain important, quantitative indicators—particularly GDP growth—play a decisive role. Achieving or exceeding local growth targets enhances promotion prospects and signals both administrative competence and political alignment with the Party's developmental agenda (Lyu et al., 2018). This performance-driven system has created strong incentives for local officials to pursue economic expansion, sometimes leading to excessive investment or even data manipulation. Yet, it has also contributed to rapid industrialization and infrastructure development.

2.2 State-Firm Relations

Growth targets ultimately matter insofar as they shape the behavior of firms—the primary engines of economic output. In China, the relationship between the government and enterprises is deeply embedded in the country's distinctive blend of state control and market-oriented reform. The government exerts substantial influence over businesses through regulatory frameworks, financial systems, and political connections, which are deeply ingrained across various sectors (Garnaut et al., 2018; Chen et al., 2019). For state-owned enterprises (SOEs), this influence is particularly direct and far-reaching (Jefferson and Rawski, 1994).[11] The state enforces alignment with its developmental goals through mechanisms like appointing party members to key managerial roles and embedding party committees within corporate governance structures (Liu and Zhang, 2018).

The government's influence extends beyond SOEs to private enterprises, which, while theoretically independent, remain subject to significant oversight and intervention. Access to critical resources such as financing, land use rights, and regulatory approvals often depends on maintaining favorable relationships with local or central authorities (Xiong, 2018; Piotroski and Zhang, 2014; Hsieh and Klenow, 2009).[12] These partnerships, whether voluntary or compelled, align private sector activities with national priorities. As a result, private firms operate within a system where their actions must partially conform to state objectives (Huang, 2008; Song et al., 2011). This government-enterprise relationship plays a pivotal role in achieving economic goals. While SOEs are direct vehicles for state influence, private firms are also affected through a range of mechanisms, from production decisions to potential data manipulation (Chen et al., 2022; Martinez, 2022). Anecdotal evidence further supports the extent of the government's reach in shaping both enterprise behavior

[11] SOEs are often viewed as instruments of national policy, tasked with achieving both economic and political objectives, such as maintaining employment, advancing strategic industries, and ensuring social stability.

[12] Moreover, private firms are frequently enlisted to support state-led initiatives, including the Belt and Road Initiative and industrial upgrading programs.

and economic outcomes.[13]

3 Data

This paper draws on three primary data sources: (1) official economic growth targets and realized GDP growth rates at various administrative levels; (2) appointment and promotion records of city-level political leaders; and (3) firm-level microdata on output, inputs and pollutants.

3.1 Growth Targets

China's growth targets are compiled from publicly available government documents and statistical bulletins. National targets are obtained from key policy documents such as the *Five-Year Plans for National Economic and Social Development* and the *Annual Report on the Work of the Government*, which outline macroeconomic goals including GDP growth, fiscal revenue, and social development indicators. Subnational targets—at the provincial and prefectural levels—are sourced from regional five-year and annual development plans, which adapt national priorities to local contexts. These documents are officially published online. The dataset spans two decades and includes hand-collected data from 339 prefecture-level cities across all 32 provincial-level administrative regions. To measure actual economic performance, the stated targets are matched with realized GDP growth rates, primarily drawn from the China City Statistical Yearbook and local statistical reports.

[13]The founder of Reading Motors, Li Guoxin, publicly accused Wang Xiao, the Party Secretary of Changle County, of pressuring the company to falsify industrial and sales output data worth 4.683 billion RMB since March 2022. This alleged data manipulation was likely driven by the need to meet local economic performance targets, a critical metric in China's cadre evaluation system (*Xinhua Net, 2023*). Similarly, in 2021, during the first round of statistical inspections, authorities held 278 individuals accountable for statistical violations, including 13 at the department level, 94 at the county level, and 162 at the township level. These inspections uncovered cases where local governments coerced enterprises into inflating their reported data by 20% to meet economic goals, leading to widespread data falsification (*Observer, 2021*). In 2018, the National Bureau of Statistics (NBS) publicly exposed five prominent cases of statistical violations, involving Tianjin's Binhai New Area, Inner Mongolia's Kailu County, Liaoning's Xifeng County, Shandong's Gaomi City, and Ningxia's Lingwu City. These cases highlighted severe falsification practices, such as fabricating reports, instructing enterprises to submit false data, and obstructing statistical law enforcement. Together, these incidents underscore the systemic pressures and challenges surrounding data reliability in the context of China's growth-oriented governance framework (*NBS, 2018*)

3.2 City Leaders

A second data source consists of a unique panel of Chinese city party secretaries—hereafter referred to as governors—covering the same period and 339 cities for which growth target data were collected. The dataset includes detailed career and demographic information on over 1,600 distinct individuals. The data are sourced from official government websites and major state-run media platforms such as *Xinhua Net*, and include key demographic and professional attributes such as age, gender, birthplace, education, tenure length, and prior positions. A core feature of the dataset is the tracking of career trajectories, with a particular emphasis on promotion outcomes. Promotions are defined as upward transitions within the Chinese Communist Party's administrative rank system, following the criteria outlined in the *Regulations on the Management of Civil Servants' Positions and Ranks (2006)*. Each official's post-tenure outcome is classified into one of three categories: promoted, non-promoted (lateral transfer or sidelined), or retired.

3.3 Manufacturing Firms

The final source of data is at the firm level, encompassing two main components: (1) economic activity indicators, including sales, inventory, output, and input usage; and (2) environmental metrics, such as energy consumption and pollutant emissions. The economic data are primarily drawn from the China Industrial Enterprise Database (CIED), compiled from annual surveys conducted by the National Bureau of Statistics. It covers all state-owned enterprises and large non-state firms—defined as those with annual revenues above 5 million RMB before 2011 and 20 million RMB thereafter—across mining, manufacturing, and utilities, with manufacturing firms accounting for over 90% of the sample. The dataset spans from 1998 to 2014 and forms a large, unbalanced panel that includes detailed information on firm identity, ownership, employment, assets, sales, value-added, R&D expenditure, profits, and over 130 other variables.

The environmental, energy consumption and pollutant emissions data come from the China Industrial Enterprise Pollution Database (CIEPD). Developed by the Ministry of Environmental Protection, the CIEPD documents firms' energy usage and emissions for 27 types of pollutants, along with corresponding treatment measures. The CIEPD is matched with the CIED at the firm level, resulting in a panel of approximately 300,000 firm-year observations. This combined dataset includes key financial indicators alongside detailed metrics on energy use and pollutant emissions, spanning over 20 distinct industries within

China's manufacturing sector. Additional details on data collection, cleaning and matching procedures, variable definitions, and examples are provided in Appendix A.

4 Political Incentives

This section documents the political incentives shaping the behavior of city governors in China. Meeting growth targets is strongly associated with improved promotion prospects, and the performance distribution of officials shows clear signs of strategic responses aligned with career advancement incentives.

4.1 A Survival Analysis

This subsection employs a survival analysis to examine the impact of economic performance on officials' promotion prospects.[14] Survival analysis is well-suited for this study for three primary reasons. First, economic performance indicators such as the GDP growth performance vary over time and influence promotion likelihood. Survival models can incorporate such time-dependent covariates (Therneau and Grambsch, 2000). Second, the study relies on panel data spanning approximately 20 years and covering multiple cities. This structure introduces censoring, as governors may leave the risk set without being promoted (e.g., due to retirement or remaining in office until the study ends). Survival analysis is specifically designed to address such incomplete observations (Klein and Moeschberger, 2006). Third, the panel structure of the dataset also results in delayed entry (Guo, 1993; Jenkins, 1995). Governors are appointed at different times throughout the observation period, meaning their "risk" of promotion begins at staggered points.[15] Formally, the observed time for each governor can be expressed as:

$$T_{\text{observed}} = \max(T_{\text{start}}, 0),$$

[14]The integration of survival analysis into political economy has also been explored extensively. (Acemoglu and Robinson, 2001) employed survival models to examine regime changes and transitions, highlighting how political institutions shape economic outcomes. (Svolik, 2012) used survival analysis to study the stability and collapse of authoritarian regimes. More directly related to this study, (Besley et al., 2008) analyzed how economic performance and institutional design influence the survival of autocratic regimes, showing that economic performance is a critical determinant of regime stability. Similarly, (Rauch and Evans, 2000) applied survival models to investigate how bureaucratic stability impacts policy implementation and effectiveness in developing nations.

[15]For example, a governor appointed in 2005 has a different observation window than one appointed in 2010.

where T_{start} is the governor's appointment date relative to the study start time. Survival analysis accounts for delayed entry by adjusting the likelihood function to ensure that individuals are not considered at risk prior to their entry point.

The promotion data are recorded at discrete annual intervals, consistent with the structure of official appointments and personnel movements, which typically follow yearly cycles. This temporal structure justifies the use of discrete-time survival models and the discrete hazard function $h(j)$ represents the probability of promotion during the j-th interval, conditional on survival (non-promoted) up to its start. The survivor function $S(j)$ represents the probability that an official has not been promoted by time j. This study employs two discrete-time models—the logit model and the complementary log-log (cloglog) model—under both logarithmic and non-parametric specifications of the baseline hazard. To further account for unobserved heterogeneity, a frailty component is incorporated. Full model specifications and implementation details are provided in the Appendix B. The logit specification models the promotion hazard as a function of both covariates and a baseline hazard term. Specifically, the log-odds of promotion at time t, conditional on not having been promoted earlier, is expressed as:

$$\log\left(\frac{h(t)}{1-h(t)}\right) = c(t) + \beta' X,$$

where $h(t)$ denotes the conditional probability of promotion in interval t, $c(t)$ captures the baseline hazard reflecting time dependence, and X includes key controls such as the GDP growth gap (actual minus target), governor age, prior experience in higher-level government positions, and educational attainment. The corresponding coefficient vector β reflects the relationships between these covariates and the promotion hazard.

Table 1, Column 1 reports estimates from a logit model predicting city governors' promotions based on key characteristics. Surpassing GDP growth targets significantly boosts promotion prospects—each one-unit increase in the actual-target gap raises the odds by 9.3%.[16] Age, prior experience, and education are also positively associated with promotion. Specifically, each additional year of age increases the odds by 3.1%; prior upper-level experience raises the odds by 15.1%; and higher education adds a 15.6% boost. Finally, longer tenures significantly increase promotion likelihood—each unit increase in log tenure raises the odds by 174%. This is evident, as in survival analysis, a longer "survival" duration typically indicates a higher likelihood of "failure" (promotion). Column 2 reports

[16] $\exp(0.089) \approx 1.093$

Table 1: Survival Analysis with Logarithmic Baseline Hazard

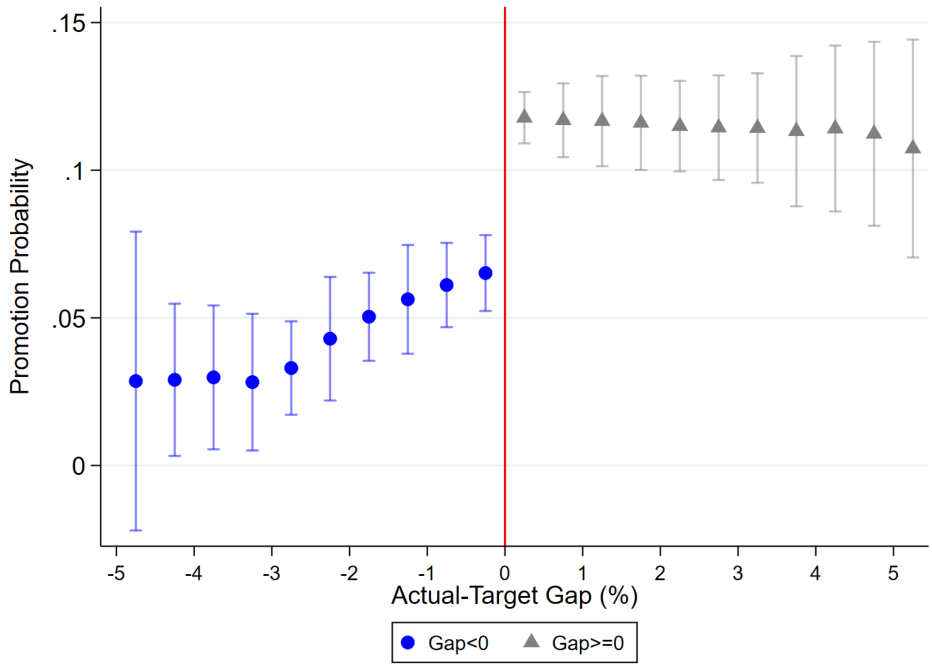
	Promotion Dummy		
	(1) Logit	(2) Complementary log-log	(3) Generalized Gamma
Actual-Target Gap	0.089***	0.080***	0.098***
	(0.020)	(0.018)	(0.021)
Age of Governor	0.031***	0.028***	0.045***
	(0.012)	(0.010)	(0.014)
Prior Experience	0.141***	0.125***	0.157***
	(0.046)	(0.042)	(0.054)
Education Level	0.145**	0.126**	0.106
	(0.068)	(0.061)	(0.079)
ln(spell length)	1.008***	0.917***	1.378***
	(0.080)	(0.072)	(0.135)
Observations	4507	4507	4504

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table presents survival analysis results using different models. The dependent variable is a promotion dummy indicating whether a politician is promoted. This result is based on a parametric baseline hazard (logarithmic form). As expected, the natural logarithm of tenure length positively correlates with promotion likelihood, indicating that longer tenures are beneficial for officials' career advancement. The first column presents the results of the logit model, the second column corresponds to the cloglog model, and the third column shows the results from the cloglog model incorporating individual-level variability. This individual heterogeneity is assumed to follow a gamma distribution. Next, regarding the covariates: Actual-Target Gap is defined as the city's annual actual growth rate minus its target growth rate. Note that this measure is simply the difference between the two values and is not represented as a dummy variable, such as when the difference is greater than or equal to zero. The age of the governor is also included as a covariate. Prior Experience indicates whether the official has previously worked in higher-level government positions. For instance, an official transferred from a provincial government department to a prefecture-level city government would be classified as having prior experience. Conversely, officials classified as "grassroots" have spent their careers working locally, starting from lower-level positions. Education level reflects the governor's educational attainment. As mentioned in the data section, officials may have three distinct types of educational backgrounds, and the variable used here is the sum of these three categories.

results from the complementary log-log model, which adopts a different functional form for the baseline hazard compared to the logit specification. Column 3 extends the model by incorporating a frailty term to account for unobserved individual heterogeneity.

Figure 2: Promotion Probability by Actual-Target Gap



Notes: Figure 2 illustrates the (unconditional) relationship between officials' promotion probabilities and their economic performance, measured by the actual-target gap. The figure reveals that promotion probabilities increase as the actual-target gap widens, with officials who exceed their targets consistently demonstrating higher promotion probabilities than those who fall short. A noticeable jump in promotion probabilities occurs at Gap = 0, marking the transition from underperformance to meeting targets.

Figure 2 plots the likelihood of promotion as a function of officials' performance scores, measured by the gap between actual and target GDP growth. The results show a clear positive relationship: better performance is associated with a higher probability of promotion. Officials who fall short of their targets (gap < 0) consistently exhibit lower promotion rates—averaging below 5%—compared to over 10% for those who meet or exceed targets. Notably, there is a sharp discontinuity in promotion probability at the threshold where the performance score crosses zero. This jump suggests that officials who narrowly miss the target receive significantly fewer promotion opportunities than those who barely achieve it, highlighting strong incentives for marginal efforts to meet growth targets.

In summary, the survival analysis results suggest that officials with stronger economic performance are promoted more frequently and at a faster pace [17]. This partially explains

[17] Figures B1 and B2 analyze the relationship between tenure duration, promotion likelihood, and survival rates, differentiating between officials who meet growth targets and those who do not. The findings indicate

their strong motivation to achieve growth targets. However, it is also possible that some officials benefit from favorable conditions by being assigned to already high-performing cities, allowing them to free-ride on existing growth momentum rather than actively contributing to performance improvements. Section 4.3 aims to explore this dynamic further.

4.2 Bunching Estimation

This section details the methodology employed to quantify the extent of politicians' deliberate efforts to meet economic growth targets. This analysis uses the bunching technique around points with discontinuities in incentives to elicit behavioral responses, a method initially introduced in the public economics literature by Saez (2010). The premise is that if politicians are driven by specific pressures to meet these targets, there will be a disproportionately high frequency of observations right at the threshold of achieving the target.

To evaluate politicians' incentives to meet growth targets, the analysis focuses on the distribution of the actual-minus-target growth gap, as used in previous literature (Lyu et al., 2018; Chen et al., 2020). This gap is defined as the difference between the annual actual GDP growth and the target growth for the corresponding year. Let Z denote the support of the gap, and z^* the threshold where a politician precisely meets the target (i.e., gap $= 0$). To quantify the bunching mass B at z^*, the initial step involves estimating the counterfactual distribution. $h_0(z^*)$ that would exist without the kink. This estimate is then compared to the observed distribution with the kink. The bunching mass B is defined as the difference between the observed spike in the distribution and the counterfactual density of the gap. Then normalize the bunching mass relative to the counterfactual in order to compare across various kinks with different counterfactual heights. Additionally, to account for potential diffuse bunching—where the concentration of observations is spread across an interval rather than centered at a single point—the bunching region is redefined to encompass a broader range. This approach accounts for situations where participants, such as politicians in this context, may not be able to precisely meet the target point z^*, resulting in a distribution of excess mass not just at z^* but within a vicinity around it.[18]

The estimation of the counterfactual without the kink follows the polynomial strategy proposed by (Chetty et al., 2011). This technique involves fitting a flexible polynomial to

that target-achieving officials experience faster career advancement.

[18]Specifically, define the bunching region as $z \in [z_L, z_U]$ surrounding a kink at z^*, where z_L and z_U represent the lower and upper bounds, respectively, of the "hump" area around z^*. This interval captures the spread of data points that are close to but not exactly at z^*, reflecting a more realistic scenario of target achievement that includes slight variations within a defined range.

the observed data around each kink, specifically excluding the bins within the bunching region. By grouping individuals into bins of width δ, the resulting polynomial provides an estimate of $\hat{C}_j$. Formally, this is achieved by estimating the following model:

$$C_j = \sum_{i=0}^{p} \beta_i (z_j)^i + \sum_{i=z_L}^{z_U} \gamma_i \mathbb{1}\left[z_j = i\right] + \varepsilon_j$$

C_j represents the observation count in bin j and p is the order of the polynomial used to fit these counts.[19] z_j is the gap mid point of bin j. The parameters z_L and z_U define the lower and upper bounds of the bunching region.[20]

The predicted counterfactual density in the absence of the kink is given by subtracting predicted mass from the observed density: :

$$\hat{B}_0 = \sum_{j=z_L}^{z_U} (C_j - \hat{C}_j) \qquad \text{with } \hat{C}_j = \sum_{i=0}^{p} \hat{\beta}_i (z_j)^i$$

$\hat{B}_0$ estimates the excess number of observations located at z^* due to the presence of a kink. $\hat{C}_j$ is the estimated count excluding the contribution of the dummies in the bunching region. To ensure comparability of results, normalize the bunching mass by the average counterfactual frequency in the excluded range:

$$\hat{b}_0 = \frac{\hat{B}_0}{\hat{C}_0}$$

Where $\hat{C}_0 = \left[\frac{z_U - z_L}{\delta}\right]^{-1} \sum_{j=z_L}^{z_U} \hat{\beta}_i(z_j)$. The standard error of the excess mass $\hat{b}_0$, is then determined through bootstrapping.[21] Panel A and Panel B of Figure C2 respectively illustrate the cases of sharp bunching (where $z_L = z_U = z^*$) and diffuse bunching (where $z^* \in [z_L, z_U]$) within the chosen excluded region. And the first lines of Panels A and B in Table 2 present the baseline estimates for the excess mass associated with sharp and diffuse bunching, respectively, along with their standard errors and t-statistics. These estimates of excess mass are statistically significant at the 1% level. An excess mass of 1.56 (2.03) indicates that there are 56% (103%) more observations at the target threshold than would

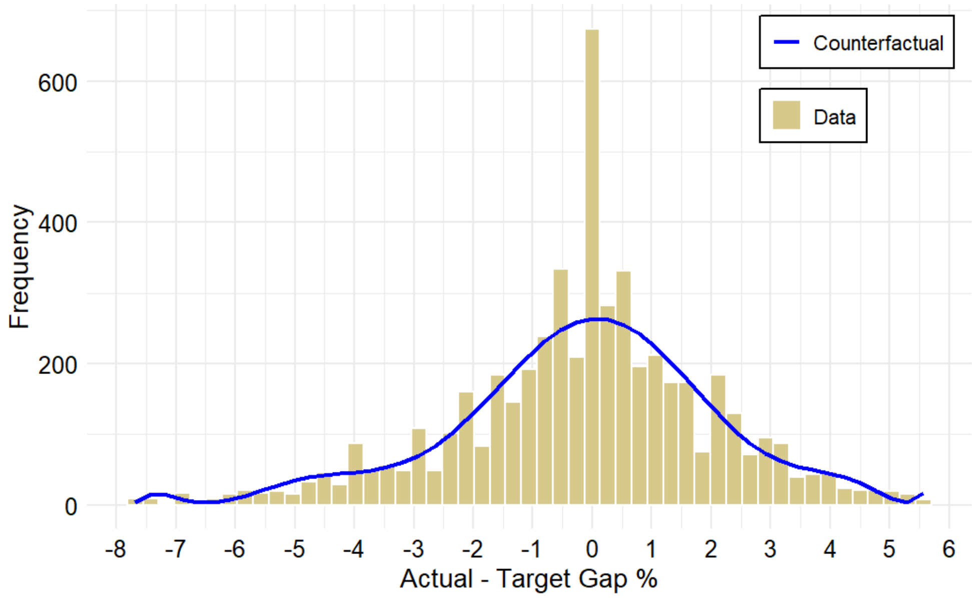
[19] This paper uses BIC criterion to determine the optimal degree of the polynomial (Bergolo et al., 2021)

[20] Following the Freedman–Diaconis rule (Freedman and Diaconis, 1981), the optimal binwidth δ which minimize the discrepancies between the height of histogram and real density is obtained by $2 \times IQR(x) * n^{-\frac{1}{3}}$. IQR stands for the interquartile range and n is the sample size.

[21] Specifically, generate 1,000 bootstrapped samples with replacement and calculate the standard deviation of the distribution of these estimates, which provides the standard error for $\hat{b}_0$.

be expected in the absence of the incentive. The analysis also accounts for potential biases arising from round-number bunching and naturally low density on the left side of the bunching region (Integration Constraint Correction). Detailed procedures are provided in the Appendix C.

Figure 3: Distribution of the Actual–Target Gap and Counterfactuals



Notes: Figure 3 presents the empirical distribution of the actual-minus-target GDP growth gap (histogram), overlaid with the estimated counterfactual distribution (blue line). The corresponding excess mass estimates and standard errors are reported in Table 2. Figure C1 presents the counterfactual distribution estimated with additional controls, including indicators for round-number gaps and localized density spikes ("nearby kinks"), to account for potential confounding patterns in the observed distribution.

In conclusion, the distribution of the growth gap exhibits notable and unusual discontinuities at points where incentives shift, potentially indicating deliberate efforts by officials. The previous subsection establishes that meeting growth targets significantly improves promotion prospects. This finding translates into intentional efforts by officials to meet these targets, particularly when performance is close to the threshold.

4.3 Analysis Using Connected Samples

The earlier analysis does not account for the fact that the difficulty of achieving economic development targets varies significantly across cities and regions. Research also suggests

Table 2: Estimates of Excess Mass

Panel A: Sharp Bunching			
	Excess Mass $\hat{b}$	Standard Error	t-statistic
Sharp	1.56	0.164	9.51***
Sharp: round #	1.518	0.287	5.29***
Sharp: correction	1.381	0.314	4.40***

Panel B: Diffuse Bunching			
	Excess Mass $\hat{b}$	Standard Error	t-statistic
Diffuse	2.033	0.378	5.38***
Diffuse: round #	1.999	0.375	5.33***
Diffuse: correction	1.543	0.774	1.99**

Notes: Sharp bunching sets the threshold exactly where the gap equals zero, whereas diffuse bunching defines an interval as the bunching region. For this study, the interval $[-0.2\%, 0.5\%]$ was selected based on visual inspection of the distribution. "Round number" controls for whether the gap is a multiple of 0.5%. "Correction" refers to the integration constraint correction detailed in the Appendix C. Figure C2 provides a graphical representation of the estimated excess mass

that appointing officials to economically prosperous and strategically important cities often signals a pre-determined path for their career advancement, reflecting strong political connections or prior approval from higher authorities (Jiang and Zhang, 2020). Failing to account for these localized conditions when analyzing the economic impact of local leaders risks introducing bias (Jones and Olken, 2005).[22] These disparities underscore the importance of adopting an analytical framework that separates leader-specific contributions from city and time specific factors. A more refined analysis should focus on the extent to which a leader's efforts to close growth gaps influence their subsequent promotion outcomes.[23]

[22]Some cities possess inherent advantages—such as favorable geographic locations, historical industrial bases, or preferential economic policies—that naturally facilitate higher GDP growth. Leaders assigned to such cities may benefit from these advantages, and attributing economic success solely to their leadership would overstate their contribution. Conversely, leaders assigned to disadvantaged cities may appear less effective due to structural challenges beyond their control, rather than any deficiency in ability or effort. For example, consider an official who has already been informally designated for promotion and is subsequently reassigned by higher authorities to a city with strong economic momentum. In such cases, the official can meet growth targets with minimal effort by simply maintaining the existing trajectory of development.

[23]Moreover, the presence of laterally transferred officials could complicate the survival analysis, as these same individuals (movers) appear in the dataset multiple times after being reassigned to different cities. Treating each city-level tenure as an independent observation may obscure individual-specific traits and

The periodic rotation of Chinese officials across cities enables this analysis, as the majority of non-promoted leaders undergo lateral transfers, some serve as governors in other prefecture-level cities. These movements create a network that allows the separation of leader effects from city fixed effects.[24] In the sample, 15% of officials were "movers," meaning they served in multiple cities during their careers. These movers connect cities into a network, forming a "connected sample." In this network, a city is considered connected if at least one official who served there also held an equivalent position in another city. Based on this definition, 82.5% of the cities in the sample are classified as connected. A detailed breakdown of all connected groups is provided in Table D1 and Figure D1.

The methodology for estimating leader effects is adapted from the framework originally developed for analyzing linked employer-employee data. Abowd et al. (1999) (AKM) introduced a seminal two-way fixed-effects model that decomposes wage variation into worker-specific and firm-specific components. This approach exploits worker mobility across firms to identify these fixed effects, enabling the estimation of individual and firm-level contributions to wage outcomes.[25]

To evaluate leaders' contributions to closing the gap between actual GDP and target GDP, a three-way fixed-effects model is employed, drawing on the framework of Best et al. (2023) and Yao and Zhang (2015). The econometric specification is as follows:

$$\text{Gap}_{ijt} = X_{ijt}\beta + \theta_i + \psi_j + \gamma_t + \epsilon_{ijt},$$

In this specification, Gap_{ijt} denotes the GDP gap (actual GDP minus target GDP) for city j in year t during the tenure of leader i. X_{ijt} represents a vector of time-varying control variables, including the logarithm of total city population, provincial targets, and the annual average nightlight intensity for each city. θ_i captures the leader-specific fixed effect,[26] reflecting the relative contribution of leader i to closing the GDP gap. ψ_j accounts

lead to bias in the estimated promotion probabilities.

[24] Specifically, comparing the same official's terms across different cities helps identify relative differences in city fixed effects, while comparing different officials' terms within the same city isolates relative differences in leader fixed effects.

[25] The AKM framework has been widely applied and extended across various domains, including managerial effects (Bertrand and Schoar, 2003) and leadership effects (Best et al., 2023; Yao and Zhang, 2015). These studies highlight the effectiveness of fixed-effects models in disentangling individual contributions from contextual effects, particularly in scenarios where mobility links individuals or entities across locations.

[26] Because leader tenures are typically short relative to the length of the city-level panel, estimates of leader fixed effects may be subject to considerable sampling variation. To mitigate this, an empirical Bayes shrinkage procedure is applied, adjusting each estimate toward the grand mean based on the number of observations per leader. (James and Stein, 1961)

Table 3: Variance Decomposition of the GDP Gap

Component	**Proportion of Total Variance**
Leader fixed effects	0.281
City fixed effects	0.064
Observed time-varying characteristics	0.294
Residual	0.362

for city-specific fixed effects, capturing unobserved, time-invariant city characteristics such as geographic advantages or industrial composition. γ_t represents year-specific fixed effects, controlling for nationwide economic trends or macroeconomic shocks. The error term, ϵ_{ijt}, captures idiosyncratic variations.[27] The AKM variance decomposition provides insights into the relative contributions of four key components in explaining the variance of the growth gap: observed time-varying characteristics, leader-specific effects, city-specific effects, and the residual.

The variance decomposition results in Table 3 provide a detailed breakdown of the factors contributing to variation in the GDP gap. Leader fixed effects account for 28.1% of the variance in the growth gap, underscoring the significant influence of individual leaders in narrowing the gap. This substantial contribution reinforces findings from Jones and Olken (2005) and supports the earlier results of this paper, demonstrating the pivotal role leaders play in achieving economic growth targets. City fixed effects, by comparison, account for only 6.4% of the variance, suggesting that static, time-invariant city characteristics—such as geography or historical industrial bases—have a relatively minor influence. This indirectly strengthens the credibility of leaders' importance in meeting targets, as growth targets are largely artificial constructs, less directly tied to inherent city attributes. Ob-

[27]A key normalization is applied to address the inherent indeterminacy in the fixed-effects model (Abowd et al., 1999, 2002). This refers to the issue that fixed effects, such as leader and city effects, cannot be independently identified without imposing a normalization constraint due to their perfect collinearity with the model's constant term. Specifically, the sum of leader effects is constrained to zero:

$$\sum_i \theta_i = 0$$

This constraint ensures that leader effects are identified as relative contributions, avoiding collinearity with city or year effects. Without this normalization, leader effects would remain undefined, as any constant could be added to all θ_i and subtracted from ψ_j without altering the model's fit. Additionally, as previously mentioned, the analysis focuses on a connected sample of cities where leader mobility creates linkages across locations. This connectivity is essential for isolating the relative effects of leaders and cities.

served time-varying characteristics, including time fixed effects and other control variables, explain approximately 29.4% of the variance. This result reflects the strong cyclical nature of growth targets, which are adjusted based on yearly economic conditions,[28] central government policy priorities, and the timing of leadership promotions.[29]

Table D2 and Figure D3 illustrate that leader-specific contributions to closing the growth gap are strongly and positively associated with promotion outcomes. Leaders ranking higher in terms of their contributions exhibit a significantly greater probability of promotion.

In conclusion, officials themselves play a significant role in determining whether growth targets are met, while the economic conditions of cities have a relatively weak relationship with target achievement. Even when officials are assigned to more economically developed cities, the findings suggest that they still need to actively strive to achieve their own contributions in order to enhance their promotion prospects. The results in this subsection are consistent with earlier findings, further reinforcing the conclusions of previous sections. Additionally, these findings mitigate concerns that earlier results might have been influenced by other confounding factors.

4.4 Summary

This section presented consistent evidence that growth targets significantly shape the career trajectories of local officials in China. First, survival analysis reveals a robust and statistically significant relationship between target fulfillment and promotion: a one-unit increase in the actual-minus-target GDP gap raises the likelihood of promotion by approximately 9–10%, with high-performing officials also advancing more quickly. Second, bunching anal-

[28]Figure A1 illustrates how current-year target adjustments respond to last year's performance. While target revisions are generally positively associated with past performance, they tend to be conservative—particularly when the previous year's targets were missed, suggesting limited willingness to lower current targets further. Notably, there is no discontinuous shift in target setting at the threshold where the previous year's target was just met. This contrasts with the bunching pattern observed in Section 4.2 and reinforces the interpretation that the bunching arises from promotion incentives rather than cyclical or mechanical target-setting dynamics.

[29]For example, China's Five-Year Plans play a crucial role in shaping economic targets by setting overarching priorities and providing a framework for resource allocation. Growth targets, such as GDP growth, are often derived from the strategic goals outlined in these plans, ensuring alignment between long-term national objectives and short-term policy implementation. Additionally, the Five-Year Plans act as benchmarks for local governments, guiding regional economic policies and serving as a basis for performance evaluations. This alignment ensures that economic goals are not only ambitious but also strategically designed to address evolving challenges, such as technological innovation, environmental sustainability, and social welfare, while maintaining overall stability and growth.

ysis detects clear discontinuities in the distribution of performance scores, with 56–103% excess mass at the threshold, suggesting strategic efforts by officials to meet or narrowly exceed growth targets. Third, the connected-sample analysis, based on a three-way fixed effects model, shows that leader-specific contributions explain over 25% of the variation in target fulfillment—substantially more than city fixed effects. Together, these results underscore that China's target-based evaluation system elicits strong behavioral responses from local leaders, who actively influence economic outcomes in pursuit of career advancement.

5 Impact on Firms

This section investigates how political incentives tied to GDP growth targets influence firm behavior. Using firm-level data, I examine whether pressure on local officials affects firms' operational decisions or reporting practices, focusing on changes in inventory and sales. In Section 6, I complement this analysis by using energy consumption and pollutant emissions as proxies for actual output.

5.1 Calculation of GDP in China

To understand how firm-level indicators might be influenced by officials' pressure to meet city-level GDP targets, it is essential to briefly explain how GDP in China's manufacturing sector is calculated. A distinctive feature of China's national accounting system is that GDP for the manufacturing sector—which contributed approximately 27% to 33% of total GDP in 2022—is calculated exclusively using the production approach.[30] Under this approach, GDP is based on the sum of value-added[31], which defined as the difference between total output and intermediate inputs[32]:

$$\text{Value-added} = \text{Total Output} - \text{Intermediate Inputs}.$$

[30]According to the *China Gross Domestic Product Calculation Handbook (2001)* and the *China's System of National Accounts (2002)*, China employs a dual-method approach, combining the production approach (75% weight) and the income approach (25% weight). However, the income approach does not apply to the manufacturing sector, where GDP is calculated solely based on the production method.

[31]as reported by local enterprises

[32]Intermediate inputs refer to the costs of raw materials and services used in production, excluding expenditures on fixed assets and employee compensation.

In the manufacturing sector, total output is further decomposed into sales revenue, changes in inventory, and value-added taxes. Specifically, it is computed as:

$$\text{Total Output} = \text{Sales} + (\text{Ending Inventory} - \text{Beginning Inventory}) + \text{Value-added Taxes}.$$

Under the production approach to GDP calculation, overproduction—marked by excessive inventory accumulation—can inflate GDP figures. This raises the possibility that local governments may sometimes encourage such practices to meet growth targets. For instance, firms might be incentivized to overproduce, artificially increasing both inventory and total output.[33] Similarly, when firms boost sales, either through genuine market demand or by employing strategies like selling to customers with lower credit ratings, total output rises. Given these dynamics, this study focuses on two key firm-level indicators: sales and inventory changes.[34] From a financial reporting perspective, sales data is often subject to external auditing and verification, requiring documentation such as transaction records, invoices, and cash flow statements. This process enhances its transparency (Chen et al., 2020; Firth et al., 2011). In contrast, inventory adjustments are typically managed through internal accounting processes, making them less transparent and easier to manipulate for artificially inflating GDP figures (Gao et al., 2017).

5.2 Model Specification

To examine the impact of growth target pressures on firm outcomes, this paper employs a threshold-based strategy that leverages the discontinuity at the growth target threshold (Imbens and Lemieux, 2008). This approach assesses whether firms exhibit significant changes in behavior or reporting practices when the actual-target gap shifts from negative to non-negative, signaling that the economic growth target has been met. The model is specified as follows:

[33] Although the manufacturing sector's GDP incorporates adjustments for fixed asset depreciation and inventory valuation to align with international accounting standards, these refinements primarily address discrepancies in inventory valuation and may not fully eliminate distortions caused by firms overproducing to meet administrative targets (Xu and Liu, 2018)

[34] Early GDP calculations in China relied on indirect estimates derived from national income data under the Material Product System (MPS) inherited from the Soviet Union. Since the 1990s, direct calculations using firm-level and sector-level production data have been adopted to enhance accuracy and reliability. For instance, the value-added approach now incorporates detailed surveys of manufacturing outputs, intermediate inputs, and tax data collected directly from enterprises.

$$y_{ijkt} = \alpha + \beta D_{jt} + \gamma(1 - D_{jt}) \cdot \text{Gap}_{jt} + \delta D_{jt} \cdot \text{Gap}_{jt} + \Gamma X_{it} + \sum_{j} \phi_j t + \mu_i + \lambda_k + \varepsilon_{ijkt},$$

In the model, y_{ijkt} denotes the outcome variable for firm i in city j industry k at time t, such as sales growth, production levels, or inventory changes. The binary indicator D_{jt} equals 1 if the actual GDP growth meets or exceeds the target ($\text{Gap}_{jt} \geq 0$) for city j in year t, and 0 otherwise. The variable Gap_{jt}, representing the difference between actual and target GDP growth rates, serves as the forcing variable. Interaction terms are included to capture the slope of the forcing variable on either side of the threshold. Specifically, γ represents the marginal effect of the actual-target gap on the outcome variable when the target is not met ($D_{jt} = 0$), while δ reflects the marginal effect when the target is achieved ($D_{jt} = 1$). The model incorporates X_{it}, a vector of firm-specific covariates (e.g., firm age, capital intensity, and ownership structure), to control for factors influencing firm behavior independently of growth targets. Additionally, μ_i accounts for firm fixed effects to control for time-invariant unobserved characteristics, while λ_k captures industry fixed effects to address sectoral heterogeneity. $\phi_r t$ represents city-specific time trends, capturing temporal variations unique to each city j. Instead of using year fixed effects—which control for uniform annual shocks across all cities but can absorb much of the variation in D_{jt}—this paper employs city-specific time trends.[35] The error term ε_{ijkt} represents unobserved heterogeneity and random shocks to the outcome variable. The primary parameter of interest, β, measures the discontinuous change in firm outcomes at the growth target threshold. This specification is designed to identify changes in firm behavior or reporting attributable to growth target pressures, although it does not necessarily imply causality.

5.3 Empirical Results

Panel A of Table 4 presents the empirical results using Inventory Changes as the dependent variable. For simplicity, I only retain the coefficient β as it is the sole variable of interest. The coefficients (β) across all five columns are positive, statistically significant ($p < 0.01$), and consistent in magnitude.

[35] Since growth targets are often linked to national benchmarks or macroeconomic trends, year fixed effects can overlap significantly with D_{jt}, leading to multicollinearity and imprecise estimation of D_{jt}'s coefficient. In contrast, city-specific time trends preserve local variation while accounting for broader temporal dynamics within each city, enabling a more precise estimation of the effects tied to growth target implementation (Audretsch et al., 2015).

In Column (1), which excludes fixed effects or controls, the coefficient is 0.030, indicating that meeting the growth target is associated with a 3.0% increase in inventory changes on average. Introducing firm fixed effects in Column (2) raises the coefficient to 0.047 ($\approx 5\%$), suggesting that firm-level heterogeneity influences the observed effect. The magnitude stabilizes in Columns (3)-(5) as additional controls, including industry and city-specific time trends, are incorporated. City-specific time trends are used in Columns (4) and (5) instead of year fixed effects to avoid multicollinearity with β. The positive βs suggest a discontinuity or "jump" in firm-level indicators when the growth target is just met.

On the left side of Figure 4 corresponds to years when the city failed to achieve its annual growth target (gap < 0), while the right side reflects years when the target was met or exceeded (gap ≥ 0). The data demonstrate that firms in cities meeting their growth targets consistently exhibit higher inventory changes. A distinct jump is observed at the threshold (gap $= 0$), where inventory adjustments reach their highest levels. This discontinuity underscores the strong link between achieving growth targets and firm behavior regarding inventory management. To ensure the observed jump is not an artifact of splitting the graph into two segments, a complete and continuous plot of inventory changes against the actual-minus-target gap is provided in Figure E1. This complete curve confirms the presence of a clear and significant jump at gap $= 0$, reinforcing the robustness of the findings.[36] [37]

Panel B of Table 4 presents the results for ln(Sales). In Column (1), which excludes fixed effects and controls, the coefficient is negative. This likely reflects the overall decreasing relationship between sales and the actual-target gap, as the jump at gap $= 0$ is short-lived and not captured by a simple linear regression (see Figure 5). In Column (2), the inclusion of firm-level fixed effects results in a positive coefficient of 0.055 ($p < 0.01$), which remains consistent across subsequent specifications. Adding industry and city-specific time trends in later columns further refines the estimates. The positive and significant coefficients in Columns (2) through (5) indicate that meeting growth targets is associated with higher sales, once firm- and industry-specific effects are controlled for.[38]

[36]Firms may adjust inventory levels, increase sales, or manipulate reporting to align with the economic goals set by local governments. Inventory accumulation, in particular, could serve as a strategy to artificially boost production indicators, contributing to the observed increase in GDP. This aligns with the broader context of political incentives in China, where local officials may intervene in firm operations to meet growth targets. However, the evidence does not establish a causal relationship between political incentives and firm distortions.

[37]The relatively low R^2 values are typical for RDD-type regressions, as the focus is on identifying local effects at the threshold rather than explaining overall variance.

[38]Standardizing by firm size is essential in this analysis. In economically advanced regions of China—where private sector activity tends to be more dynamic and competitive—firms are generally

Table 4: Impact on Firms

Panel A: Inventory Changes

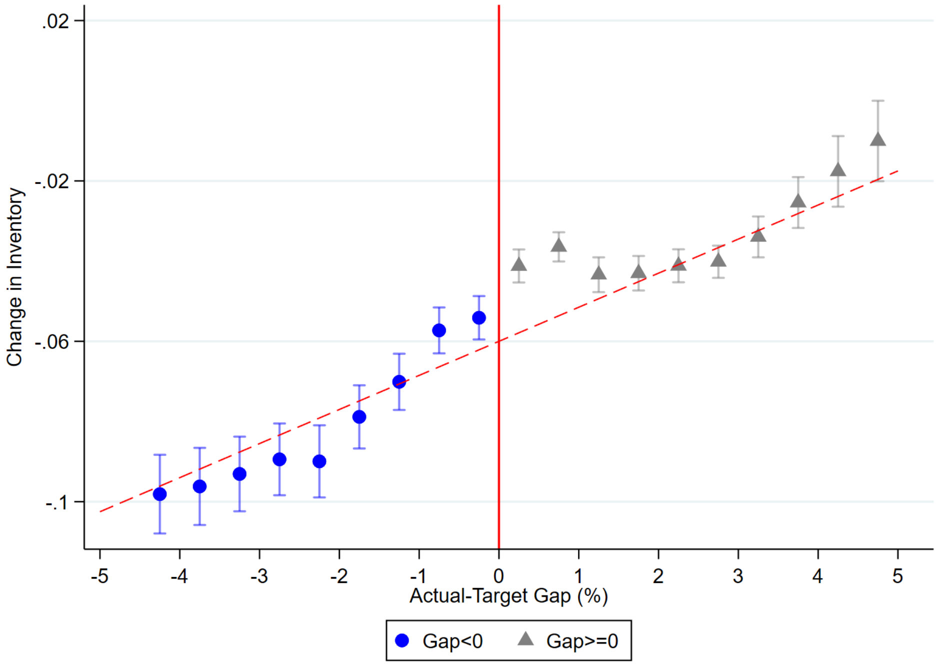
	ln of Inventory$_t$ − ln of Inventory$_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
β	0.030***	0.047***	0.063***	0.062***	0.061***
	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)
Firm FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
City Trends				✓	✓
Controls					✓
Observations	214769	214769	191275	191275	189981
R^2	0.0005	0.0008	0.0014	0.0014	0.0017

Panel B: Sales

	ln of Sales$_t$				
	(1)	(2)	(3)	(4)	(5)
β	-0.037***	0.055***	0.044***	0.044***	0.044***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Firm FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
City Trends				✓	✓
Controls					✓
Observations	309535	309535	281408	281408	279518
R^2	0.0017	0.0029	0.0036	0.0037	0.0098

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table presents the empirical results for two firm-level indicators. Panel A uses change in inventory as the dependent variable, while Panel B uses ln(sales). As discussed in Section 5.1, change in inventory is defined as the difference between (ln of) end-of-period and (ln of) beginning-of-period inventory. Both dependent variables are standardized by firm size, defined as the ln(total assets) in year $t-1$. The results in both panels are shown across five columns. Column 1 includes no fixed effects or controls, Column 2 adds firm fixed effects, Column 3 incorporates industry fixed effects, Column 4 includes city-specific time fixed effects, and Column 5 adds firm-level controls. The results across Columns 2 to 5 are notably consistent, with little variation compared to Column 1. Firm-level controls include variables such as firm age, employment and ownership type (e.g., private, state-owned, or foreign).

Figure 4: Change in Inventory by Gap

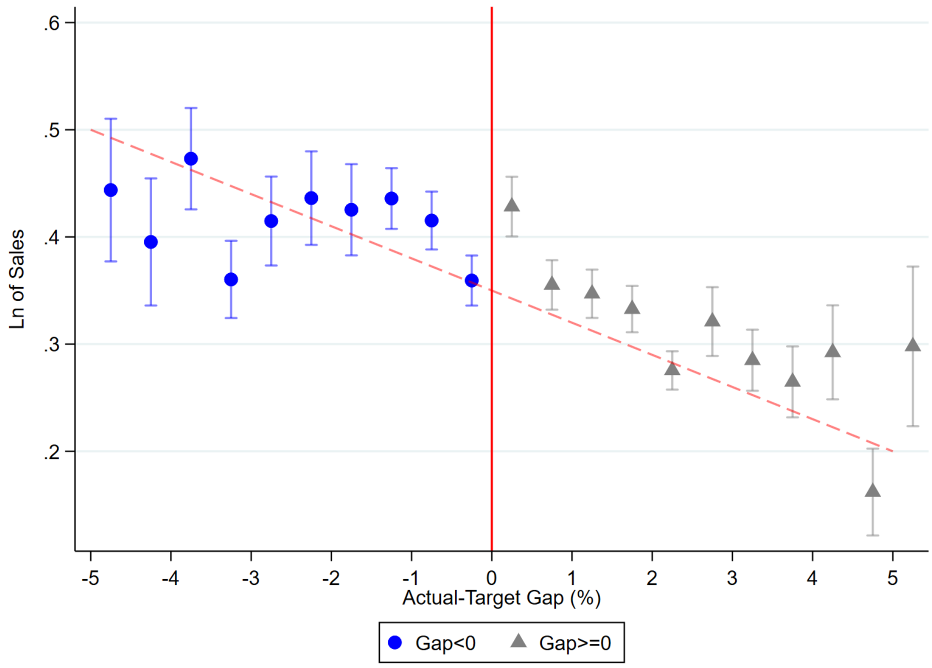


Notes: This figure plots the firm-level ln(change in inventory) as a function of the city's economic performance (actual-target gap). The line one the left represents years when the city failed to meet its annual target, while the right side represents years when the city at least achieved its target. The figure shows that cities meeting their targets not only exhibit higher levels of inventory changes overall but also display a clear jump at the threshold (gap = 0). At this point, the change in inventory reaches its peak. Because separating the graph into two sides can artificially introduce or amplify a discontinuity, I have also plotted a complete curve for change in inventory in Figure E1. The jump at gap = 0 remains clearly visible.

In conclusion, although causality cannot be definitively established, firm-level variables closely linked to GDP calculations exhibit positive distortions at the target threshold, potentially reflecting the pressures to meet growth targets. This pattern mirrors the bunching behavior observed among officials at the threshold, where promotion incentives intensify. The robustness of the firm-level results is confirmed across a range of tests, including sample restrictions, pseudo-thresholds, and alternative variable specifications. Further heterogeneity analysis reveals that these observed jumps are more pronounced in regions facing higher growth pressure and in years where cities are closer to meeting their targets. Detailed de-

smaller on average. Given that the unit of observation is the individual firm, failing to account for size would disproportionately weight larger firms, which naturally exhibit higher absolute values across key variables. Normalization ensures that firm-level outcomes are comparable across heterogeneous economic environments and mitigates potential biases arising from regional differences in firm structure.

Figure 5: Ln of Sales by Gap



Notes: This figure plots the firm-level ln(sales value) in year t as a function of the actual-target gap. Overall, sales exhibit a decreasing trend as the gap widens. Similarly to Figure 5, the red line on the left represents years when the city failed to meet its annual target, while the right side corresponds to years when the city at least met its target. A jump at gap = 0 is still visible, although it quickly dissipates. Same as above, in Figure E2, I have plotted the complete curve without imposing a discontinuity at gap = 0, where the jump remains observable.

scriptions of robustness checks and heterogeneity analyses are provided in Appendix E and Appendix F.

6 Mechanism

The previous section provided clear evidence that meeting growth targets is strongly positively correlated with firm-level GDP-related indicators, such as changes in inventory. As expected, this relationship is even more pronounced among groups with higher incentives. However, a critical question remains: To what extent do the observed distortions in output-related indicators at the threshold reflect genuine economic activity, and how much is attributable to data manipulation?[39] Rather than questioning the authenticity of the data itself, this paper focuses on determining how much of the observed growth pressure translates into actual economic activity at the firm level. To address this, the study adopts an approach based on the relationship between firms' inputs and outputs. The central assumption is that while firms may have incentives to manipulate output-related indicators, they are less likely—or find it much harder—to manipulate observable metrics that are closely tied to output but difficult to falsify or offer little incentive for manipulation (Zeng and Zhou, 2024). Examples include energy consumption and pollution records: the former represents inputs that are less subject to manipulation,[40] while the latter reflects "undesirable outputs" that occur alongside production. These inputs or "undesirable outputs" are typically unrelated to growth targets and are collected by different agencies. The first subsection delves into the details of pollution and input-related data, while the second subsection examines the extent to which concerns about data manipulation are justified.

6.1 Pollution and Energy Consumption

Pollution and energy consumption are closely tied to the production activities (Shapiro and Walker, 2018), provoking the question: Are energy usage and pollutant generations also influenced by whether growth targets are met? Moreover, can a similar discontinuity at the target threshold be observed for these indicators? The Chinese Ministry of Ecology and Environment conducts annual surveys of manufacturing firms, collecting data on various water and air pollutants, energy usage, and certain raw material inputs. Notably, many of these firms overlap with those in the CIED dataset. Given the varying combinations of inputs used and pollutants generated across firms, it is essential to standardize or aggregate energy consumption and pollutants to enable meaningful inter-firm comparisons and mit-

[39] China's data—whether official national accounts or firm-level financial reports—has long been scrutinized by both external observers and academics. Prior researches have examined data reliability from various perspectives, often suggesting adjustments to enhance credibility (Chen et al., 2019; Firth et al., 2011).

[40] In China, labor quantity is not a reliable variable input for measuring firms' economic activities. This is largely due to the widespread use of "labor dispatching," where companies hire a significant portion of their workforce through third-party agencies. These dispatched workers are formally employed by labor dispatch firms but are assigned to work at industrial enterprises. Although they are technically considered temporary employees, many remain in the same firms for extended periods. Companies rely on dispatched workers to enhance workforce flexibility and reduce labor costs. However, because these workers are not officially registered as employees of the firms they work for, they are not included in employment surveys conducted by the National Bureau of Statistics (NBS). As a result, firms may systematically underreport their actual workforce size. (Brandt et al., 2014)

igate issues of intercorrelation (Bu and Shi, 2021; Rijal and Khanna, 2020).[41] A detailed discussion of these distinctions and the standardization methods is provided in Section 3 and in Appendix A.

Panel A reports energy consumption in logarithmic form, covering industrial water usage, coal, natural gas, and diesel consumption. Panel B shows pollutants generated, including wastewater, sulfur dioxide, smoke and dust, and ammonia nitrogen. The final columns of both panels aggregate total energy consumption and pollutant generations for each firm. The results reveal a strong positive correlation between energy consumption, pollutants, and whether the city meets its economic targets. A similar jump at the target threshold is observed, mirroring the pattern seen in firm-level inventory changes and outputs. This suggests that, even if data manipulation occurs, at least part of the observed jumps in inventory changes and firm output at the threshold reflect real economic activity, rather than being solely driven by manipulation.[42] Figures G1 and G2 provide graphical representations of the results reported in Table 5. All energy consumption and pollutant emission variables exhibit a clear jump at the threshold and follow a similar overall pattern across indicators.

Table 5 presents firm-level results for energy consumption and pollutants, employing the same framework as in Section 5.

6.2 Disentangling "True" Output from Data Manipulation

This section employs pollution and energy consumption data as proxies for output, much like prior studies that have used nighttime light data as a proxy for GDP (Zeng and Zhou, 2024; Henderson et al., 2012; Martinez, 2022). The objective is to quantify how much of the observed jump in output at the target threshold is likely attributable to genuine economic activity versus data manipulation. Suppose the total output Y_{it} for firm i at time t can be decomposed into two components:

$$Y_{it} = Y_{T,it} + Y_{M,it} = f_{it}(L, K, e) + g_{it}(D)$$

[41] For pollutants, distinguishing between those generated and those discharged is particularly important, as firms employ different pollution treatment technologies that can significantly reduce emissions.

[42] Notably, the coefficients for energy consumption and pollutants remain relatively stable and fall within a narrow range. This indicates that the relationship between most inputs, undesirable outputs, and overall output is constrained, which is an important consideration for interpreting the results in the subsequent subsection.

Table 5: Pollution and Energy Consumption

Panel A: Energy Consumption

ln of	*Industrial Water Usage*	*Coal Consumption*	*Natural Gas*	*Diesel Consumption*	*Total Energy*
	(1)	(2)	(3)	(4)	(5)
β	0.081***	0.038***	0.026***	0.031***	0.071***
	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)
Firm FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
City Trends	✓	✓	✓	✓	✓
Observations	342158	276915	276915	276915	276915

Panel B: Pollutants

ln of	*Wastewater*	*Sulfur Dioxide*	*Smoke and Dust*	*Ammonia Nitrogen*	*Total Pollution*
	(1)	(2)	(3)	(4)	(5)
β	0.031***	0.024***	0.043***	0.015***	0.098***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.007)
Firm FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
City Trends	✓	✓	✓	✓	✓
Observations	304899	276915	276915	195904	193854

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table presents the firm-level results for energy consumption and pollutants. Panel A examines the impact of target achievement on energy consumption, including industrial water usage, coal, natural gas, and diesel consumption. Panel B reports the results for pollutant emissions, including wastewater, sulfur dioxide (SO_2), smoke and dust, and ammonia nitrogen. The final columns in both panels show the total energy consumption and total pollutants generated by each firm, obtained by aggregating all types of energy consumed and pollutants emitted. The results indicate a significant positive correlation between energy use, pollutant emissions, and target achievement.

where $Y_{T,it}$ represents true output within a standard production function framework, driven by genuine economic activity and inputs such as energy (e), labor (L), and capital (K), without manipulation. In contrast, $Y_{M,it}$ represents manipulated output, reflecting the artificially inflated portion of Y_{it} arising from behaviors motivated by the target D_{jt}. Let e_{it} denote energy usage and p_{it} denote pollutants generated, which can also be interpreted as undesirable outputs for firm i in year t (Atkinson and Dorfman, 2005). The variable D_{jt}, as defined earlier, is a target threshold dummy that equals 1 if the city j meets its growth target in year t, and 0 otherwise.

The key assumption is that the relationship between energy usage and pollution, $\frac{\partial p_{it}}{\partial e_{it}}$, is proportional to the relationship between energy usage and true output, $\frac{\partial Y_{T,it}}{\partial e_{it}}$, with a proportionality constant $\alpha > 0$:

$$\frac{\partial p_{it}}{\partial e_{it}} = \alpha \cdot \frac{\partial Y_{T,it}}{\partial e_{it}}$$

This implies that energy influences both true output and pollution at a constant rate. Additionally, manipulated output ($Y_{M,it}$) depends solely on the target threshold (D_{jt}) and is independent of energy usage:

$$\frac{\partial Y_{M,it}}{\partial e_{it}} = 0$$

This reflects the assumption that officials only have incentives to manipulate output for meeting growth targets. Under these assumptions, it is straightforward to estimate the proportion of the observed output "jump" at the target threshold that can be accounted for by corresponding increases in firm-level energy consumption or pollutant emissions. (Details are provided in Appendix G)

Table 6 presents the estimates of "true" output proportion ($\gamma_1 \sim \gamma_4$),[43] representing the proportion of true output by industry type. Since the value of γ is sensitive to the scale of the variables, all variables are standardized to have a mean of zero and a standard deviation of one to ensure comparability and consistency in the analysis. Only industries where output exhibits a significant jump at the target threshold are included in this table.

[43] To estimate γ_1, reliable true output data is required. In the absence of such data, this paper employs Principal Component Analysis (PCA) to estimate a latent output variable. Using data on energy consumption, labor, and capital, PCA captures the common variance among these input and observable variables, treating this latent variable as the true output regardless of potential manipulation (Kao et al., 2011). This approach effectively identifies the underlying factors that collectively represent unobserved true output. The output elasticity of energy consumption is then estimated using a Levinsohn-Petrin (Levinsohn and Petrin, 2003) production function approach, with the latent output serving as the dependent variable. To estimate the components necessary for calculating γ_2, regression-based techniques are employed to approximate the partial derivatives that define the relationships between output, energy consumption, pollution, and target completion. These estimations are conducted using two-way fixed effects models. γ_3 leverages the observed relationship between energy consumption and industrial output in the U.S. to infer the true output proportion of China. For γ_4 U.S. industrial pollution data are employed to generate a more accurate approximation of α (Levinson, 2009; Shapiro and Walker, 2018). This approach allows for variation in the elasticity between output and pollution across industries.

The final row provides results for the full sample, which includes industries without significant jumps. Overall, approximately 10–15% of the output jump at the threshold may be attributed to potential manipulation[44]. Put differently, around 10–15% of the observed firm-level output jump at the threshold cannot be explained by corresponding changes in energy consumption or pollutants generated. This conclusion holds if the energy and pollution data are reliable.[45]

This aligns with findings from previous related literature.[46] For nearly every industry, γ_2 values are higher than γ_1, and both share similar patterns. γ_3 and γ_4 are supplements to γ_1 and γ_2. γ_3 mirrors the definition of γ_1, but uses U.S. industrial output—which is assumed to be free from manipulation—as the benchmark. The relationship between energy consumption and output in the U.S. is applied in place of the corresponding Chinese data to estimate the proportion of real output. The results show a strong similarity between the two contexts. γ_4 further relaxes the assumption on α, allowing it to vary by industry to account for sector-specific output–pollution elasticities, while taking the normalization such that the overall sample's α remains equal to 1. Missing values indicate industries where severe data gaps in energy or pollution data prevent the calculation of these estimates.

Industries where γ_2 significantly exceeds γ_1, such as the *Textile Industry* (70.2% vs. 88.2%) and *Non-Ferrous Metal Smelting* (47.7% vs. 87.9%), suggest that pollution is a stronger indicator of true output than energy usage, likely due to inefficient technologies and reliance on pollutant-heavy energy sources like coal. In contrast, industries where γ_1 closely aligns with γ_2, such as *Coal Mining and Washing* (56.1% vs. 56.9%) and *Non-Metallic Mineral Products* (93.6% vs. 94.9%), reflect a direct relationship between energy use and pollution, where energy consumption translates more directly into pollutant generation due to the nature of production processes. Certain industries, such as *Leather and Related Products* (41.2% vs. 49.5%) and *General Equipment Manufacturing* (33.4% vs.

[44]While it is plausible that 10–15% of the observed discrepancy falls within a reasonable margin of error and may not constitute manipulation per se, the primary objective of this analysis is not to quantify the extent of manipulation. Rather, the aim is to assess the extent to which political incentives translate into real economic effects.

[45]However, Ghanem and Zhang (2014) highlighted that even pollution data in China is subject to potential manipulation.

[46]Li et al. (2024) estimated that 5–10% of China's GDP data may be overstated due to fabrication, while Firth et al. (2011) observed significant discrepancies between the aggregated local GDP figures reported by certain Chinese cities and regions and the national GDP data, with local reports potentially overstating actual values by 15–20%. Similarly, Chen et al. (2019) highlighted that since the mid-2000s, the National Bureau of Statistics has consistently revised down local governments' reported GDP figures by an average of 5%. Holz (2014) noted that since 1997, the aggregated provincial GDP in China has often exceeded the national GDP, with the gap reaching as high as 19.3% by 2004.

Table 6: True Output Proportion by Industry Type

Industry Name	**Obs.**	γ_1 (%)	γ_2 (%)	γ_3 (%)	γ_4 (%)
Agricultural and By-Product Processing	39,665	71.2%	84.5%	–	–
Food Manufacturing	21,394	82.9%	95.8%	98.1%	98.9%
Beverage Manufacturing	17,993	–	87.3%	–	90.1%
Textile Industry	51,811	70.2%	88.2%	86.6%	88.9%
Leather and Related Products	8,723	41.2%	49.5%	58.9%	49.9%
Coal Mining and Washing	19,439	56.1%	56.9%	–	–
Wood Processing and Bamboo Products	8,459	44.3%	–	43.6%	–
Paper and Paper Products	29,027	79.4%	96.8%	83.0%	97.4%
Chemical Materials Manufacturing	72,249	88.7%	96.1%	71.0%	96.9%
Rubber Products	7,398	65.3%	–	99.9%	–
Non-Metallic Mineral Products	80,311	93.6%	94.9%	66.2%	94.6%
Ferrous Metal Smelting	21,321	56.9%	72.4%	48.0%	72.3%
Non-Ferrous Metal Smelting	15,985	47.7%	87.9%	85.2%	87.8%
Metal Products	22,305	33.6%	89.2%	24.6%	90.8%
General Equipment Manufacturing	24,815	33.4%	26.5%	35.2%	25.2%
Electrical Machinery Manufacturing	13,046	42.2%	45.0%	59.9%	44.0%
All Sample		90.1%	84.9%	84.6%	84.9%

Notes: This table presents the two metrics of true output proportion, γ_1 and γ_2, across different industries, along with the γ_3 and γ_4 based on U.S. industrial data. All values are expressed in percentage terms.

26.5%), exhibit relatively low true output proportions (< 60%), indicating stronger incentives for manipulation or weaker alignment of energy and pollution proxies with actual economic activity. For example, *Leather and Related Products* may rely on low energy and pollution intensity, making these proxies less reflective of output, while *General Equipment Manufacturing* often employs advanced, energy-efficient technologies that reduce the correlation between these proxies and true economic activity. Overall, while low true output proportions in some industries may suggest significant data manipulation or weak proxy alignment, the broader findings highlight that growth targets often lead to substantial real economic activity. Firms appear to have meaningfully expanded production, whether driven by political pressures or favorable economic conditions.

7 Conclusion

This study examines how local officials' incentives influence economic outcomes within China's performance-driven governance system. The findings highlight the substantial impact of growth targets on both political and economic behaviors. Using a combination of bunching analysis and survival models, the study reveals that local officials strategically adjust economic performance metrics to meet growth targets, particularly when promotion incentives are strong. Achieving targets provides significant advantages for officials' career advancement. At the firm level, the evidence shows a clear relationship between political and growth pressures and GDP-related indicators. These findings are robust across alternative dependent variables and specific subsamples. When considering quarterly GDP as an midpoint performance measure, officials who fall behind early in the year tend to intensify efforts in the remaining months to catch up, further strengthening the link between meeting targets and firm-level economic activity. Moreover, using firm-level energy consumption and pollution data as reference points, the study finds that a significant portion of the output jump at the target threshold can be explained by corresponding changes in pollution and energy usage. This suggests that local officials' actions go beyond simple data manipulation and have tangible effects on real economic activity.

The findings of this study hold significant policy implications. As Rong (2013) illustrates, the core operational logic of a hierarchical, pressure-driven governance system involves the top-down transmission of directives through the exertion of pressure, coupled with the superior's absolute authority to reward or punish subordinates. This structure inevitably translates the superior's often "vague" intentions into specific and narrowly focused targets.[47] Without such quantifiable measures, it becomes challenging for superiors to assess subordinates' performance or ensure the effective transmission of their intentions. However, in the absence of robust oversight and accountability mechanisms, such systems are prone to unintended consequences and opportunities for rent-seeking. This paper provides valuable empirical insight to deepen our understanding of these dynamics.

This study has several limitations, highlighting opportunities for future research. Both the bunching analysis and threshold based specification, while valuable, lack the ability to establish definitive causal relationships. While we observe firms responding to growth pres-

[47]For instance, directives like "developing the economy" are often translated into GDP growth targets, while "managing the COVID-19 pandemic" is reduced to metrics such as infection rates. Similarly, "emissions reduction" is measured by CO_2 emissions, and "poverty alleviation" is quantified by the number of households removed from poverty.

sures, the specific mechanisms through which governments influence firms remain unclear. Future research could explore this in greater depth, leveraging more direct data linking government actions to firm behavior. For example, some studies have examined how local governments establish subsidiaries as financing vehicles to fund infrastructure projects and achieve economic targets—an intriguing direction that warrants further investigation.[48]

[48] Example studies include Bao et al. (2024) and Mo (2018).

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Appendix A Supplementary Data Details

Appendix A.1 Growth Targets and Actual Growth

Data on China's economic growth targets are compiled from publicly available government documents and statistical records. Central growth targets are outlined in key documents such as the *Five-Year Plan for National Economic and Social Development*[49] and the annual *Report on the Work of the Government*[50], which serve as official declarations of national macroeconomic priorities.[51] These sources, available on government websites, offer detailed information on annual GDP growth targets, fiscal revenue goals, social development objectives, and other related metrics. At the provincial and prefectural levels, growth targets are extracted from local *five-year and annual plans*, which adapt national objectives to region-specific contexts. These documents are publicly released as finalized reports, mirroring the publication process at the central level. The data collection aims to compile a nationwide dataset spanning 20 years. This process involves manually extracting information from official documents and websites of 339 prefecture-level cities across all 32 provincial-level administrative units in China, covering the past two decades.

Economic performance data supplement these growth targets, providing realized growth rates, per capita GDP, and other key indicators. These are sourced from the *China City Statistical Yearbook*[52] and regional statistical publications, enabling comparisons between

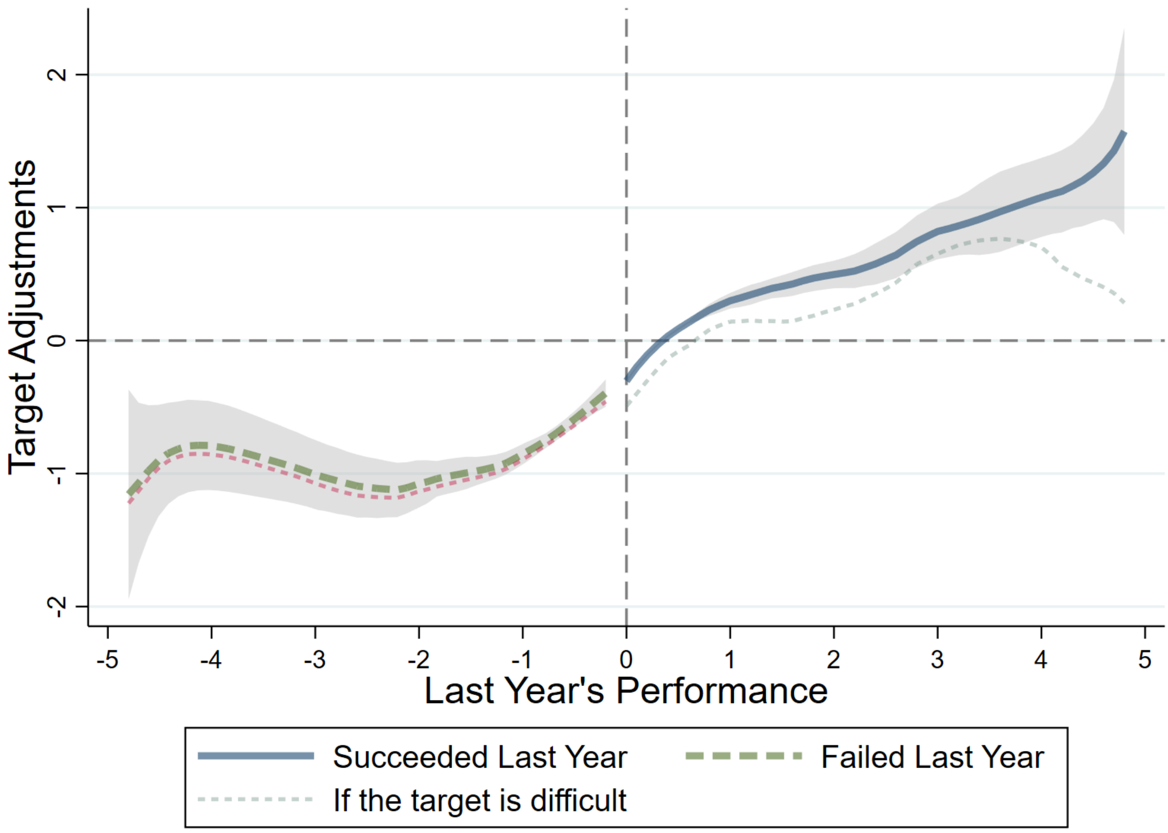
[49]First introduced in 1953, these plans are developed by the National Development and Reform Commission (NDRC) and approved by the National People's Congress (NPC). Each plan sets specific goals for economic growth, industrial restructuring, technological innovation, environmental protection, and social welfare. While originally a hallmark of China's centrally planned economy, the Five-Year Plans have evolved into a hybrid framework, blending market-driven strategies with state-led guidance. They provide a policy roadmap for all levels of government, businesses, and investors, ensuring that national objectives are aligned with local implementation efforts. The plans also reflect China's long-term vision, balancing short-term economic goals with sustainable development and societal progress.

[50]Typically delivered by local city governors during the annual session of the local People's Congress, these reports provide a comprehensive review of the government's achievements over the past year and outline the policy priorities, economic targets, and social development goals for the year ahead. Key areas covered include GDP growth, employment, fiscal policies, environmental protection, and technological innovation. Serving as a guiding framework, the report aligns the activities of government agencies, regional authorities, and state-owned enterprises with national objectives. Often regarded as a barometer of China's economic and political direction, it reflects the broader priorities of the central government while addressing regional challenges.

[51]These documents are typically published early in the year, usually between January and February. Higher-level government work reports are released before those of lower-level governments, ensuring that growth targets are set in advance and reflect the priorities of higher authorities. This sequencing allows local targets to be established after observing the objectives outlined by upper-level leadership.

[52]An authoritative publication that provides comprehensive statistical data on the social and economic development of cities across China. Published annually by the National Bureau of Statistics of China. It

Figure A1: Target Ratcheting



Notes: This figure plots current-year growth targets against prior-year performance, specifically whether the previous target was met or missed. This shows that cities with stronger past performance tend to set higher targets for the following year. When a city meets or exceeds its target, the subsequent year's target is typically adjusted upward—albeit conservatively, usually by less than half of the previous year's excess. In contrast, downward adjustments following a missed target are smaller and more constrained. Notably, there is no discontinuity in target adjustment at the point where the prior-year target was just met, suggesting that the observed bunching at the target threshold is more likely driven by discontinuities in promotion probabilities rather than in the target-setting process itself.

targeted and achieved economic outcomes across national, provincial, and prefectural levels.

covers a wide range of indicators, including population demographics, GDP, industrial output, infrastructure development, education, public health, environmental protection, and fiscal revenue. The yearbook organizes data by city and year, enabling detailed comparisons across different regions and time periods.

Appendix A.1.1 City Party Secretaries

The dataset on Chinese city party secretaries[53], including their demographics and promotion outcomes, was meticulously compiled from official government websites and news platforms such as *Xinhua Net*, The dataset covers two decades of leadership transitions across the previously mentioned 339 cities, including observations on over 1,800 party secretaries. This dataset captures key demographic and professional attributes, such as age, gender, place of origin, education level[54], tenure length[55] prior positions, and career experiences (Mei and Wang, 2017). For simplicity, party secretaries will be referred to as governors throughout the remainder of this paper.

The centerpiece of the dataset is information on officials' career trajectories and promotion outcomes. In this context, a promotion is defined as an increase in an official's rank within the Communist Party hierarchy,[56] for example, advancing from rank r to $r+1$. This paper leverages the *Regulations on the Management of Civil Servants' Positions and Ranks (2006)* to determine the administrative rank associated with each position held at different career points. Promotions are specifically examined in relation to the official's next position after serving as a city governor, with a focus on whether their advancement

[53] The decision to use data on party secretaries rather than mayors stems from the fundamental structure of China's political system, where the Chinese Communist Party (CCP) wields authority over all levels of government. As the top-ranking CCP official in a city, the party secretary holds ultimate decision-making power, particularly in critical areas such as political appointments, policy priorities, and resource allocation. In contrast, the mayor, while responsible for the city's day-to-day administration and economic management, operates under the direct oversight of the party secretary. This makes the party secretary the most influential figure in shaping city-level outcomes.

[54] Chinese officials typically acquire their education through three primary pathways. The first is traditional academic study, culminating in a degree upon graduation. The second involves earning a degree while concurrently holding an official position; these selective part-time programs are not open to the general public. The third pathway is through party schools, which exclusively admit Communist Party members and primarily focus on party-related knowledge rather than standard academic curricula. An official's educational background may include a combination of these pathways, but degrees obtained through traditional academic study are generally considered the most reflective of an individual's capabilities. Nevertheless, this paper does not delve into these complexities and instead uses the highest degree obtained by the official, regardless of whether it was earned through part-time study or from a party school.

[55] In China, the official term for party secretaries is five years, but in practice, the average tenure in the sample is less than four years due to frequent political rotations and reshuffles. The timing of promotion or reassignment is uncertain, as no fixed legal framework dictates these transitions. Instead, officials are often reassigned or promoted under the party's meritocratic system, which emphasizes career advancement based on performance, typically measured by economic and political achievements.

[56] Some studies have adopted alternative definitions of promotion, including transitions to more influential roles within the same rank (Zeng and Zhou, 2024). These roles are considered important because they significantly increase the likelihood of subsequent promotion. However, this paper retains the most direct definition of promotion—advancement to a higher rank—due to the subjective and potentially contentious nature of defining "more important" positions.

is linked to the city's economic performance during their tenure. At the end of a governor's tenure, their career outcomes fall into one of three categories[57]:

$$\text{Promotion} = \begin{cases} 1 & \text{if promoted to a higher administrative rank,} \\ 0 & \text{if transferred to an equivalent-level position,} \\ -1 & \text{if retired (typically due to reaching the retirement age).} \end{cases}$$

Thus, Promotion $= 1$ indicates a rise by at least one administrative rank after the end of their term, Promotion $= 0$ represents lateral transfers[58], and Promotion $= -1$ reflects retirement [59] The appendix includes an example of an official's resume, illustrating the typical format and details encountered during data collection.

Appendix A.1.2 One Example CV

[57]There is indeed a fourth category includes officials who are removed from their positions due to criminal convictions or expulsion from the Communist Party. While the frequency of such cases has increased in recent years, these instances were rare during the sample period analyzed in this paper and are therefore excluded from consideration.

[58]In China, it is rare for officials to exit the government job market after completing a term in office. Government officials typically have limited or no "outside options" and, are usually reassigned to positions of equivalent rank if not promoted. Similarly, demotions are uncommon. The most likely scenario for sidelined officials is reassignment to less influential departments at the same rank, effectively marginalizing them. This reassignment can be interpreted as a form of demotion or a step toward retirement.

[59]Officials reassigned to positions in the National People's Congress (NPC) or the Chinese People's Political Consultative Conference (CPPCC) after reaching a certain age are often considered effectively retired, despite retaining their rank and benefits (Qiao, 2013). Accordingly, this paper categorizes such officials as retired rather than assigning them to other classifications.

Figure A2: Example CV

Personal Résumé

Education

- **1985.07–1989.08**: Student of Chinese Language and Literature at Changchun Normal College
- **1989.08–1990.11**: Teacher at Tonghua Normal School
- **1990.11–1991.10**: Deputy Secretary to the Youth League at Changchun Normal College
- **1991.10–1994.09**: Secretary to the Youth League at Changchun Normal College

Rank 1 • **1996.04:** Joined the Chinese Communist Party

Rank r • **2001.08-2008.03:** The Standing Committee Member of the Liaoyuan Municipal Party Committee, Jilin Province

Rank r • **2008.03-2010.04:** The Standing Committee Member of the Songyuan Municipal Party Committee, Jilin Province

Rank r+1 • **2010.04-2011.03:** The Deputy Secretary of the Songyuan Municipal Party Committee, Jilin Province

Rank r+1 • **2012.09-2015.09:** The Director of the Department of Human Resources and Social Security of Jilin Province

Rank r+1 • **2015.09-2019.09:** The Secretary of the Baishan Municipal Party Committee, Jilin Province

Rank r+2 • **2019.09-2020.06:** The Vice Governor of the People's Government of Jilin Province

Appendix A.1.3 CIED Financial Statements

This paper's micro-level firm data primarily comes from the China Industrial Enterprise Database (CIED), a comprehensive dataset maintained by the National Bureau of Statistics of China. It includes all state-owned industrial enterprises and non-state-owned enterprises with annual revenue above specific thresholds—5 million RMB prior to 2011 and 20 million RMB afterward. The dataset primarily focuses on three sectors: mining, manufacturing, and the production and supply of electricity, gas, and water, with manufacturing enterprises accounting for over 90% of the sample. Covering the period from 1998 to 2014, it comprises millions of observations, forming a substantial but unbalanced panel dataset[60]. The database contains two broad categories of information: (1) basic firm characteristics, such as enterprise codes, names, ownership types, addresses, and workforce details, and (2) financial and operational variables, including total assets, fixed assets, sales revenue, value-added, R&D expenditure, and profits. With approximately 130 indicators, the CIED provides a rich resource for analyzing firm performance, productivity, and behavior across various dimensions.

Despite its inherent limitations,[61] the CIED database remains one of the few widely used datasets for studying micro-level manufacturing firms in China. To address its shortcomings, this paper complements the analysis with data from the China Stock Market and Accounting Research (CSMAR) database.[62] Although the CSMAR database includes a smaller number of firms, it offers significantly greater precision and a broader range of variables, making it a valuable complement to the analysis. This paper follows the data-matching approach outlined by Brandt et al. (2012)[63] and adopts the cleaning methods

[60]Note that the databases on economic targets and official information cover the period from 2000 to 2021, spanning a longer timeframe compared to the firm-level dataset.

[61]While widely regarded as a valuable resource for microeconomic and firm-level research, the database has several notable limitations that researchers must address (Brandt et al., 2014). First, it suffers from inconsistencies in identifiers, such as enterprise codes and names, complicating the construction of accurate longitudinal panel data. Frequent changes due to restructuring or renaming can result in overestimating the number of unique firms or failing to match records for the same firm over time. Second, the database contains significant data gaps and variable inconsistencies. Furthermore, discrepancies in the definitions and measurements of variables like "capital" can introduce measurement errors and affect research outcomes. Third, the dataset includes outliers and anomalous values in variables such as profits, assets, and production, requiring rigorous cleaning and filtering to ensure reliability. Lastly, a selection bias is inherent in its design, as it covers only state-owned enterprises and non-state enterprises exceeding the revenue threshold, excluding smaller firms. This exclusion limits its representation of China's industrial sector, particularly for studies on market dynamics or firm heterogeneity.

[62]The CSMAR database is a comprehensive dataset that focuses on publicly listed firms in China, offering detailed information on financial performance, corporate governance, and stock market indicators. Compared to the CIED, CSMAR provides higher data quality, with fewer missing values and greater consistency, owing to its emphasis on publicly traded companies subject to stricter regulatory oversight. However, its primary limitation lies in its narrower scope, as it excludes private and smaller firms, making it less representative of China's broader industrial landscape.

[63]Firms are matched using a combination of identifiers, including enterprise codes, names, legal representatives, addresses, postal codes, industry codes, main products, administrative districts, and establishment years. This methodology ensures consistency by reconnecting firms that underwent restructuring or reorganization, resulting in changes to enterprise codes or names, thereby preserving continuity across transitions. Industry codes are also standardized to ensure compatibility across different classification systems. Specifically, the 1994 GB/T4754-1994 classification is aligned with the 2002 GB/T4754-2002 standard, and the 2013 classification is similarly mapped to the 2002 standard. This harmonization enables consistency across different time periods and enhances the comparability of industry-level data.

proposed by Lam et al. (2017) to construct a coherent panel dataset.[64] The final sample comprises over 200,000 distinct firms and more than 600,000 firm-year observations.[65]

Appendix A.1.4 Energy Consumption and Pollution Records

To measure firms' genuine economic activities, this paper relies on data on industrial pollution and energy consumption, primarily sourced from the China Industrial Enterprise Pollution Database (CIEPD). This database records information on 27 types of industrial pollutants, energy consumption, and pollution treatment indicators. Compiled with approval from the National Bureau of Statistics and designed by the Ministry of Environmental Protection, it focuses on state-owned enterprises and large non-state-owned industrial firms. The dataset offers comprehensive firm-year indicators, covering raw material usage, energy consumption, solid waste, gaseous emissions, and water pollutants. For each pollutant type, it provides detailed information on emission quantities and treatment status, offering valuable insights into firms' environmental impact and mitigation efforts. Notably, the China Industrial Enterprise Pollution Database (CIEPD) can be matched with the China Industrial Enterprise Database (CIED), enabling the construction of firm-year observations that integrate financial indicators with detailed data on pollutants and energy consumption.[66]

Distinguishing between pollutant emission and pollutant generation is crucial due to the heterogeneity in firms' environmental management capacities. A firm's actual pollutant generation may not equal its emissions, as pollutant generation consists of two components: emissions and the amount treated through pollution control measures.[67] Given the variation in energy types and pollutant categories across industries, firms typically consume different types of energy and produce distinct pollutants. To enable meaningful inter-firm comparisons and to avoid inter-correlation among energy sources or pollutants, it is essen-

[64]Samples with missing or fewer than 10 employees were excluded from the analysis. Observations inconsistent with generally accepted accounting principles, such as those with profit margins exceeding 1 or negative net fixed asset values, were also removed. Additionally, samples missing key financial indicators, such as industrial output value or industrial sales value, were excluded. Following Lam et al. (2017), the 2010 data, which has been widely questioned for its reliability, was omitted from the study. To maintain continuity, 2009 and 2011 were treated as consecutive years in the analysis. Continuous explanatory variables were winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers.

[65]However, 30% of the firms have only one year of observation, while the longest observed firms have up to 16 years of data.

[66]Following the approach of Chen and Chen (2019), the initial matching is based on firm names and legal representative codes. This is followed by matching using organization codes and years. The resulting matched dataset is then consolidated, with duplicate entries removed to ensure accuracy and consistency.

[67]Formally, pollutant generation equals pollutant emissions plus pollutant treatment.

tial to aggregate all energy types and pollutants into unified metrics. For pollutants, this study converts various pollutants generated into standardized pollution equivalent units[68] based on the *Pollutant Discharge Fee Collection Standards (2003)*. This regulation assigns specific pollution equivalents to different pollutants[69] and sets discharge fees at 0.7 RMB per pollution equivalent for water pollutants and 0.6 RMB for air emissions. Following Li and Chen (2019), this study applies a weighting adjustment to aggregate pollution equivalents from industrial water pollutants and air emissions, based on the relative discharge fee ratio between the two categories. For energy consumption, China employs "standard coal" as the benchmark for measuring and converting various forms of energy usage. Following the *General Principles for Calculation of Comprehensive Energy Consumption (2008)*, this study converts different types of energy inputs[70] into their equivalent standard coal consumption, incorporating it as an energy input alongside capital and labor. The detailed procedures for calculating pollution equivalents and standard coal equivalents are provided in the next subsections.

Appendix A.1.5 Pollution Equivalents

To standardize all pollutants into comparable units, the emission quantities are first converted into kilograms. Then, pollutant equivalents are calculated using the following formula:

$$\text{Pollutant Equivalent Quantity} = \frac{\text{Emission Quantity of the Pollutant (kg)}}{\text{Equivalent Quantity Value of the Pollutant (kg)}}$$

The Equivalent Quantity Value of the Pollutant is determined according to the specifications outlined in Table 1-5 of the *Pollutant Discharge Fee Collection Standards (2003)*.

[68]The concept of pollution equivalents refers to a standardized measure that compares the harmful effects, toxicity to organisms, and treatment costs of various pollutants to a baseline pollutant. Pollution equivalents serve as a comprehensive metric to assess the environmental impact of different pollutants or emission activities, considering both their detrimental effects on the environment and the technical and economic feasibility of treatment. For pollutants within the same medium, equal pollution equivalent values indicate a roughly equivalent level of environmental harm.

[69]The pollutants included in the analysis primarily consist of: chemical oxygen demand (COD) and ammonia nitrogen emissions from industrial wastewater; sulfur dioxide (SO_2), nitrogen oxides (NO_x), smoke, and industrial dust emissions from industrial air pollutants.

[70]The energy inputs calculated in this study include total coal consumption, total fuel oil consumption, total clean gas consumption, and total industrial water usage.

Appendix A.1.6 Aggregate Energy Consumption

Each type of energy consumption is first converted into its respective unit: water consumption is measured in 10,000 tons, electricity consumption in 10,000 kWh, coal usage in 10,000 tons, natural gas usage in 10,000 cubic meters, gasoline usage in 10,000 tons, diesel usage in 10,000 tons, and district heating in 10,000 GJ. The standardized energy consumption is then calculated by converting all energy variables into equivalent standard coal consumption using the following formula:

$$\begin{gathered}
\text{Standard Coal Equivalent} = (\text{Water Consumption} \times 0.0002429) \\
+(\text{Electricity Consumption} \times 1.229) + (\text{Coal Usage} \times 0.7143) \\
+(\text{Natural Gas Usage} \times 13.3) + (\text{Gasoline Usage} \times 1.4714) \\
+(\text{Diesel Usage} \times 1.4571) + (\text{District Heating} \times 0.03412)
\end{gathered}$$

This calculation consolidates all energy types into a unified measure of standard coal equivalent, ensuring consistency and comparability across observations *(General Principles for Calculation of Comprehensive Energy Consumption (2008))*.

Appendix B Further Details on Survival Analysis

Appendix B.1 Logit Model

The discrete time logit model is a widely used framework in survival analysis, particularly suitable for datasets where events are recorded at discrete intervals, such as annually, monthly or events observed at the end of each governor's term. The fundamental equation of the discrete time logit model expresses the log-odds of the hazard probability as a linear function of covariates and a baseline hazard term:

$$\log\left(\frac{h(t)}{1-h(t)}\right) = c(t) + \beta' X$$

where $h(t)$ represents the conditional probability that a governor is promoted during interval t, given that they have not been promoted before t. The baseline hazard function, $c(t)$, captures the temporal dependency of the promotion hazard, and $\beta' X$ is a linear combination of covariates:

$$\beta = [\beta_1, \beta_2, \beta_3, \ldots, \beta_k]^\top, \quad X = [X_1, X_2, X_3, \ldots, X_k]^\top,$$

$X_1, X_2, \ldots, X_k$ represent the covariates influencing promotion probabilities. These include factors such as the GDP growth gap (actual minus target), the governor's age, experience in higher-level government positions, and education level. Rearranging this equation, the hazard probability can be expressed as:

$$h(t) = \frac{\exp(c(t) + \beta' X)}{1 + \exp(c(t) + \beta' X)}.$$

This framework allows the inclusion of covariates that vary across both individuals and time, reflecting the dynamics of political performance and its influence on career outcomes. In this study, the baseline hazard function $c(t)$ is specified to capture the duration dependence inherent in governor promotions. A common specification is a logarithmic form (Jenkins, 2005):

$$c(t) = (q-1)\ln(t),$$

where q determines whether the hazard rate increases, decreases, or remains constant over time. This flexibility is particularly relevant given the structured evaluation cycles in China's political system, where promotion opportunities are tied to term length. In addition to the parametric specification, this study also considers a non-parametric approach to account for the baseline hazard. The non-parametric method involves creating dummy variables for each discrete time interval to represent the baseline hazard $c(t)$ without imposing a specific functional form. For example, if J is the maximum observed time interval, the baseline hazard is expressed as:

$$c(t) = \sum_{j=1}^{J} \gamma_j \mathbb{I}(t = j),$$

The estimation of the discrete time logit model is conducted using maximum likelihood estimation (MLE). For each individual i, the contribution to the likelihood depends on whether the event of interest (promotion) is observed ($d_i = 1$) or censored ($d_i = 0$) during a given interval t. The log-likelihood function is then written as:

$$\ln L = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[d_{it} \ln h(t) + (1 - d_{it}) \ln (1 - h(t)) \right].$$

Substituting the hazard function $h(t)$ for the discrete time logit model the log-likelihood becomes:

$$\ln L = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[d_{it} \left(c(t) + \beta' X \right) - \ln \left(1 + \exp(c(t) + \beta' X) \right) \right].$$

Once the parameters $\hat{\beta}$ and $\hat{c}(t)$ are estimated, the hazard rate for individual i at time t is calculated using:

$$\hat{h}_i(t) = \frac{\exp\left(\hat{c}(t) + \hat{\beta}' X_i\right)}{1 + \exp\left(\hat{c}(t) + \hat{\beta}' X_i\right)}.$$

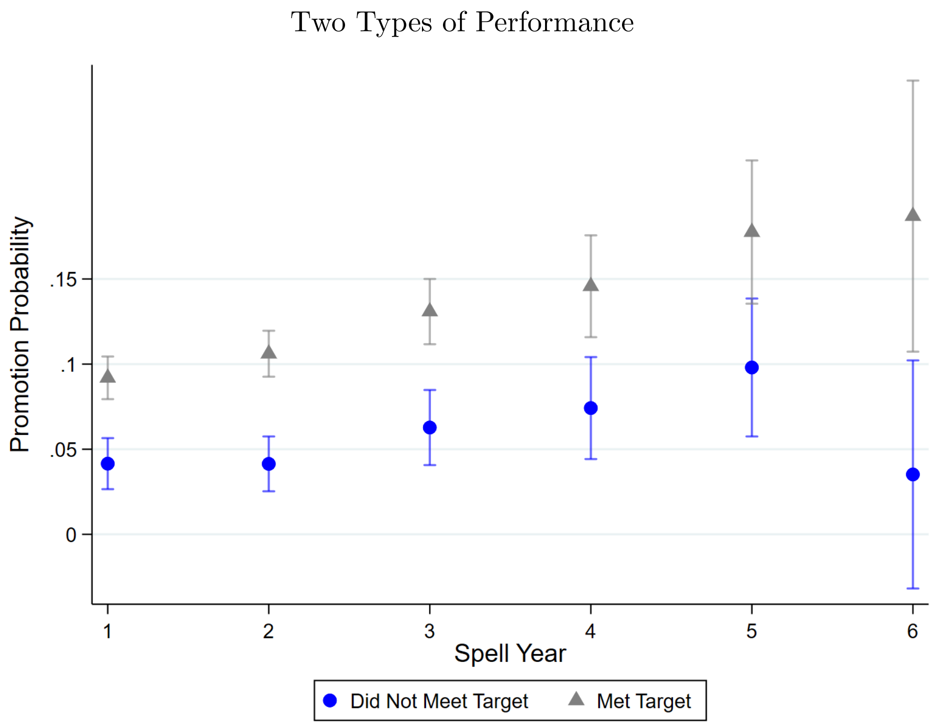
The corresponding survival probability, which represents the likelihood of not being promoted up to time t, is given by:

$$\hat{S}_i(t) = \prod_{j=1}^{t} \left[1 - \hat{h}_i(j) \right].$$

Here, the product accumulates the probabilities of not experiencing the event in each interval from the start until t.

Figure B2 shows the survival probabilities of the two groups of officials as a function of

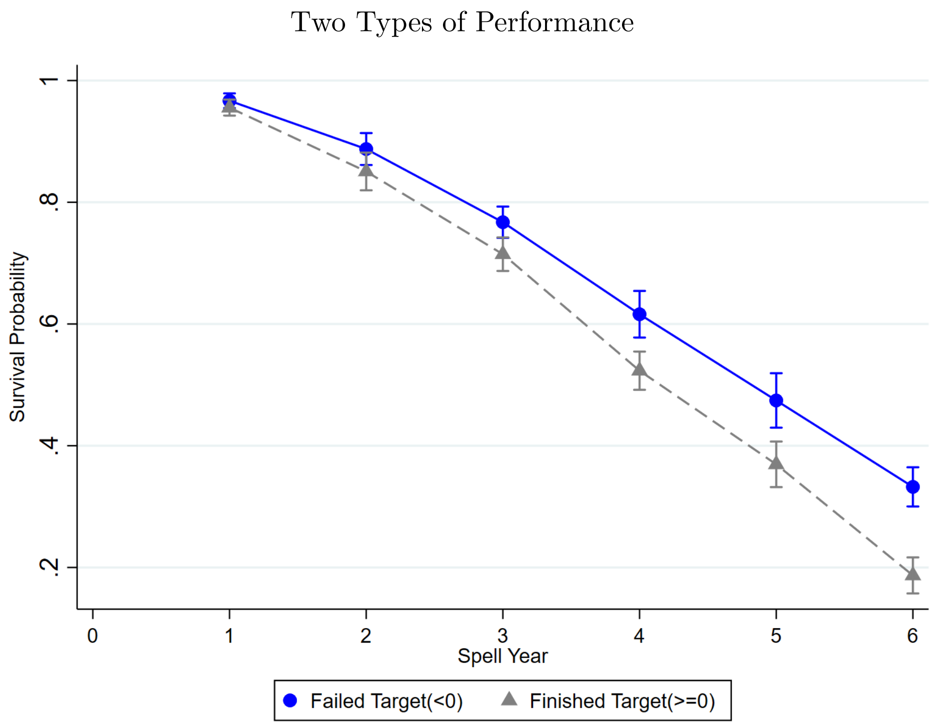
Figure B1: Promotion Probability by Time in Office



Notes: Figure B1 separates officials into two groups—those who met their GDP growth targets and those who did not—and plots their promotion probabilities as a function of tenure length. Each group is constructed conditionally: for example, the second group includes only those who failed to meet the target in the first year, with subsequent groups defined analogously

survival length. Survival probability reflects the likelihood that an official remains in their current position without being promoted. For both groups, survival probability declines as length increases, consistent with the cumulative risk of promotion (or exit) over time. Officials who meet their GDP growth targets (Gap ≥ 0) consistently have lower survival probabilities than those who fail to meet targets (Gap < 0). This inverse relationship highlights the faster promotion rates of target-achieving officials, who are more likely to leave their current positions for higher roles. The steep decline in survival probabilities for target-achieving officials reflects their accelerated career trajectories. In contrast, officials who fail to meet targets experience a slower decline in survival probabilities, indicating longer tenures in their current roles due to delayed promotion or stagnation. This divergence underscores the meritocratic nature of the promotion process, officials who fail to meet growth targets are promoted more slowly, resulting in higher survival probabilities in their current positions.

Figure B2: Survival Rate by Time in Office



Notes: Figure B2 divides officials into two groups: those who achieved their GDP growth targets and those who did not. The figure illustrates the survival probabilities of two groups of officials as a function of tenure length. The second group includes only observations where the target was not achieved in the first year, and the same logic applies to subsequent groups. In other words, this graph tracks the survival rate over time conditional on initial performance, failed the first year target.

Appendix B.2 Non-parametric Baseline Hazard

The first column of Table B1 presents the results of the logit model using a non-parametric specification for the baseline hazard. The odds ratio for the Actual-Target Gap indicates that a one-unit increase in the gap raises the odds of promotion by approximately 9.5%. Similarly, the odds of promotion increase by 3.1% for each additional year of the governor's age, 16.2% for higher education levels, and 15% for prior governmental experience. All results are highly significant and align closely with those from the parametric model, underscoring their robustness. The primary focus of this non-parametric analysis is the dummy variables $j = 1$ to $j = 9$, which represent the log-hazard for each discrete time interval, capturing the non-parametric baseline hazard. These coefficients offer insights into the evolution of promotion probabilities over time. All $j = 1$ to $j = 9$ coefficients are negative, indicating a generally low baseline hazard across these intervals. The magnitude of the coefficients decreases over time (i.e., becomes less negative), suggesting a rising hazard rate as tenure lengthens.[71] However, the relatively modest magnitude of the $j = 9$ coefficient suggests that promotion likelihood may stabilize or even decline slightly at extended durations. This non-monotonicity could stem from institutional or political constraints, where prolonged tenure might indicate stagnation or reduced opportunities for advancement (Li and Zhou, 2005). In summary, the non-parametric baseline hazard reveals an increasing promotion probability over time, particularly during early intervals.

Appendix B.3 Complementary Log-Log Model

The second model employed in this study is the complementary log-log (cloglog) model[72]. Both the cloglog and logit models are widely used to estimate discrete-time event probabilities; however, they differ in their underlying assumptions and functional forms. Specifically, the cloglog model is based on a proportional hazards framework, modeling the hazard rate as:

$$h(t) = 1 - \exp\left(-\exp\left(c(t) + \beta' X\right)\right),$$

In contrast, the logit model assumes proportional odds and uses the logistic function $\frac{\exp(\cdot)}{1+\exp(\cdot)}$. The cloglog model approximates continuous-time proportional hazards models, such as the Cox model (Cox, 1972), when time is divided into discrete intervals. This characteristic makes it especially appropriate for this study, as promotions are recorded on an annual basis, even though the political processes driving them likely unfold in a more continuous manner. On the other hand, the logit model is more flexible, as it does not assume a connection to continuous-time processes. Substituting the cloglog hazard function $h(t)$, the log-likelihood becomes:

$$\ln L = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[d_{it} \cdot \ln\left(1 - \exp\left(-\exp\left(c(t) + \beta' X\right)\right)\right) - (1 - d_{it}) \cdot \exp\left(-\exp\left(c(t) + \beta' X\right)\right)\right].$$

The hazard rate and survival probability are calculated in a manner similar to that described in previous section.

[71] For example, the coefficient for $j = 1$ is -4.752, while for $j = 9$, it is -1.675. This pattern reflects an increasing probability of "failure" with longer survival, although the trend is not strictly monotonic.

[72] also known as the *Prentice-Gloeckler (1978) model*

Table B1: Survival Analysis with Non-parametric Baseline Hazard

	Promotion Dummy		
	(1)	(2)	(3)
	Logit	Complementary log-log	Generalized Gamma
Actual-Target Gap	0.091***	0.081***	0.111***
	(0.020)	(0.018)	(0.024)
Age of Governor	0.031***	0.027***	0.058***
	(0.012)	(0.010)	(0.018)
Education Level	0.150**	0.132**	0.153
	(0.068)	(0.061)	(0.100)
Prior Experience	0.140***	0.125***	0.230***
	(0.046)	(0.042)	(0.072)
$j = 1$	-4.752***	-4.540***	-6.712***
	(0.640)	(0.565)	(0.983)
$j = 2$	-3.800***	-3.635***	-5.532***
	(0.644)	(0.567)	(0.973)
$j = 3$	-3.865***	-3.690***	-5.429***
	(0.655)	(0.576)	(0.966)
$j = 4$	-3.116***	-3.026***	-4.387***
	(0.660)	(0.581)	(0.946)
$j = 5$	-2.991***	-2.912***	-3.887***
	(0.672)	(0.591)	(0.947)
$j = 6$	-2.888***	-2.816***	-3.464***
	(0.692)	(0.605)	(0.975)
$j = 7$	-3.053***	-2.983***	-3.284***
	(0.726)	(0.638)	(1.046)
$j = 8$	-2.981***	-2.915***	-2.651**
	(0.818)	(0.714)	(1.192)
$j = 9$	-1.675*	-1.927***	-1.012
	(0.904)	(0.728)	(1.445)
Observations	4508	4508	4504

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Similar to Table 1, this table presents the results of survival analysis using a non-parametric baseline hazard. The three columns correspond to the results of three different models, all utilizing the same covariates. Dummy variables $j = 1$ to $j = 9$ represent the log-hazard for each discrete time interval (duration interval) and define the non-parametric baseline hazard. These dummy variables are associated with specific time periods, and their coefficients provide insight into how the hazard rate evolves across different durations. The coefficients for j_1 to j_9 are all negative, indicating that the baseline hazard remains generally low during these intervals. However, the coefficients tend to become less negative over time, suggesting a rising hazard rate across intervals, albeit not in a strictly monotonic fashion. This pattern is consistent with the idea that promotion probabilities may increase as time elapses, a common characteristic observed in many survival processes.

The second column of Table 1 presents the results from the complementary log-log (cloglog) model, which estimates the hazard rate of promotion under the proportional hazards assumption. The coefficients are slightly smaller than those obtained from the logit model.[73] The odds ratios derived from the cloglog model demonstrate consistent and highly significant relationships between the covariates and the likelihood of promotion. Specifically, a one-unit increase in the Actual-Target Gap corresponds to an approximate 8.3% increase in the promotion probability. Similarly, the effects of other covariates are broadly consistent with those observed in the logit model. These results further confirm the robustness of the covariates across different survival modeling approaches. Column 2 of Table B1 provides the results of the cloglog model with a non-parametric baseline hazard. The observed differences between this specification and the cloglog model with a logarithmic baseline hazard are comparable to those noted between the two corresponding logit specifications.

Appendix B.4 Survival Model with Frailty

In survival analysis, accounting for unobserved heterogeneity, often termed frailty, is essential (Heckman and Singer, 1984). Frailty represents individual-specific factors that influence the hazard rate but are not directly observed in the data. Neglecting frailty can result in biased parameter estimates, particularly when systematic differences between individuals are omitted. In this study, frailty captures unobserved factors affecting city governors' promotion probabilities, such as personal political networks or managerial skills, which are challenging to quantify. Incorporating frailty addresses several potential biases. First, it prevents misestimation of duration dependence, avoiding exaggerated declines or understatements of the hazard rate over time. Second, it ensures that the effects of observed covariates—such as GDP growth performance, prior government experience, and education—remain accurate and are not diminished by omitted unobserved variables. One way to incorporate frailty is by introducing a random effect into the hazard function, which scales the hazard rate for each individual (Meyer et al., 1991). The frailty-adjusted hazard function is expressed as:

[73] The coefficients are slightly smaller than those in the logit model, reflecting differences in the underlying assumptions of the two approaches. The logit model assumes a symmetric cumulative distribution function (logistic distribution), which assigns more weight to outcomes in the middle of the probability range. This often results in larger coefficients when covariates have a strong effect. In contrast, the cloglog model assumes an asymmetric distribution, placing greater emphasis on extreme values. This asymmetry can dampen coefficient magnitudes, particularly if the effects of covariates are less pronounced in these tails.

$$h(t|X, v) = 1 - \exp\left(-\exp\left(c(t) + \beta' X + \ln(v)\right)\right),$$

where v introduces individual-level variability in the hazard. The corresponding survivor function is:

$$S(t|X, \sigma^2) = \int_0^\infty S(t|X, v) f(v; \sigma^2) dv,$$

where $S(t|X, v) = \exp\left(-\sum_{j=1}^{t} \exp(c(j) + \beta' X + \ln(v))\right)$, and $f(v; \sigma^2)$ is the probability density function of v, typically assumed to follow a Gamma distribution with a mean of 1 and variance σ^2. The log-likelihood function is given by:

$$\ln L = \sum_{i=1}^{N} \ln\left[(1 - d_i) A_i + d_i B_i\right],$$

where d_i is an indicator variable that equals 1 if the event (promotion) occurs for individual i and 0 otherwise. The terms A_i and B_i are components of the likelihood that account for the integration over the frailty distribution. The component A_i captures the likelihood of observing no promotion up to the last interval T_i, and is defined as:

$$A_i = \left[1 + \sigma^2 \sum_{j=1}^{T_i} \exp\left(c(j) + \beta' X_{ij}\right)\right]^{-\frac{1}{\sigma^2}},$$

where $c(j)$ represents the baseline hazard at time j, and $\beta' X_{ij}$ denotes the linear combination of covariates for individual i at time j. The term B_i accounts for the likelihood contribution from the event occurring in the last observed interval. It is specified as:

$$B_i = \begin{cases} 1 - A_i, & \text{if } T_i = 1, \\ \left[1 + \sigma^2 \sum_{j=1}^{T_i - 1} \exp\left(c(j) + \beta' X_{ij}\right)\right]^{-\frac{1}{\sigma^2}} - A_i, & \text{if } T_i > 1. \end{cases}$$

As $\sigma^2 \to 0$, the frailty model simplifies to the standard complementary log-log model without frailty, where unobserved heterogeneity is ignored.

The third column of Table 1 presents the results of the survival model with frailty. Compared to the logit and cloglog models, the coefficients in the frailty model are larger in magnitude. This reflects the model's ability to capture unobserved individual differences that might otherwise dilute the effects of observable covariates. While the direction and significance of the results remain consistent with previous models, the larger coefficients emphasize the amplified roles of all the covariates when individual heterogeneity is accounted for. A one-unit increase in the GDP growth gap raises the promotion probability by 10.3% ($p < 0.01$), while each additional year of the governor's age increases it by 4.6% ($p < 0.01$). Prior governmental experience boosts promotion probability by 17% ($p < 0.01$), and higher education levels are associated with an 11% increase ($p < 0.05$). These findings underscore the importance of both observable and unobservable factors in shaping promotion outcomes. The non-parametric results also remain largely consistent.

Appendix C Additional in Bunching Estimation

Appendix C.1 Round Number Bunching And Fixed Effects

Targets are often set as round numbers, such as 6 or 7.5 percent in a given year, prompting self-reported actual values to align similarly in order to achieve a gap of zero. However, the reference point effect (Kahneman and Tversky, 1979) can cause round numbers to attract more bunching due to their simplicity, neatness, and convenience. This means that observed bunching may be influenced by factors unrelated to incentive changes. Therefore, I control for round number bunching to prevent overestimating responses at round-numbered kinks. Politicians may bunch at these points for reasons beyond simply meeting the target. This accounts for the perception that gaps, such as 1 percent below or 2.5 percent above, are considered "rounder" and thus may attract more bunching. Failure to control for round number bunching can significantly bias the bunching estimate upwards if z^* is also a round number (Kleven and Waseem, 2013; Dube et al., 2020). Additionally, since politicians might prefer consistently exceeding the target to distinguish themselves from others, I include fixed effects for bins in the set of $K = \{z_1^*, z_2^*\}$ that are outside the excluded region but included in the counterfactual estimation. This helps to net out any potential influence of nearby kinks from the counterfactual. Not controlling for other bunching masses can exert a downward bias on the bunching estimate at z^* by inflating the counterfactual estimate (Mavrokonstantis and Seibold, 2022). Formally, I re-estimate the observed frequency in bin j by incorporating round-number dummies (the third term) and nearby-kink dummies (the fourth term):

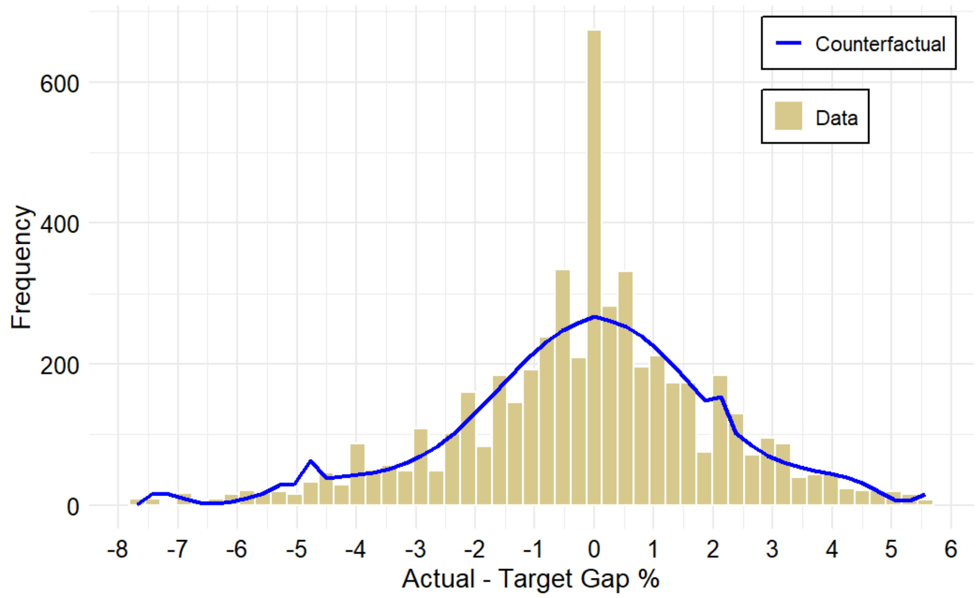
$$C_j = \sum_{i=0}^{p} \beta_i (z_j)^i + \sum_{i=z_L}^{z_U} \gamma_i \mathbb{1}\left[z_j = i\right] + \sum_{r \in R} \rho_r \mathbb{1}\left[\frac{z_j}{r} \in \mathbb{N}\right] + \sum_{k \in K} \theta_k \mathbb{1}\left[z_j \in K \wedge z_j \notin [z_l, z_u]\right] + v_j$$

Panel C and Panel D of Figure C2 and second lines of Table 2 show the results after adding these controls. The estimates remain significant.

Appendix C.2 Integration Constraint Correction

The initial estimate $\hat{b}_0$ may be biased because it overlooks how politicians internally respond. For example, if halfway through the year they discover that economic growth is below expectations, they might intensify efforts in the latter half to ensure they meet the

Figure C1: Counterfactuals with Controls



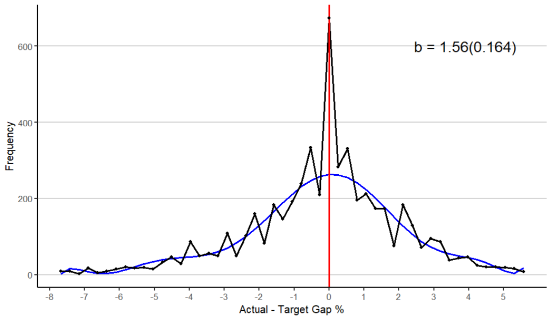
Notes: "Round number" effects are captured by indicators for whether the gap is a multiple of 0.5%, addressing the possibility that officials disproportionately report figures rounded to psychologically salient values. "Nearby kink" controls target other regions in the distribution where abnormal clustering is observed outside the main bunching region. Two such intervals are identified: [2%, 3%] and [–1%, –0.2%]. After incorporating these controls, the estimated excess mass declines, indicating that part of the observed bunching is attributable not only to promotion incentives but also to reporting tendencies favoring round numbers and specific intervals.

growth target. Consequently, the empirical distribution below z^* naturally appears lower than it would be without this distortion. Thus, the straightforward calculation mentioned earlier tends to overestimate the excess mass by disregarding the additional mass at the kink originating from points to the left of z^*. As a result, the observed distribution below the bunching region inaccurately represents the true counterfactual due to the shift it has undergone.

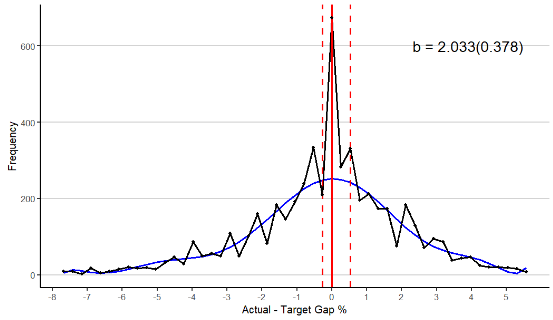
Following the approach outlined by Chetty et al. (2011) for adjusting the counterfactual density to the left of the kink, known as the integration constraint correction, involves shifting the counterfactual distribution upwards on the left side z^* until the number of observations in the empirical distribution aligns with the count in the counterfactual distribution. Despite some skepticism[74], subsequent literature has affirmed the plausibility and

[74] Conflicting perspectives in the literature regarding the adjustment of the counterfactual density in the presence of significant extensive responses (Kleven, 2016)

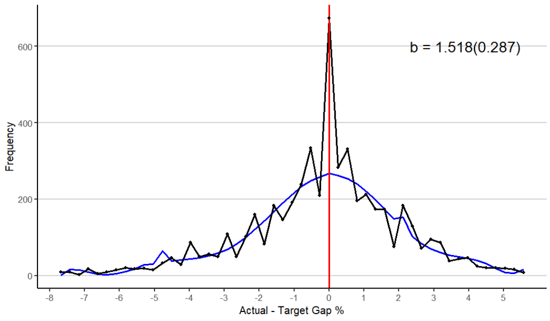
Figure C2: Gap Distribution And Bunching Estimator



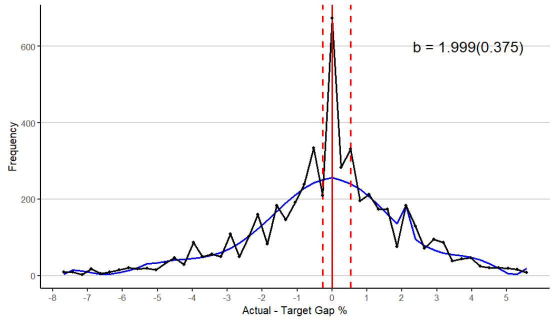
(a) Panel A: Sharp Bunching



(b) Panel B: Diffuse Bunching



(c) Panel C: Sharp Bunching: Round #

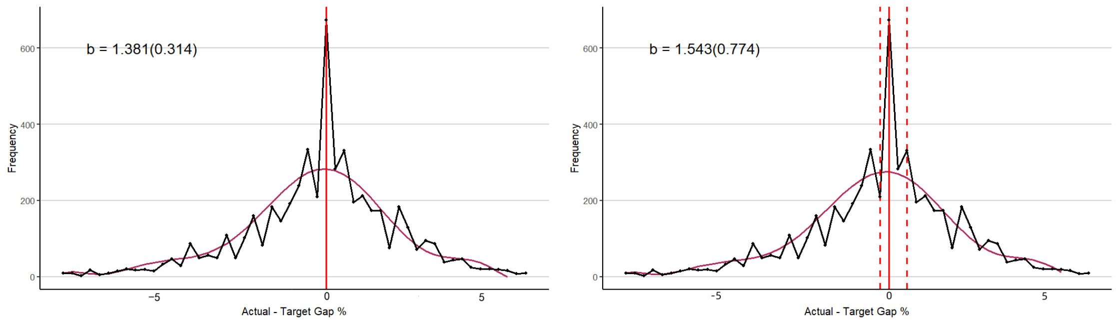


(d) Panel D: Diffuse Bunching: Round #

Notes: Figure C2 illustrates the empirical distribution of the actual minus target gap (black line) alongside the estimated counterfactual distribution (blue line). The estimated excess mass is shown in the upper right corner of each panel, with bootstrapped standard errors in parentheses. Panels A and B present the baseline estimates: sharp bunching focuses on a gap of zero as the bunching threshold, while diffuse bunching considers a range (in this case, [-0.2, 0.5]) as the bunching region. The selection of the bunching window is based on visual inspection. Panels C and D show sharp and diffuse bunching, respectively, with added controls for round numbers and nearby kinks. "Round number" refer to the inclusion of dummies for multiples of 0.5% in the actual minus target gap, examining whether these values induce additional bunching in the gap distribution. Specifically, I controlled for whether the gaps are multiples of 0.5%. "Nearby kinks" dummies address other regions of extra mass in the distribution outside the main bunching region. In my analysis, I identified two distinct intervals of extra mass: between 2% and 3%, and between -1% and -0.2%. The estimates of excess mass decrease after adding more controls, suggesting that beyond the incentive to meet targets, officials tend to report GDP figures that gravitate towards round numbers.

validity of this approach (Mortenson and Whitten, 2020; Bergolo et al., 2021). This approach specifically involves defining the counterfactual distribution $\hat{C}_j$ as the fitted values obtained from the regression:

Figure C3: Bunching Estimator After Correction



(a) Panel A: Sharp Bunching

(b) Panel B: Diffuse Bunching

Notes: Figure C3 presents the adjusted sharp and diffuse bunching estimators following the integration constraint correction. This correction involves shifting the counterfactual distribution upward to the right of the bunching region.

$$C_j\left(1+\mathbb{1}[j<z_L]\frac{\hat{B}_0}{\sum_{j=z^*-1}^{\infty} C_j}\right)=\sum_{i=0}^{p}\beta_i(z_j)^i+\sum_{i=z_L}^{z_U}\gamma_i\mathbb{1}\Big[z_j=i\Big]+\sum_{r\in R}\rho_r\mathbb{1}\left[\frac{z_j}{r}\in\mathbb{N}\right]$$
$$+\sum_{k\in K}\theta_k\mathbb{1}\Big[z_j\in K\wedge z_j\notin[z_l,z_u]\Big]+v_j$$

The calculation proceeds iteratively until it reaches a fixed point. The empirical estimate of $\hat{B}$ is then derived from this corrected counterfactual representing the excess mass around the kink relative to the average density of the counterfactual distribution between $[z_L, z_U]$:

$$\hat{b}=\frac{\hat{B}_0}{[(z_U-z_L)/\delta]^{-1}\sum_{j=z_L}^{z_U}\hat{C}_j}$$

Note that the denominator of $\hat{b}$ is the average density of counterfactual gap distribution within the bunching window. Panel A and Panel B of Figure C3 illustrate the sharp bunching and diffuse bunching after the correction, respectively. The corrected estimate of excess mass is presented in the third lines of Table 2. As anticipated, a marginal decline in significance is observed following the correction. This is attributed to the upward adjustment of the counterfactual below z^*.

Appendix D Connected Sample

Appendix D.1 Connected Cities

Table D1 presents the "connectedness" of cities within the sample. Among the 339 cities analyzed, 59 are classified as "isolated," as no governors in these cities have served in equivalent positions in other cities during the past 20 years. These cities cannot be linked by movers. The remaining 280 cities have at least one mover—an official who, during their career, held the same position in another city.[75] The isolated cities in the sample include data on 317 officials, while the non-isolated cities account for observations from over 1,500 officials. The spatial distribution of non-isolated cities is relatively uniform, covering cities across 31 provinces, which represents 97% of China's total provincial-level administrative regions. The lower part of Table D1 provides details on non-isolated cities, which can be further grouped based on their networks. Most connected groups are small, typically linked by only one or two officials, and these connections often occur within the same province. However, Group 1 stands out as a significantly larger subsample, encompassing three-quarters of all non-isolated cities through a single interconnected network. The remaining one-quarter of non-isolated cities form separate, independent networks. The subsequent analysis focuses primarily on all non-isolated cities, with additional emphasis on Group 1 cities.

Appendix D.2 Link to Promotion Outcomes

This subsection serves as a robustness check for the previous sections on political incentives by linking leaders' individual contributions to closing the growth gap with their promotion outcomes. The aim is to mitigate the influence of external factors, such as city-level economic conditions and other sources of endogeneity. It is worth noting that to address the inherent indeterminacy of the fixed-effects model, a constraint ($\sum_i \theta_i = 0$) was imposed on leader fixed effects. This constraint ensures that the estimated fixed effects represent each leader's deviation relative to the average of all leaders, rather than their absolute contribution[76]. Without an external reference point or absolute benchmark, the model cannot attribute economic growth solely to the effect of a particular leader but can only identify their relative ranking among all leaders. This approach is akin to estimating relationships

[75] Most movers were transferred within the same province or to neighboring provinces.

[76] For example, $\theta_i > 0$ indicates that the leader's contribution to meet target exceeds the average, while $\theta_i < 0$ suggests it falls below the average.

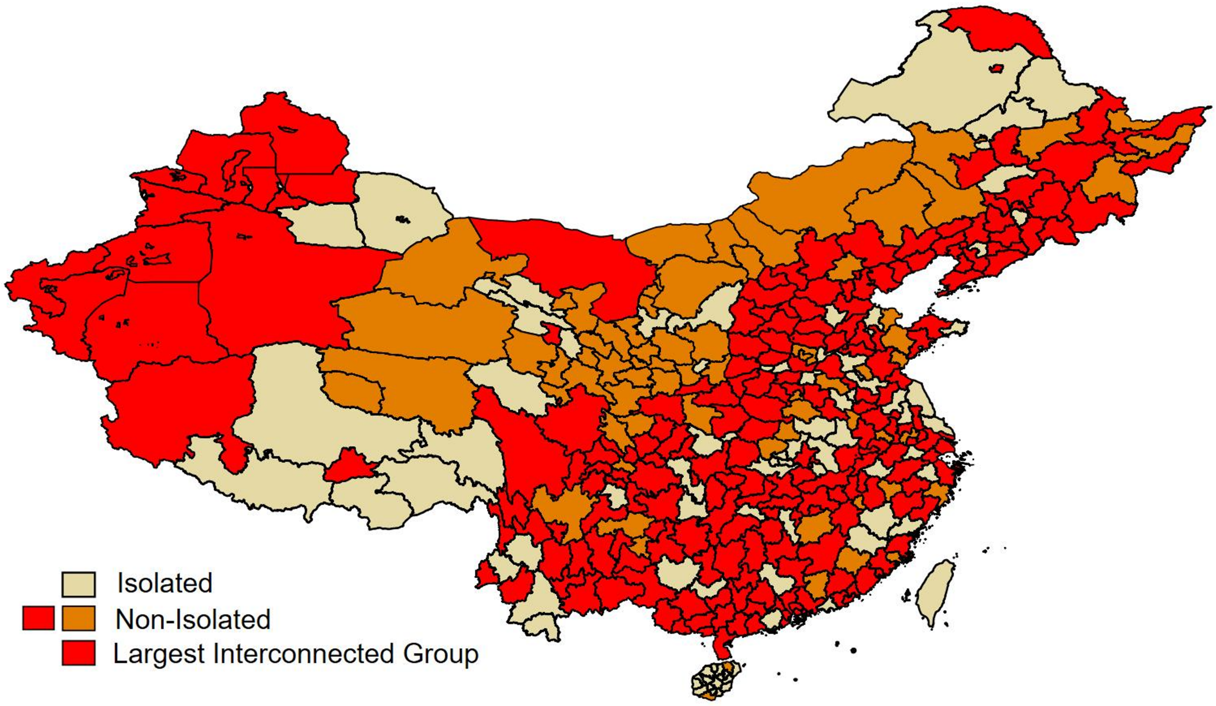
Table D1: Connected Groups

Group	Observations	Officials	Movers	Cities	Prov. Invol.
Isolated	1353	317	0	59	25
Non-isolated	6274	1532	274	280	31
Interconnected Groups within Non-isolated Cities					
Group 1	4695	1139	220	208	27
Group 2	552	136	24	26	4
Group 3	136	36	7	6	2
Group 4	92	20	4	4	3
Group 5	67	18	2	3	1
Group 6	60	14	2	3	1
Group 7	69	18	2	3	1
Group 8	70	15	1	3	2
Group 9	46	11	1	2	1
Group 10	44	11	1	2	1
Group 11	46	13	1	2	2
Group 12	44	14	1	2	1
Group 13	46	13	1	2	1
Group 14	46	12	1	2	1
Group 15	44	10	1	2	1
Group 16	40	10	1	2	1
Group 17	46	9	1	2	1
Group 18	44	13	1	2	1
Group 19	43	7	1	2	1
Group 20	44	13	1	2	1
Total	6274	1532	274	280	

Notes: This table summarizes the distribution of observations across isolated and non-isolated groups, including a breakdown of interconnected groups within non-isolated cities. The columns in the table provide information on the number of observations, officials, movers, cities, and provinces involved in each group. Provinces involved refers to the number of distinct provinces represented by the cities within each group. Movers denotes officials who held the same position (governor) in (at least) two different cities. Groups 1–20 represent mutually-exclusive, single interconnected networks of cities.

within a network of interconnected nodes: one can determine how much stronger one node is compared to another, but not the absolute strength of each node. This section, in fact, examines the relationship between leaders' relative rankings in meeting growth targets and

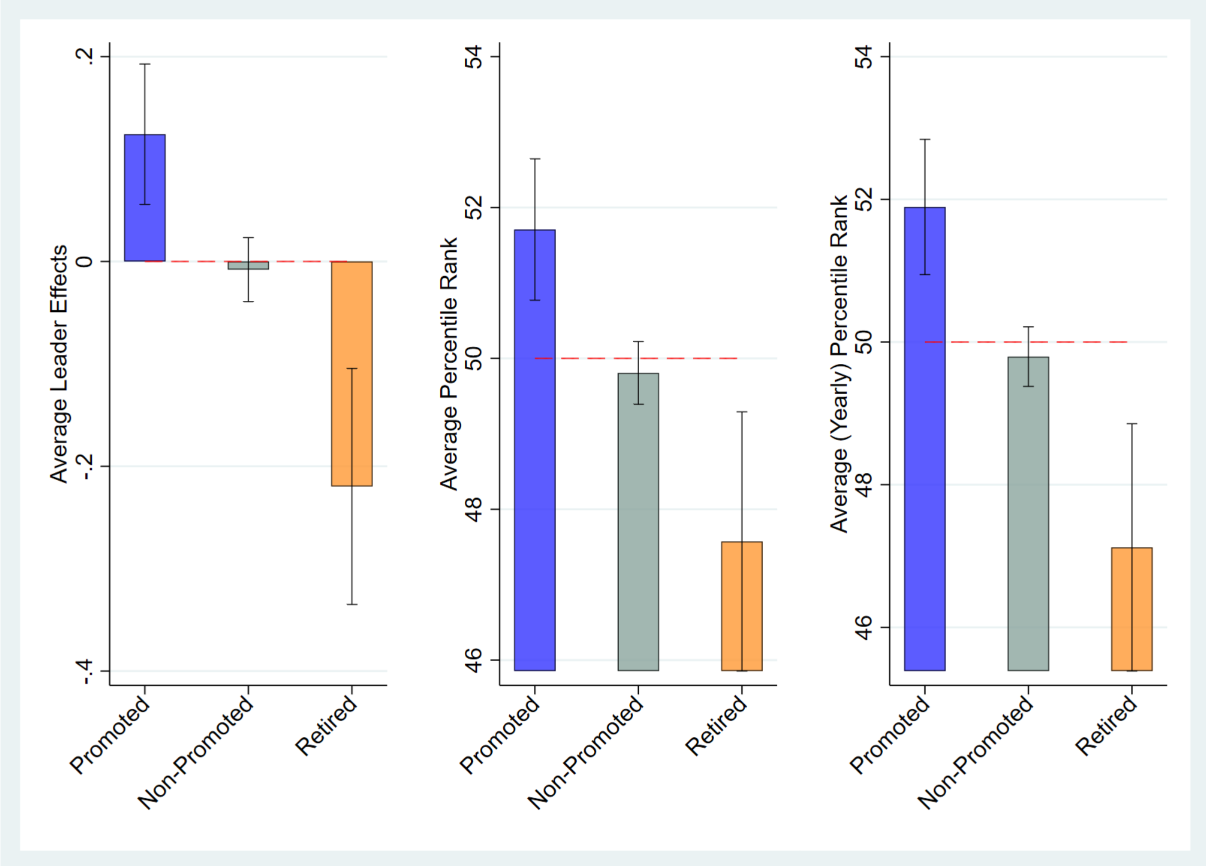
Figure D1: Connected Cities



their promotion outcomes. If the findings from the previous sections are robust, leaders with higher relative contributions to closing the growth gap should demonstrate a greater likelihood of promotion.

Figure D2 illustrates the average leader fixed effects across different promotion outcomes: promoted, non-promoted, and retired. The middle panel presents the average percentile rankings of leader fixed effects after converting them into their relative ranks within the distribution. The rightmost panel further refines this analysis by calculating yearly percentile rankings to account for potential variations in promotion competition across different years. The results show that, on average, promoted officials exhibit above-average (rank $> 50\%$) performance in meeting growth targets compared to their peers. Non-promoted officials, including those laterally transferred, demonstrate performance close to but slightly below the average. Retired officials, on the other hand, perform the worst on average, likely reflecting their diminished incentives for achieving growth targets due to limited promotion prospects, often related to age or retirement eligibility (Zeng and Zhou, 2024). The average percentile rank results align with these findings and remain robust, whether calculated across the full sample or on a year-by-year basis. Notably, the average

Figure D2: Average Leader Effects by Promotion Status



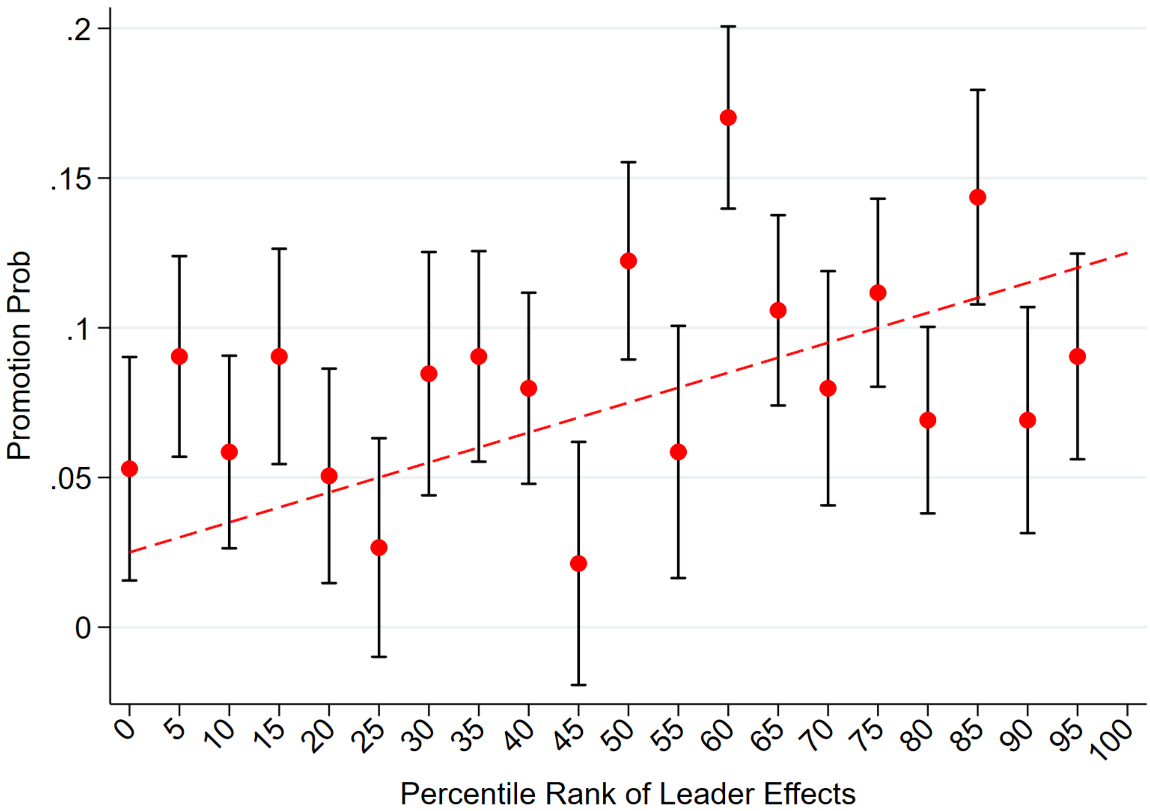
Notes: This figure presents the average leader effects across different promotion outcomes, along with the corresponding percentile ranks derived from their distribution. The rightmost panel illustrates leaders' yearly percentile ranks, calculated annually to provide a year-specific relative ranking.

rank of officials corresponding to city-year observations where the growth gap equals zero (i.e., targets are precisely met) is approximately 51%. This is very similar to the average rank of officials who were promoted, suggesting that promoted officials are, on average, likely to have successfully achieved their targets.

Figure D3 illustrates the relationship between an official's promotion probability and their rank in the distribution of leader effects. While some variation exists, the overall trend indicates that officials with higher relative contributions to meeting growth targets are more likely to be promoted.

The regression results presented in Table D2 further reinforce the relationship depicted in Figure D3. The dependent variable is a promotion dummy, and the demographic controls used at the leader level are nearly identical to those in Section 4.1. However, the

Figure D3: Promotion Probability by Percentile Rank of Leader Effects



main independent variable here is the leader's percentile rank in contributing to closing the growth gap, rather than the actual-minus-target gap. The left three columns report results for all non-isolated cities, while the right three columns focus on the Group 1 cities subsample.[77] Columns (3) and (6) use yearly-calculated ranks as the main independent variable instead of ranks derived from the entire sample. The results, however, remain highly consistent regardless of which rank measure is used. Specifically, the findings suggest that a 1% improvement in a leader's rank relative to others increases their promotion probability by 0.17–0.18%. For example, a 20% improvement in rank corresponds to a 3.4–3.6% higher likelihood of promotion. Given the average promotion probability is only about 8–10%, this effect is substantial. Additionally, longer tenure is associated with a

[77]Group 1 cities represent the largest subset of non-isolated cities connected by a single, cohesive network, mutually exclusive from other groups.

Table D2: Leader Effects and Promotion Outcomes

	Promotion Dummy					
	All Non-Isolated Cities			*Group 1 Cities*		
	(1)	(2)	(3)	(4)	(5)	(6)
Percentile Rank	0.0015**	0.0018**	0.0019**	0.0016**	0.0017**	0.0017**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure		-0.0931***	-0.0932***		-0.0956***	-0.0957***
		(0.013)	(0.013)		(0.016)	(0.016)
Prior Experience		0.0814***	0.0813***		0.0846***	0.0847***
		(0.024)	(0.024)		(0.029)	(0.029)
Education Level		0.1776***	0.1776***		0.1757***	0.1758***
		(0.037)	(0.037)		(0.047)	(0.047)
Age of Governor		0.0003	0.0003		0.0011	0.0011
		(0.006)	(0.006)		(0.008)	(0.008)
Observations	3857	3775	3775	2726	2656	2656
Year FE	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table presents regression results examining the relationship between a leader's fixed-effects percentile rank and their promotion outcomes. The left panel includes all non-isolated cities, while the right panel focuses on Group 1 cities—defined as the largest mutually exclusive group of cities connected by a single, interconnected network within the non-isolated sample. Columns (1) and (4) exclude demographic characteristic controls, while Columns (2) and (5) incorporate them. Columns (3) and (6) use year-by-year percentile ranks instead of full-sample rankings.

lower likelihood of promotion, consistent with the idea that high-performing officials are more likely to be promoted quickly—aligning with the findings in Section 4.1. The influence of other demographic characteristics on promotion remains largely consistent with earlier conclusions. Results from the full sample and the Group 1 subsample are also remarkably similar, further validating the robustness of the findings.

Appendix E Robustness Tests

Appendix E.1 Validation with Listed Firms Subsample

The first robustness test narrows the sample to focus exclusively on listed firms within the entire sample, using an alternative data source. Previous studies have raised concerns about the overall quality of the CIED dataset, citing missing key variables or low-quality observations for some firms in certain years (Dai et al., 2021; Brandt et al., 2014). In contrast, listed firms typically provide higher-quality, standardized data due to regulatory requirements, minimizing the risk of measurement errors in critical variables like inventory changes (Chen et al., 2015). Moreover, listed firms often represent larger, more economically significant enterprises whose behavior is likely to be more responsive to political pressures, making them a valuable focus for this analysis (Piotroski et al., 2015; Dyreng et al., 2016). Although listed firms are not fully representative of all firms in the economy, focusing on them reduces the sample size to approximately one-tenth of the original dataset.

Table E1 presents results specifically for listed firms, with data sourced from the CSMAR database rather than the previously used CIED, serving as a robustness check for Table 4. The magnitude of changes in inventory is even larger, which aligns with expectations, as listed firms are typically larger, more responsive, and possibly more susceptible to any influence. The significance of sales decreases slightly, potentially due to the alternative dataset lacking direct sales data for listed firms, requiring the use of proxies. Nonetheless, the overall direction of the results remains consistent with the previous findings.[78]

Appendix E.2 Placebo Analysis

In this subsection, a Placebo Analysis, or Pseudo Gap Test, is performed, conceptually resembling a falsification test. Specifically, alternative artificial thresholds for the running variable are created, such as ± 2 or ± 3. This involves redefining the dummy variable D in the main specification by shifting the critical point for target completion—for instance, setting gap ≥ -3 or gap ≥ 2. The regression discontinuity design is then re-estimated around each pseudo gap to evaluate whether significant discontinuities (jumps) appear at these artificial thresholds. The primary goal of this analysis is to rule out spurious patterns (Athey and Imbens, 2017). Ideally, pseudo gaps should be placed as far as possible from the

[78] The sales data from the CIED is intentionally not used in this analysis, not only due to the limited sample size but also because one of the primary objectives of this robustness test is to address potential unreliability in the original dataset.

Table E1: Robustness Test (1): Listed Firms Subsample

Panel A: Inventory Changes					
	$\ln \text{Inventory}_t - \ln \text{Inventory}_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
β	0.068***	0.070***	0.070***	0.067***	0.068***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Firm FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
City Trends				✓	✓
Controls					✓
Observations	18026	18026	18026	18026	17985
R^2	0.0050	0.0063	0.0063	0.0084	0.0128
Panel B: Sales (a proxy)					
	$\ln \text{Sales}_t$				
	(1)	(2)	(3)	(4)	(5)
β	0.018	0.020**	0.020**	0.015*	0.014*
	(0.012)	(0.009)	(0.009)	(0.009)	(0.009)
Firm FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
City Trends				✓	✓
Controls					✓
Observations	19162	19162	19162	19162	19119
R^2	0.0058	0.0096	0.0096	0.0228	0.0381

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table replicates the specification in Table 4, but limits the sample to publicly listed firms. Direct sales data are not available for listed firms; instead, sales are approximated by multiplying net accounts receivable by the accounts receivable turnover ratio. The results remain consistent, especially for inventory change regressions.

actual target completion threshold (gap = 0) to minimize the influence of diffuse bunching, as discussed in Section 4. Nevertheless, the analysis considers all pseudo gaps at ±1, ±2, and ±3.

Table E2: Robustness Test (2): Placebo Analysis

Panel A: Placebo – Inventory Changes							
	$\ln \text{Inventory}_t - \ln \text{Inventory}_{t-1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D_{jt} = 1$ if	gap ≥ 0	gap ≥ 1	gap ≥ 2	gap ≥ 3	gap ≥ -1	gap ≥ -2	gap ≥ -3
β	0.061***	-0.000	-0.000	0.003	0.064***	-0.000	-0.003
	(0.008)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)
Observations	189981	189981	189981	189981	189981	189981	189981
R^2	0.0017	0.0013	0.0013	0.0013	0.0017	0.0015	0.0017

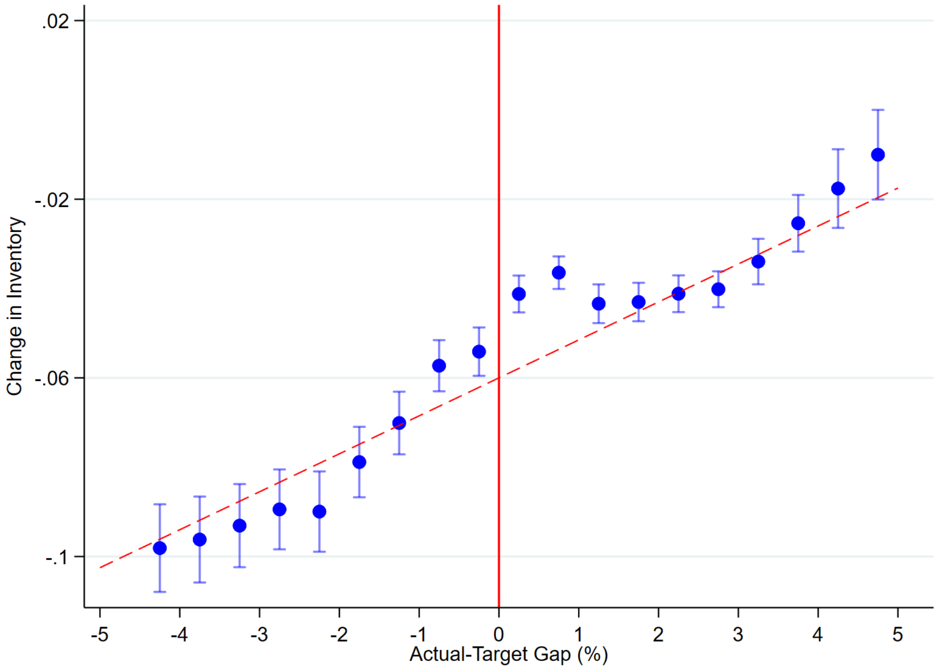
Panel B: Placebo – Sales							
	$\ln \text{Sales}_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D_{jt} = 1$ if	gap ≥ 0	gap ≥ 1	gap ≥ 2	gap ≥ 3	gap ≥ -1	gap ≥ -2	gap ≥ -3
β	0.044***	-0.002	0.015	0.015	0.004*	-0.000	-0.005
	(0.004)	(0.005)	(0.014)	(0.031)	(0.002)	(0.003)	(0.003)
Observations	279519	279519	279519	279519	279519	279519	279519
R^2	0.0098	0.0015	0.0089	0.0088	0.0014	0.0015	0.0017

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table presents robustness test results for placebos in inventory change and sales. Panel A reports results for inventory change, while Panel B reports similar results for sales. Each column corresponds to a specific gap value (Gap=1, Gap=2, Gap=3, etc). This means that the gap definition used in each column corresponds to different threshold specifications. Column (1), where gap = 0, aligns with the last column of Table 4, representing the main results. Subsequent columns redefine the breakpoint location, effectively redefining the values of the dummy variable D. For instance, gap = 2 indicates that $D = 1$ if gap ≥ 2. Overall, the results remain robust under these alternative definitions.

Table E2 presents the results of the pseudo gap analysis for inventory changes and sales. Column (1) corresponds to the last column of Table 4, representing the main results. Subsequent columns report the outcomes under alternative definitions of the target completion threshold. The findings reveal that, apart from the actual threshold, most results are statistically insignificant. This suggests that the observed anomalies in firms' behavior are strongly tied to whether the target was genuinely met, rather than to noise,

Figure E1: Change in Inventory by Gap



data peculiarities (e.g., irregularities in the data distribution), model misspecification, or spurious correlations. Notably, under the gap ≥ -1 scenario—where the threshold shifts to consider gap ≥ -1 as meeting the target—both inventory changes and sales show some positive significance. This may be attributed to diffuse bunching, where observations near the true target threshold reflect increased efforts to meet the goal. The closer a city comes to achieving its target, the greater the likelihood of intensified efforts, a pattern further corroborated by the heterogeneity analysis in the next section.[79] Importantly, no other points, particularly those to the right of the threshold, display unusual jumps, further reinforcing the robustness of the results.

Appendix E.3 Alternative Dependent Variables

[79]It is worth noting that the "treatment" in this study is not as "clean" as in other RDD applications, where agents below the threshold are entirely unaffected by the treatment. However, this does not substantially undermine the overall robustness of the results.

Figure E2: Ln of Sales by Gap

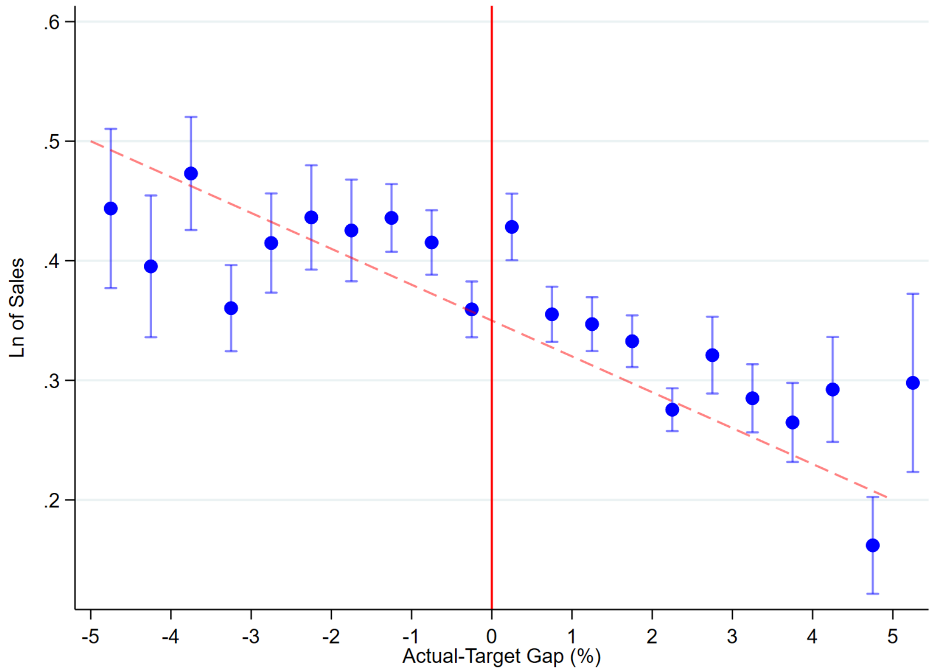


Figure E3: Supplemental: Change in Inventory by Gap

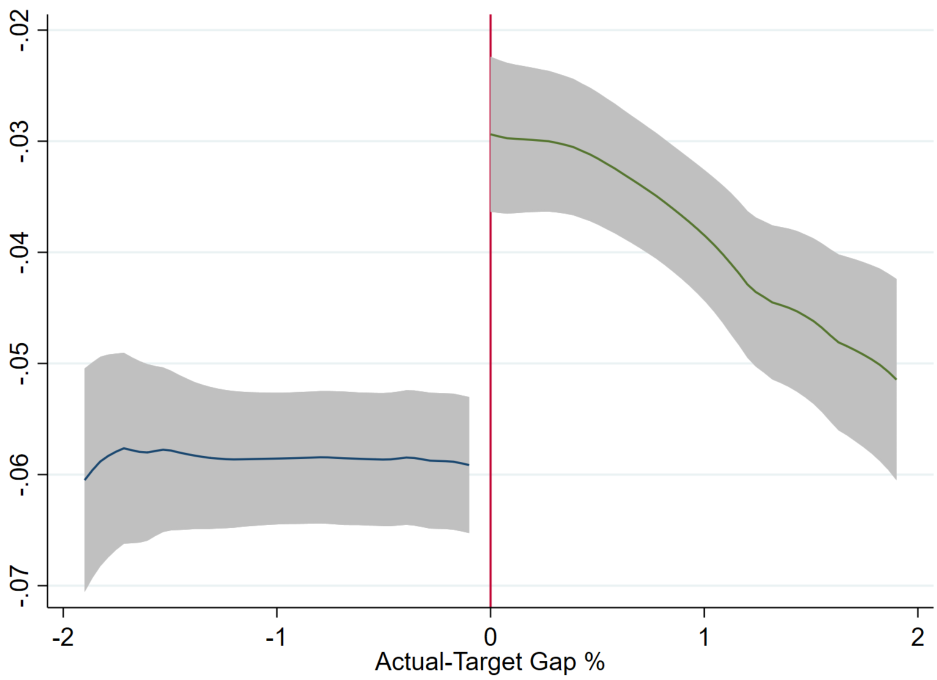


Figure E4: Supplemental: Ln of Sales by Gap

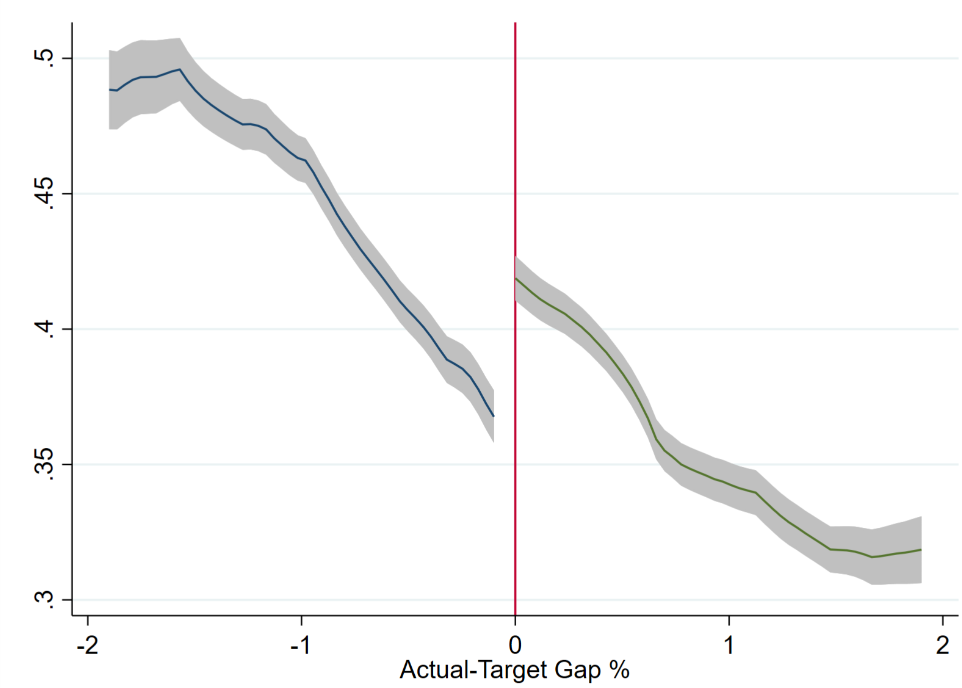


Table E3: Robustness Test (3): Alternative Dependent Variables

	Output		*Revenue*		*Overproduction*		*Intermediate Inputs*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β	0.072***	0.067***	0.044***	0.043***	0.063***	0.053***	-0.064***	-0.065***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)	(0.008)	(0.005)	(0.005)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
City Trends	✓	✓	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓		✓
Observations	295435	293358	335378	330269	188225	185473	297170	296970

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table presents the results of the same specification when the dependent variable is replaced with alternative measures: output, revenue, intermediate input, and an indicator of whether the firm engaged in overproduction during the period. Overproduction is an accounting-based measure, and the detailed calculation steps are provided in Appendix E.

In this subsection, the main dependent variable is replaced with alternative firm-level indicators closely tied to local GDP calculations to test the robustness of the results. The first alternative is output, which directly contributes to the GDP formula. The second is revenue, a close proxy for sales. The third is overproduction, a composite measure incorporating both sales and inventory.[80] In addition, the last one is intermediate input, which contributes negatively to GDP calculations.

Table E3 reports the results for four alternative dependent variables. Variables contributing positively to GDP calculations show a strong positive correlation with target completion, while those contributing negatively are negatively correlated with target completion. The proxy for output, gross industrial output value, may reflect price effects and is thus used primarily as a robustness check. Revenue results closely mirror those for sales in both magnitude and significance. Overproduction, a constructed measure combining inventory and sales, also exhibits a positive and significant relationship with target completion. However, it is derived from indirect calculation rather than direct data. Intermediate inputs, on the other hand, are negatively correlated with target completion. Due to substantial data gaps in many years, this variable serves as a reference rather than a key focus. Overall, the results remain robust when alternative dependent variables are used.

Appendix E.4 Calculation of Overproduction

Overproduction is measured by analyzing the abnormal levels of production relative to expected levels, given sales and other production inputs. The steps to calculate overproduction are detailed below.

To estimate normal production levels, the following regression model is used:

$$\frac{\text{PROD}_{it}}{\text{Assets}_{it-1}} = \alpha_1 \frac{1}{\text{Assets}_{it-1}} + \alpha_2 \frac{\text{Sales}_{it}}{\text{Assets}_{it-1}} + \alpha_3 \frac{\Delta\text{Sales}_{it}}{\text{Assets}_{it-1}} + \alpha_4 \frac{\Delta\text{Sales}_{it-1}}{\text{Assets}_{it-1}} + \epsilon_{it},$$

where:

- PROD_{it}: Total production for firm i in year t, calculated as the cost of goods sold plus the change in inventory.
- Assets_{it-1}: Total assets in the previous period.

[80] Overproduction, an accounting concept, is typically defined as abnormal production levels exceeding expected levels (Roychowdhury, 2006). It also serves as a substitute for inventory, as overproduction increases inventory levels, directly impacting GDP under the production approach.

- Sales_{it}: Sales in year t.
- ΔSales_{it}: Change in sales from year $t-1$ to year t.
- $\Delta\text{Sales}_{it-1}$: Change in sales from year $t-2$ to year $t-1$.
- ϵ_{it}: Residual, which captures the deviation from expected production levels.

The residual term ϵ_{it} from the regression represents the abnormal production, which is used as a proxy for overproduction.

Appendix E.5 Alternative Measure of Target Completion

The running variable can also be replaced with an alternative measure. Previously, target completion was determined by whether a city's actual GDP growth rate exceeded the economic growth target set by the municipal government (gap ≥ 0). An alternative measure, however, uses provincial-level data: the difference between the province's annual GDP growth rate and its growth target. While a province meeting its target does not guarantee that all cities within it achieved their respective goals, provincial governments serve as the direct superiors of city governors and have authority over personnel decisions. Thus, provincial-level performance provides a meaningful proxy for the pressure local officials face to meet growth targets.

Table E4 presents the results using the provincial actual-target gap as the running variable. The dependent variables, firm-level ln(inventory changes) and ln(sales), remain consistent with the main analysis. The results for inventory changes are highly robust, with coefficients showing similar size, sign, and significance compared to those obtained using the city-level gap. For sales, the signs and significance are consistent, but the coefficients are larger in magnitude. This indicates that the sales results are also relatively robust. The increased magnitude for sales may result from the provincial-level GDP gap exhibiting less variation than the city-level gap. Moreover, the higher volatility in sales data compared to inventory changes likely amplifies this effect, as reduced variation in the provincial gap makes its influence more pronounced, resulting in larger coefficients for sales.

Table E4: Robustness Test (4): Alternative Measure of Target Completion

Panel A: Inventory Changes

	ln of Inventory$_t$ − ln of Inventory$_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
β'	0.039***	0.060***	0.093***	0.093***	0.094***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.009)
Firm FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
City Trends				✓	✓
Controls					✓
Observations	233686	233686	209951	209951	208685
R^2	0.0008	0.0012	0.0023	0.0023	0.0026

Panel B: Sales

	ln of Sales$_t$				
	(1)	(2)	(3)	(4)	(5)
β'	-0.070***	0.078***	0.083***	0.083***	0.086***
	(0.006)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	339496	339496	311053	311053	309183
R^2	0.0009	0.0066	0.0064	0.0066	0.0142
Firm FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
City Trends				✓	✓
Controls					✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table presents the results when the method for determining target completion is changed from "city actual growth - city target growth ≥ 0" to "provincial actual growth - provincial target growth ≥ 0." The dependent variables remain firm-level ln(inventory changes) and ln(sales).

Appendix F Heterogeneity Analysis

Appendix F.1 Provincial Pressure and Quarterly Inventory

If growth targets effectively influence firm behavior, firms in regions under greater growth pressure are likely to respond more actively to meet these targets. However, quantifying the level of growth pressure faced by governments is challenging and subject to debate. One approach, explored in prior research, considers pressure exerted by higher-level governments (Li et al., 2018; Chen et al., 2020). Since 2005, provincial governments in China have published cumulative GDP growth rates at the end of each quarter as part of quarterly assessments, offering a valuable measure of local growth pressure. For instance, if mid-year GDP growth (cumulative growth at the end of second quarter) falls short of the annual target, firms are expected to respond more intensely in the second half of the year to make up for the shortfall.[81]

Table F1: Yearly Target Completion Rate Based on Success or Failure of Previous Quarters

	If Succeeded Q1	If Succeeded Q2	If Succeeded Q3
Target Completion Rate	81.92%	85.72%	93.67%
	If Failed Q1	If Failed Q2	If Failed Q3
Target Completion Rate	19.28%	10.48%	4.49%

Table F1 reports the annual target completion rate[82] conditional on a city's GDP performance in the first three quarters. Results show a strong positive association between quarterly performance and year-end target fulfillment, particularly as the year progresses. Cities with GDP growth already above target by Q3 are more likely to achieve the annual goal. In contrast, if a city falls short of the target in Q1, the probability of recovery by year-end drops to below 20%. These findings suggest that early- and mid-year economic performance serves as a strong predictor of final outcomes, both for external observers and for local officials.

To test this hypothesis and further supplement the earlier findings, quarterly firm-level

[81] Ideally, having quarterly GDP data at the city level would be optimal, as it aligns with the dimensionality of the firm-level data observed. However, city-level quarterly GDP data is not available. Nevertheless, using provincial-level data can still serve as a reasonable proxy for city-level data (as demonstrated section E.5) and also to some extent reflect the pressure exerted by higher-level governments.

[82] defined as the probability of meeting or exceeding the GDP growth target by the end of the year (Q4)

data is required. Fortunately, all listed firms in China release quarterly financial reports, including inventory data. By combining these two, the following specification is estimated to explore this relationship:

$$y_{ijtq} = \beta_1 \text{Gap}_{tqp} + \beta_2 Q_c + \sum_{k>c} \beta_k Q_c \times q_k + \sum_{r=1}^{3} \gamma_r q_r + \Gamma X_{it} + \sum_{j} \phi_j t + \mu_i + \lambda_s + \epsilon_{itq}$$

Here, y_{ijtq} represents the change in inventory for firm i in city j, year t, and quarter q. Gap_{tqp} denotes the difference between actual GDP growth in quarter q and the annual GDP target for province p in year t. Q_c is a dummy variable for $c = [1, 2, 3]$, indicating whether GDP growth by the end of the first c quarters failed to meet the annual target.[83] The term $\beta_k Q_c \times q_k$ captures the cumulative effects of missing the target during the first c quarters on subsequent quarters. For example, if $c = 1$, this interaction term captures the impact of the first quarter's GDP growth falling below the annual target on the outcomes in the second, third, and fourth quarters, with the fourth quarter representing annual GDP growth. $\sum_{r=1}^{3} \gamma_r q_r$ represents quarter fixed effects, with the fourth quarter serving as the reference group. The terms ΓX_{it}, $\sum_j \phi_j t$, μ_i, and λ_s correspond to firm-specific covariates, city-specific time trends, firm fixed effects, and industry fixed effects, respectively, same as in the previous sections.

Distinguishing between cases where the annual GDP target was ultimately achieved, despite quarterly shortfalls, and those where the target was missed is essential. Quarterly GDP underperformance is strongly correlated with failing to meet the annual target. For instance, among observations where first-quarter GDP fell short of the target, about 20% managed to achieve the annual goal. This figure drops to 11% for cases where GDP for the first two quarters remained below the target and plummets to just 3% when the shortfall persisted through the first three quarters. When the pressure to meet targets becomes overwhelming or the probability of success too low, the marginal returns to effort diminish. Significant effort may not sufficiently raise the likelihood of promotion, or the rewards for promotion may appear inadequate. In such cases, an official's participation constraint may no longer hold, leading them to withdraw from the "promotion contest" by exerting little or no effort (Li et al., 2019). This distinction aims to identify officials who remain active participants—likely putting in effort to meet the targets—and separate them from those who effectively abandon the contest or reduce their efforts.

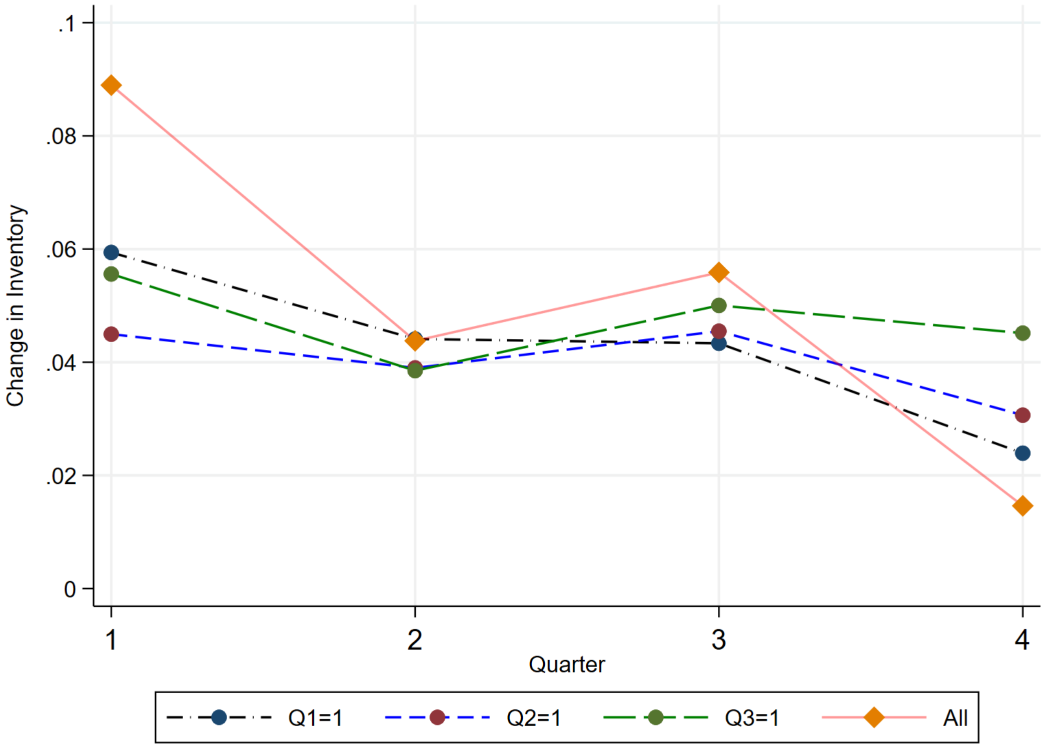
[83] For instance, $Q_2 = 1$ implies that by the end of the second quarter, actual GDP growth was below the annual target, while $Q_3 = 1$ indicates that GDP growth remained below target by the end of September.

Table F2 examines the effect of "quarterly GDP falling short of the annual target" on firms' quarterly inventory changes. Columns (1)–(3) present results for provinces where officials actively participated and ultimately met their annual targets. Columns (4)–(6) mirror these results but use the full sample, including cases where officials reduced efforts or abandoned the goal. The coefficients for Gap_{tqp} are positive and significant across all specifications, indicating that larger gaps between quarterly GDP and the annual target are associated with greater increases in quarterly inventory. This positive correlation is intuitive. Columns (1) and (4) assess the impact of missing the GDP target in the first quarter on inventory changes in the subsequent three quarters. Firms begin increasing inventory from the second quarter, with the effect intensifying as the year-end approaches. Similar trends are observed in the full sample, though with slightly lower magnitudes and significance. Columns (2) and (5) analyze cases where GDP fell short of the target during the first two quarters. Firms start increasing inventory in the third quarter, with a continued and growing effect through the fourth quarter. The full sample shows comparable patterns. Finally, Columns (3) and (6) focus on cases where GDP was below target for the first three quarters. In Column (3), where officials ultimately met the annual target, inventory increases peaked in the fourth quarter, reflecting a final effort to close the gap. By contrast, Column (6) shows no significant inventory increase in the fourth quarter, suggesting officials deemed the target unattainable, ceased efforts, or faced insurmountable economic barriers. This aligns with the fact that 97% of cases with GDP shortfalls in the first three quarters failed to recover by year-end. The coefficients for Q_1, Q_2, and Q_3 are negative, reflecting weaker economic performance in provinces that failed to meet their targets. However, the presence of growth pressure offsets these negative values.

Figure F1 visualizes the results from Table F2, depicting firms' quarterly inventory changes and their trends under varying quarterly performance levels. The figure shows that when GDP falls short in the first quarter (black line), firms compensate with a steeper recovery trajectory in subsequent quarters relative to the benchmark.[84] Similar catch-up patterns are observed for second-quarter (blue line) and third-quarter (green line) shortfalls. Notably, when GDP underperforms across all three quarters, the fourth quarter experiences the highest inventory growth as firms strive to close the gap. A stepwise pattern emerges

[84] The change in inventory is generally highest in the first quarter, as firms often negotiate new supplier contracts at the beginning of the year, leading to bulk purchases during Q1. This results in a significant accumulation of raw material inventories and intermediate goods. Conversely, the change in inventory is usually lowest at year-end, as firms strategically deplete existing stocks in Q4 to minimize excess inventory carrying costs. This practice is especially prevalent in industries dealing with perishable goods or rapidly depreciating inventory.

Figure F1: Change in Inventory by Quarter
with Distinct Quarterly Performance



Notes: This figure illustrates firms' quarterly changes in inventory across quarters 1 through 4, along with trends in inventory changes under varying levels of quarterly performance, conditioned on meeting the year-end target. $Q1 = 1$ indicates that GDP in the first quarter fell short of the target, $Q2 = 1$ signifies that GDP in both the first and second quarters consecutively fell short, and $Q3 = 1$ reflects underperformance in all three quarters. The trend line for the full sample serves as a benchmark for comparison.

in the fourth-quarter growth rates for $Q3$, $Q2$, and $Q1$, with diminishing effects as earlier-quarter shortfalls are considered. This sequential trend is particularly noteworthy.

A similar analysis can be conducted using the CIED manufacturing firm dataset. Although the CIED data is only available annually and therefore unsuitable for direct comparison, provincial-level quarterly GDP data provides a useful proxy for measuring political pressure from higher-level governments. In China, higher-level authorities exert significant control over lower-level governments, including the power to appoint and dismiss officials. This hierarchical structure compels local governments to align with top-down directives and macroeconomic policies (Wu and Chen, 2016). When a province's quarterly GDP falls short of its target, it reflects growth pressure from higher authorities, prompting provincial leaders to push cities within their jurisdiction to meet annual targets. In contrast, cities that have already achieved their goals face less pressure, as local governors have weaker incentives to stimulate further growth. Additionally, if the provincial government fails to meet its target, underperforming city governors are often the first to be held accountable. Thus, this analysis focuses on cities that have not yet achieved their annual targets.

Table F3 examines the impact of provincial-level growth pressure on firms' inventory changes. The table closely mirrors the structure and elements of Table F2.[85] Here, D' indicates that a city failed to meet its annual growth target, which is negatively correlated with inventory changes. The interaction term $Q_c \times D'$ captures the influence of provincial quarterly underperformance on city-level outcomes. The results reveal that while failing to meet annual targets (D') is generally associated with lower inventory changes, weak provincial quarterly GDP performance prompts cities that failed to meet their targets to make greater efforts to bridge the gap. Regardless of whether the shortfall occurs in the first quarter or extends across multiple quarters, cities react by ramping up inventory adjustments. In other words, while failing to meet city targets is generally linked to reduced inventory changes, this effect is mitigated under stronger provincial pressure. In the subsample, weaker provincial quarterly GDP performance leads to increased efforts at the city level, revealing a stepwise pattern of inventory growth based on the duration of the province's shortfall within a year, consistent with earlier findings. Although the results remain significant, the stepwise pattern is absent in the full sample, likely due to the inclusion of disengaged officials who put forth limited effort.

Although listed firms represent a smaller and less representative sample, and quarterly GDP data is available only at the provincial level, the combined findings from Tables F2 and F3 strengthen the overall validity of the analysis. Together, the results suggest that when officials recognize that their current efforts may fall short of achieving targets, they are likely to intensify their efforts to close the gap.

Appendix F.2 Sample Restriction Around the Threshold

For cities with a small negative GDP gap, the additional effort required to close the gap is relatively minimal, increasing the likelihood of local governments exerting extra effort (e.g., incentivizing firms) to meet the target. In contrast, cities with a large negative gap face

[85] Since quarterly GDP data is only available starting from 2005, while the CIED database spans 2000–2015, the total sample size for this analysis is reduced to two-thirds of the original.

low probabilities of success, leading local officials to perceive such efforts as unproductive and abandon attempts to catch up. This analysis examines how the relationship between city-level GDP targets and firm-level outcomes evolves when the sample is restricted to cities with GDP gaps closer to the threshold. The aim is to determine whether the discontinuity in firm outcomes becomes more pronounced when focusing on cities narrowly missing or just meeting their targets. Narrowing the sample to cities near the threshold also minimizes the influence of extreme values and outliers, as cities far from the threshold are less representative of marginal dynamics and may introduce unnecessary variation into the estimates.

Table F4 presents the results of narrowing the sample to smaller intervals around the target threshold. In each panel, the first column corresponds to the last column of Table 4. For cities within 1 percentage point of the target, shown in Column (2), meeting the GDP target increases inventory changes by approximately 3.1%. This effect is twice as large as that observed in the full sample, indicating that cities closer to the target exert greater pressure on firms to adjust inventories. This reflects heightened incentives or coercion as cities approach the threshold.[86] When the sample is further narrowed to cities within 0.5 percentage points of the target, as shown in Column (3), meeting the GDP target increases inventory changes by 3.7%. The effect continues to grow, suggesting that firms in cities very close to the threshold are more responsive to growth incentives. This is likely due to the intensified urgency for local governments to meet their targets, where the marginal benefit of additional effort is greater. These results align with earlier findings from the bunching analysis, where effects were shown to increase as observations concentrated near the threshold, reinforcing the validity of both sets of results.

[86] It is important to note that cities ending up within 0.5% or 1% of their growth targets is the result of significant effort. Without such deliberate efforts, cities might fall further behind their targets, potentially by a larger margin, such as 2%. This aligns with the purpose of this analysis: outcomes closer to the target—whether slightly exceeding or falling just short—are more likely the product of intensified efforts.

Appendix G True Output Proportion

Using the assumptions outlined in Section 6, the relationship between pollution and target completion can be expressed using the chain rule:

$$\frac{\partial p_{it}}{\partial D_{it}} = \frac{\partial p_{it}}{\partial e_{it}} \cdot \frac{\partial e_{it}}{\partial D_{it}}$$

The relationship between total output Y_{it} and D_{it} is expressed as:

$$\frac{\partial Y_{it}}{\partial D_{it}} = \frac{\partial Y_{T,it}}{\partial D_{it}} + \frac{\partial Y_{M,it}}{\partial D_{it}}.$$

True output is only affected indirectly through energy:

$$\frac{\partial Y_{T,it}}{\partial D_{it}} = \frac{\partial Y_{T,it}}{\partial e_{it}} \cdot \frac{\partial e_{it}}{\partial D_{it}}$$

Substituting:

$$\frac{\partial Y_{it}}{\partial D_{it}} = \frac{\partial Y_{T,it}}{\partial e_{it}} \cdot \frac{\partial e_{it}}{\partial D_{it}} + \frac{\partial Y_{M,it}}{\partial D_{it}}$$

The proportion of true output's contribution to the total output jump at the target threshold can be expressed as:

$$\text{True Output Proportion} = \frac{\frac{\partial Y_{T,it}}{\partial D_{it}}}{\frac{\partial Y_{it}}{\partial D_{it}}} = \frac{\frac{\partial Y_{T,it}}{\partial e_{it}} \cdot \frac{\partial e_{it}}{\partial D_{it}}}{\frac{\partial Y_{it}}{\partial D_{it}}} = \gamma_1$$

Using the pollution-energy relationship, the proportion of true output, normalized by pollution, can be derived. From the assumption:

$$\frac{\partial p_{it}}{\partial e_{it}} = \alpha \cdot \frac{\partial Y_{T,it}}{\partial e_{it}}$$

the energy elasticity of true output[87] can be expressed as:

$$\frac{\partial Y_{T,it}}{\partial e_{it}} = \frac{\frac{\partial p_{it}}{\partial e_{it}}}{\alpha}$$

Using the relationship:

$$\frac{\partial p_{it}}{\partial D_{it}} = \frac{\partial p_{it}}{\partial e_{it}} \cdot \frac{\partial e_{it}}{\partial D_{it}}$$

we can rearrange to solve for $\frac{\partial e_{it}}{\partial D_{it}}$:

$$\frac{\partial e_{it}}{\partial D_{it}} = \frac{\frac{\partial p_{it}}{\partial D_{it}}}{\frac{\partial p_{it}}{\partial e_{it}}}$$

Substituting these back into the true output proportion gives:

$$\text{True Output Proportion} = \frac{\frac{\partial p_{it}}{\partial e_{it}} \cdot \frac{\partial e_{it}}{\partial D_{it}}}{\alpha \cdot \frac{\partial Y_{it}}{\partial D_{it}}} = \frac{\frac{\partial p_{it}}{\partial e_{it}} \cdot \frac{\frac{\partial p_{it}}{\partial D_{it}}}{\frac{\partial p_{it}}{\partial e_{it}}}}{\alpha \cdot \frac{\partial Y_{it}}{\partial D_{it}}} = \frac{\frac{\partial p_{it}}{\partial D_{it}}}{\alpha \cdot \frac{\partial Y_{it}}{\partial D_{it}}} = \gamma_2$$

[87] γ_1 represents the lower bound of the true output proportion since it is estimated using only energy, labor, and capital to predict true output. However, true output is clearly influenced by additional factors beyond these three.These include technological efficiency (Syverson, 2011), natural conditions (Ploeg, 2011), and firm-specific characteristics such as economies of scale (Allcott et al., 2016), capital quality (Fleisher et al., 2010), and accumulated experience. Conversely, γ_2, when setting $\alpha = 1$, serves as an upper bound for the true output proportion. In reality, the proportionality constant α in China is likely greater than 1 for several reasons. First, many industries, such as steel, cement, and manufacturing, are highly energy-intensive but often operate inefficiently, resulting in a low marginal contribution of energy to true output (Wang et al., 2019). Second, China's reliance on coal and other high-pollution energy sources leads to a disproportionately large increase in pollution for each additional unit of energy consumed. Third, regions with weak enforcement of environmental regulations often lack effective pollution control technologies, further amplifying the pollution impact of energy use. By assuming $\alpha = 1$, the analysis simplifies the relationship, treating the efficiency of turning energy into pollutants as equivalent to the efficiency of turning energy into true output. This simplification provides an upper bound without introducing excessive additional assumptions about α.

Figure G1: Energy Consumption

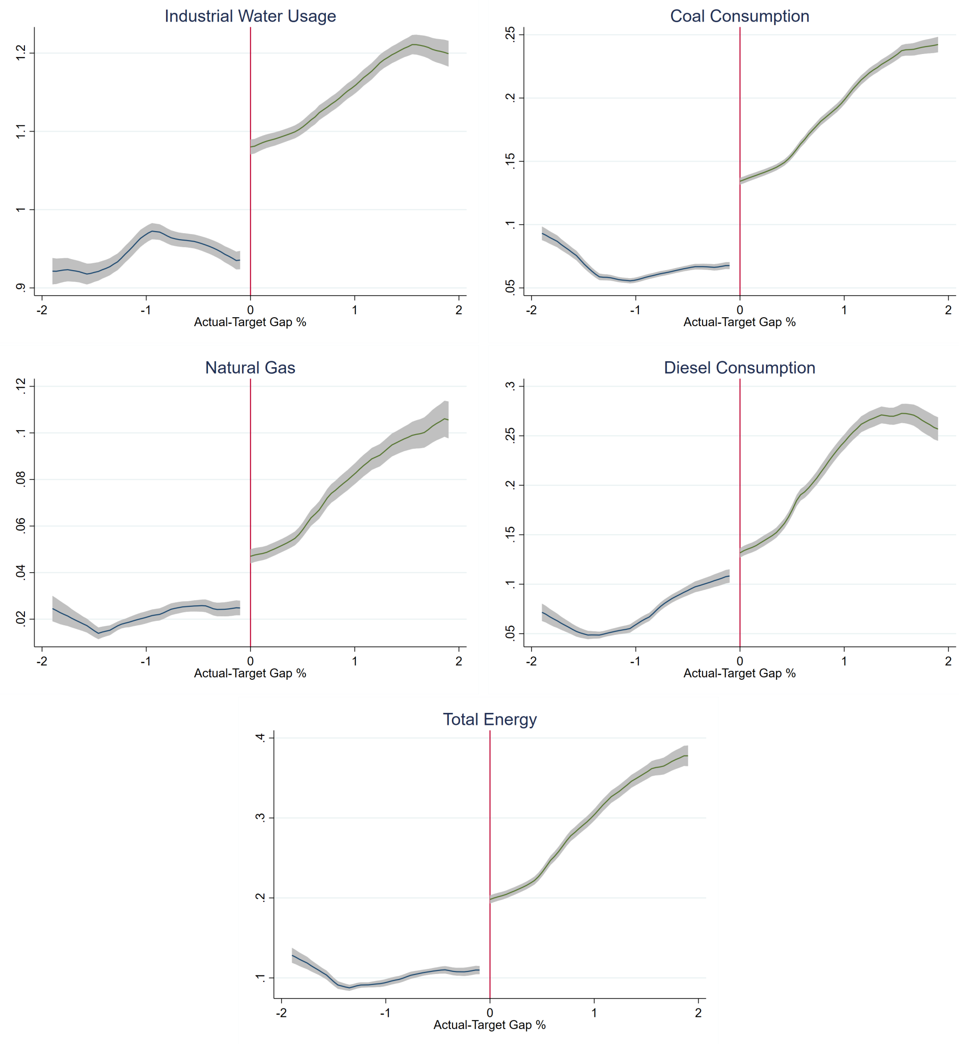


Table F2: Growth Pressure Effects on Quarterly Inventory

	Quarterly Change in Inventory					
	Subsample: Finished Provincial Annual Target			*All Sample*		
	(1)	(2)	(3)	(4)	(5)	(6)
Gap_{tqp}	0.001**	0.001***	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quarter 2 effect	0.028***			0.013*		
	(0.007)			(0.007)		
Quarter 3 effect	0.030***	0.023***		0.017**	0.013**	
	(0.007)	(0.008)		(0.007)	(0.005)	
Quarter 4 effect	0.044***	0.040***	0.059**	0.021**	0.017**	0.009
	(0.009)	(0.010)	(0.023)	(0.008)	(0.007)	(0.007)
Q_1	-0.042***			-0.028***		
(if failed quarter 1)	(0.006)			(0.006)		
Q_2		-0.035***			-0.024***	
(if failed quarters 1-2)		(0.005)			(0.004)	
Q_3			-0.012			-0.015***
(if failed quarters 1-3)			(0.009)			(0.003)
q_1 (Quarter 1 FE)	0.046***	0.042***	0.039***	0.086***	0.083***	0.080***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
q_2 (Quarter 2 FE)	-0.009***	-0.009**	-0.011***	0.031***	0.034***	0.031***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
q_3 (Quarter 3 FE)	-0.007*	-0.007**	-0.007**	0.041***	0.041***	0.043***
	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
Observations	33086	33086	33086	70379	70379	70379

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table presents the results of the above specification. Columns (1)–(3) are based on a subsample of provinces that met their annual growth targets by year-end, even if they failed to meet the target in certain quarters. Columns (4)–(6) mirror Columns (1)–(3) but use the full sample. Column (1) and Column (4) examine the effects of a province failing to meet its GDP growth target in the first quarter on subsequent quarters. Columns (2) and (5) consider the impact of consecutive GDP shortfalls in the first and second quarters on the remaining quarters. Finally, Columns (3) and (6) analyze the effects of GDP shortfalls across the first three quarters on the final quarter. The terms q_1, q_2, and q_3 represent quarter fixed effects.

Table F3: Higher-Level Pressure and Unmet Targets

	Yearly Change in Inventory					
	Subsample: Finished Provincial Annual Target			*All Sample*		
	(1)	(2)	(3)	(4)	(5)	(6)
D'	-0.017***	-0.018***	-0.013***	-0.018***	-0.018***	-0.014***
(if $\text{gap}_{jt} < 0$)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
$Q_c \times D'$	0.021***	0.024***	0.043**	0.014***	0.016***	0.010***
	(0.005)	(0.005)	(0.022)	(0.002)	(0.002)	(0.003)
Q_1	-0.034***			-0.032***		
(if failed quarter 1)	(0.002)			(0.002)		
Q_2		-0.038***			-0.035***	
(if failed quarters 1–2)		(0.003)			(0.002)	
Q_3			-0.035***			-0.028***
(if failed quarters 1–3)			(0.008)			(0.002)
Observations	153,413	153,413	153,413	231,606	231,606	231,606

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Notes: This table presents firms' yearly changes in inventory, accounting for growth pressure from higher-level governments, using the same database as the main results. The structure of the table mimics that of Table F2, with results reported for both a subsample and the full sample to exclude discouraged officials. D' is a dummy variable equal to 1 if the city fails to meet its target. The interaction term $Q_c \times D'$ captures the impact of poor provincial quarterly economic performance on cities' target completion. Here, weak provincial quarterly economic performance is interpreted as growth pressure exerted by higher-level governments.

Table F4: Sensitivity with Narrower Bandwidths

Panel A: Inventory Changes

	All (1)	$Gap \in [-1, 1]$ (2)	$Gap \in [-0.5, 0.5]$ (3)
β	0.061***	0.182***	0.209***
	(0.008)	(0.020)	(0.039)
Firm FE	✓	✓	✓
Industry FE	✓	✓	✓
City Trends	✓	✓	✓
Controls	✓	✓	✓
Observations	189,981	85,652	53,770
R^2	0.0017	0.0039	0.0088

Panel B: Sales

	All (1)	$Gap \in [-1, 1]$ (2)	$Gap \in [-0.5, 0.5]$ (3)
β	0.044***	0.091***	0.102***
	(0.004)	(0.007)	(0.018)
Firm FE	✓	✓	✓
Industry FE	✓	✓	✓
City Trends	✓	✓	✓
Controls	✓	✓	✓
Observations	279,519	137,580	80,833
R^2	0.0098	0.0121	0.0190

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Notes: This table presents the results when the sample is restricted to smaller intervals around the target threshold. Both inventory changes and sales are analyzed. In each panel, the first column corresponds to the last column of Table 4. The second column shows the results when the sample is restricted to cases where the gap falls within the range of -1 to 1. Similarly, the third column further narrows the sample to cases where the gap lies within the range of -0.5 to 0.5.

Figure G2: Pollutants