

Regulatory Scrutiny and Strategic Discharge: Evidence from Hospital Inspections in China*

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Abstract: Healthcare audits and inspections are widely used by governments to curb wasteful healthcare spending, yet their effectiveness depends critically on how providers respond to regulatory scrutiny. We study this issue in the context of an on-site hospital inspection program in a large Chinese city. Using administrative health claims data and a stacked difference-in-differences design, we find that inspections increase inpatient discharges by 17% during the on-site inspection period. Patients discharged during this period experience a roughly 25% increase in 30-day readmission rates, driven primarily by readmissions to the same specialty at other hospitals. This pattern provides evidence of premature discharge. Mechanism analyses point to regulatory pressure, with stronger effects in hospitals with heavier workloads and in departments with greater baseline treatment variation. Although inspections significantly reduce length of stay and inpatient expenditures during the index hospitalization, these reductions are offset by increases in post-discharge inpatient utilization, leaving no detectable reduction in overall inpatient resource use over the 90-day follow-up period. These findings suggest that intensive on-site inspections can induce strategic provider responses that compromise healthcare quality and weaken the expected fiscal benefits of enforcement. (*JEL* Codes: I13, I18, I11, H51)

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1. Introduction

Wasteful healthcare spending accounts for a substantial share of total health expenditure and has long placed financial pressure on public health insurance systems worldwide. International estimates range from roughly 6 percent for fraud and payment errors to around 20 percent when unnecessary and low-value care are also included (Gee and Button, 2015; OECD, 2017). Governments have therefore responded by expanding audits and inspections intended to deter inappropriate utilization and contain healthcare spending. Recent evidence from U.S. public insurance programs suggests that such practices can generate substantial fiscal savings without detectable harm to patients (e.g., Howard and McCarthy, 2021; Shi, 2024).

However, these benefits are not guaranteed because providers may respond strategically to regulatory scrutiny. When oversight relies on incomplete measures of performance, providers may concentrate their efforts on monitored dimensions while neglecting unmeasured ones (Baker, 1992; Alexander, 2020), or engage in window dressing by temporarily improving measured performance during inspections (Chen and Dillender, 2025). This concern is particularly relevant if providers respond to scrutiny by reducing treatment indiscriminately, because lower utilization may then reflect reductions in necessary care rather than genuine reductions in waste, leading to adverse consequences for patient outcomes. Thus, the overall effect of enforcement remains an important empirical question, and understanding it requires a closer examination of how enforcement is implemented and how providers respond.

We study this question in China, where the structure and scale of the healthcare system make both the potential savings and quality consequences of enforcement particularly salient. Although healthcare delivery is dominated by public hospitals in China, these institutions rely heavily on self-generated revenues to cover operating costs and pursue surpluses (Xu et al., 2019). These revenue incentives operate within a near-universal public health insurance system covering about 1.4 billion people, in which patients bear only part of the cost of covered care and providers retain considerable discretion over treatment decisions (Yip et al., 2019). Together, these features create scope for fraudulent billing and unnecessary care, making the potential savings from intensive oversight substantial and motivating the government's stringent enforcement efforts. The central government launched its nationwide campaign in 2018 and reclaimed RMB 160 billion in improper public insurance reimbursements through 2025 (National Healthcare Security Administration, 2026). Yet regulators are more likely to identify easily observable indicators, such as length of stay or spending, and the accounting measure does not capture potential changes in healthcare quality that are more difficult to evaluate. If enforcement compromises care and thereby increases subsequent utilization, its net fiscal savings may be smaller.

To examine this possibility, we study a similar local enforcement program introduced by City A, an eastern coastal city in China, in 2014, four years before the nationwide campaign. We use administrative claims data covering an annual 5% stratified random sample of City A's publicly insured population. The data capture all inpatient utilization for sampled individuals within each calendar year, including admission and discharge dates, hospital and department identifiers, and expenditures. The program was implemented in three rounds during 2014 and 2015. Our baseline analysis focuses on the first two rounds, both of which were carried out in 2014, as many outcomes following the third round in late 2015 cannot be fully observed. In each round, regulators conducted on-site inspections at a group of hospitals for approximately 40 days, reviewing both historical billing records and the treatment of current inpatients for evidence of improper billing and utilization. Long stays and high expenditures were a particular focus as potential signs of unnecessary care. Hospitals across different tiers were targeted and typically notified only a few days before the on-site inspections began. The direct scrutiny imposed by the inspections, together with the potential financial and professional penalties for detected violations, gave hospitals strong incentives to reduce fraud and inappropriate utilization. However, the same pressures could also lead hospitals to reduce necessary care if they become overly cautious, fail to distinguish appropriate from inappropriate utilization, or have to divert time and attention from patient care to responding to inspectors.

To assess hospitals' overall responses, we aggregate patient claims into a balanced hospital-level panel at 10-day intervals. Using the stacked difference-in-differences (DID) design proposed by Cengiz et al. (2019), we compare outcomes of hospitals that undergo an on-site inspection with a control group of uninspected hospitals that includes both never-treated and not-yet-treated units. This empirical framework helps address the estimation bias from the treatment-effect heterogeneity in our staggered policy adoption setting (de Chaisemartin and D'Haultfœuille, 2020).

Event-study results show no evidence of differential trends between inspected and control hospitals before inspections begin. During the on-site inspection period (the first 40 days after inspections begin), inspected hospitals increase inpatient discharges by approximately 17%. The effect dissipates once inspections conclude, indicating that hospitals' responses are concentrated in periods of active regulatory scrutiny. Admissions do not increase correspondingly during the on-site inspection period. This suggests that the increase in discharges does not reflect an inflow of newly admitted patients. Instead, these changes imply lower bed occupancy while inspectors are present. After inspections end, inpatient admissions show a brief increase, potentially reflecting hospitals' efforts to restore bed occupancy.

The increase in discharges may represent reductions in unnecessary inpatient stays, but it may also reflect earlier discharge of patients who still require care. To distinguish between these possibilities, we turn to a claim-level analysis of 30-day readmission rates. Using a similar stacked DID framework, we

compare patients discharged from inspected hospitals before, during, and after the inspection period with patients discharged from uninspected control hospitals over the corresponding periods. Results show that inspections increase 30-day readmissions by about 15% overall. The effect is concentrated among patients discharged during the active inspection period, for whom the 30-day readmissions increase by approximately 25%. The effect no longer exists for patients discharged after inspections conclude. This temporal pattern closely mirrors the surge in inpatient discharges documented at the hospital level, suggesting that the accelerated discharges during inspections have negative consequences for healthcare quality. Further analysis shows that the increase in readmissions occurs primarily across hospitals rather than at the index hospital and is driven by patients readmitted to the same specialty at another hospital. Readmissions involving different specialties change little. These patterns suggest that some patients leave inspected hospitals before completing the treatment they require and subsequently continue that care elsewhere, providing further evidence of premature discharge.

The estimates are robust across a series of sensitivity checks. Restricting the sample to patients admitted before the start of on-site inspections leaves the results unchanged, suggesting that the increase in readmissions is not driven by selective admission of patients during inspections. A placebo event-study using 2013 data, when no enforcement rounds took place, reveals no detectable effects. The findings also remain stable when alternative readmission windows are used. In addition, the estimates are highly comparable across alternative sample definitions and model specifications, including more granular fixed effects, the inclusion of all inspection rounds, alternative event-time definitions, the exclusion of primary hospitals, and the use of 7-day and 15-day event-time intervals. These results indicate that the findings are robust to alternative samples, outcome definitions, or empirical specifications.

We further discuss several potential mechanisms underlying these effects. First, consistent with treatment compression, patients discharged during the inspection period have stays that are about 10% shorter and expenditures that are about 13% lower, and these reductions dissipate once inspections conclude. Second, we find evidence consistent with inspection-related administrative demands straining provider capacity: the increase in readmissions is concentrated in hospitals with higher pre-inspection workloads, relative to hospitals of the same tier. Third, the effect is stronger in departments with greater baseline variation in treatment expenditures, consistent with regulatory pressure inducing more standardized treatment and discharge decisions that may not accommodate heterogeneous patient needs. Finally, inspections change the age composition of discharged patients. The discharge shares of patients below age 50 and those aged 50–74 increase during the inspection period. Meanwhile, the subsequent increase in readmissions is concentrated only among patients aged 50–74. Readmissions do not increase significantly among younger patients, who may be better able to recover outside the hospital following earlier discharge,

or among the oldest patients, for whom hospitals may have less scope or willingness to accelerate discharge decisions.

We finally investigate whether reductions in resource utilization during the index visit translate into net savings over longer horizons. While on-site inspections significantly reduce inpatient days and expenditures during the index visit, these reductions are gradually offset by increases in cumulative inpatient utilization over the 10–90 days following discharge. As a result, we find little evidence of meaningful reductions in overall inpatient resource use. These findings suggest that the apparent savings generated by on-site inspections are accompanied by deteriorating healthcare quality and increased subsequent healthcare utilization. Consequently, the net fiscal benefits of the enforcement program may be substantially smaller than those implied by reductions in index-visit expenditures alone.

This paper contributes most directly to the small literature on the effectiveness of healthcare audits and enforcement. The effectiveness of such enforcement is theoretically ambiguous, as it depends critically on how it is implemented and how providers adapt under regulatory pressure. Prior empirical evidence, drawn primarily from the U.S. context, documents substantial recoveries and reductions in healthcare spending without harming patient outcomes (Becker et al., 2005; Perez and Wing, 2019; Howard and McCarthy, 2021; Shi, 2024; Leder-Luis, 2025). For example, Shi (2024) examines Medicare’s Recovery Audit Contractor program, under which private auditors retrospectively review claims for medically unnecessary inpatient admissions, and finds that each dollar spent on auditing generates \$24–\$29 in savings, without increasing 30-day inpatient revisits. Our study complements this literature by examining a distinct form of enforcement: intensive on-site inspections. Compared with aggregate enforcement activities and retrospective claims audits studied in prior work, on-site inspections expose providers and ongoing treatment decisions to more direct regulatory scrutiny. The concentrated presence of inspectors may create more immediate pressure to comply while also diverting providers’ time and attention from patient care, potentially leading to different consequences for healthcare quality.

Existing research on on-site inspections in healthcare is limited to two recent studies of nursing-home quality inspections, both of which document strategic responses to the timing and risk of inspections.² Chen and Dillender (2025) identify short-lived window-dressing during inspections. Nursing homes temporarily increase staffing and certain care inputs, yet most responses reverse once inspections end. Gandhi et al. (2026) show that nursing homes reduce effort when inspection risk is low and increase it as the next inspection approaches, with patient survival following a similar pattern. Like these studies, we find strategic and temporary responses to on-site enforcement in the hospital setting. Specifically, inspected hospitals

² Strategic adaptation to monitoring incentives is also widely documented in other regulatory settings, such as tax enforcement (e.g., Almunia and Lopez-Rodriguez, 2018) and environmental regulation (e.g., Zou, 2021; Bo et al., 2026; Zhao and Yuan, 2026).

increase patient discharges while reducing length of stay and inpatient expenditures. These responses are consistent with the inspection program's focus on unusually long inpatient stays and high costs. The consequences of such responses may be particularly salient in this setting, where even modestly earlier discharges can interrupt ongoing treatment and compromise recovery. By documenting increased readmissions among patients discharged during inspections, our study highlights how regulatory scrutiny focused primarily on financial and utilization metrics can distort real treatment decisions and generate adverse consequences for patient outcomes.

Of further relevance to the present study is a broad literature examining policies designed to promote the efficient use of healthcare funds. These policies include payment reforms that alter provider reimbursement and revenue incentives (e.g., Cutler, 1995; Ellis and McGuire, 1996; Gross et al., 2024), utilization restrictions implemented through instruments such as prior authorization and off-label prescription regulation (e.g., Brot-Goldberg et al., 2023; Tunçel, 2025), and quality incentives based on information disclosure, pay-for-performance, and readmission penalties (e.g., Dranove et al., 2003; Mullen et al., 2010; Gupta, 2021; Deore et al., 2024). Audits and inspections pursue a similar objective by seeking to reduce fraudulent billing and wasteful utilization and to promote more standardized provider practices. Our findings show, however, that these interventions may also have unintended consequences for healthcare quality. They therefore point to the importance of accounting for provider responses and downstream patient outcomes when designing and evaluating such policies intended to improve the use of healthcare funds.

The rest of the paper proceeds as follows. Section 2 describes the policy context of the hospital inspection program in China. Section 3 presents the data and sample. Sections 4 and 5 report the empirical designs and results for the hospital-level and claim-level analyses, respectively. Section 6 concludes.

2. Background

2.1 China's Health Care System

China's health care delivery system is dominated by public hospitals, which account for more than 80 percent of both inpatient admissions and total health spending (National Health Commission, 2025). Despite their public ownership, Chinese public hospitals operate under strong incentives to generate revenue. These incentives are rooted in the fiscal decentralization that followed the economic reforms of the 1980s. As direct government subsidies fell to 10 percent or less of public hospital revenue, public hospitals were allowed to retain operating surpluses and profits from drug sales and diagnostic tests to compensate for administratively set, below-cost prices for beds, nursing, and surgical services (Yip et al., 2012; Yip and Hsiao, 2014). Public hospitals also have strong incentives to expand, as advancement within

the tiered grading system raises hospital prestige and the administrative status of hospital leadership. These arrangements further encourage hospitals to increase service volume and revenue. Meanwhile, physician compensation is often tied to departmental revenue through bonus systems, transmitting the institutional incentive to generate revenue to the individual clinician (Yip et al., 2010; Yip et al., 2019).

These hospital-side incentives are reinforced by the expansion and payment structure of public health insurance. China has near-universal public health insurance covering approximately 95 percent of the population. The system was established with two components: the Urban Employee Basic Medical Insurance (UEBMI) for formally employed urban workers, and the Urban and Rural Resident Basic Medical Insurance (URRBMI) for urban and rural residents without formal employment.

As the dominant payer in China's health care market, the basic medical insurance system plays a central role in shaping both provider and patient behavior. During our study period, hospitals were reimbursed predominantly through retrospective fee-for-service payment, under which revenue increased with the volume and intensity of services provided.³ For patients, coverage and cost sharing vary across cities, hospital tiers, and procedures. Inpatient care generally receives more generous coverage than outpatient care, creating a complementary demand-side incentive for inpatient utilization.

These financial incentives have coincided with rapid growth in health care spending and inpatient utilization. Total health expenditure, measured in real terms, increased from RMB 458.7 billion (US\$55.4 billion) in 2000 to nearly RMB 5.6 trillion (US\$780.6 billion) in 2024.⁴ The number of hospital admissions also rose more than sevenfold during this period. By 2024, China recorded approximately 18,000 hospital admissions per 100,000 people, substantially above the OECD average despite its younger population.⁵

2.2 The Hospital Inspection Program

The rapid growth of healthcare spending and concerns about unnecessary utilization make enforcement against improper billing and utilization an increasingly important policy priority in China. City A, the setting for our study, introduced an enforcement program in 2014. A key instrument of the program was the on-site inspection of targeted healthcare institutions, an approach that the central government later adopted and termed “flight inspection” when it launched a nationwide campaign in 2018. Since its launch, the national campaign has recouped substantial amounts of improper reimbursement. From 2018 to 2025, 4.66 million institutions were inspected, 1.88 million were found to have committed violations, and RMB 160

³ Following earlier pilots in a limited number of cities, the national DRG and DIP pilot began in 2019, with broader rollout accelerated after 2022.

⁴ Total health expenditure is adjusted for inflation using the consumer price index (CPI) and expressed in constant 2000 prices. The conversion from RMB to US dollars is based on the annual average RMB–US dollar exchange rate in each corresponding year.

⁵ Data are sourced from the China Health Statistics Yearbook 2024 and the OECD database.

billion was returned to the public insurance fund.⁶ These numbers illustrate the scale and intensity of the campaign. Yet it remains unclear how hospitals adjust treatment decisions under regulatory scrutiny and whether these responses affect health care quality, which we examine using the earlier program in City A.

City A is one of China's largest cities and one of its most important healthcare markets, home to a large number of tertiary hospitals. The enforcement program was organized by the city's Healthcare Security Administration and implemented by inspection teams comprising government administrators and medical experts. The program began in 2014 and included three rounds. The first two rounds, the focus of our baseline analysis, took place between March and April 2014 and between July and September 2014, respectively. The third round was conducted more than one year later, from October to December 2015. Each round targeted about 90 hospitals across different tiers.⁷ Table 1 provides a detailed timeline of the three inspection rounds. The inspection monitors five groups of indicators: spending metrics, resource utilization measures, clinical compliance indicators, healthcare quality outcomes, and fraud metrics. Spending and resource-use indicators such as average inpatient expenditure and average length of stay are readily observable. By contrast, quality outcomes like 30-day readmission rates demand follow-up data and are therefore less emphasized in on-site inspections.

[Insert Table 1 here]

Each round consisted of a pre-inspection audit, an on-site inspection, and a post-inspection evaluation. For the first two rounds, the pre-inspection stage lasted 3–7 days, the on-site inspection stage lasted 40 days, and the post-inspection stage lasted 12 days. During the pre-inspection stage, inspection teams obtained administrative billing and claim records from the preceding year and conducted preliminary audits to identify suspicious utilization and billing patterns.⁸ Since this was conducted internally by regulators using administrative records already available in their systems, without requiring hospitals to submit additional files or data, hospitals were generally unaware that they were under review at this stage.

During the on-site inspection, inspection teams went to the targeted hospitals in person to investigate flagged cases. Hospitals were typically notified only a few days before the visit, leaving them limited time to prepare. The inspection involved reviewing relevant medical records, treatment documentation, prescriptions, and reimbursement claims. The inspectors might also interview physicians and hospital administrators about past cases and request supporting documents and explanations concerning clinical

⁶ Healthcare institutions in the national campaign include hospitals, pharmacies, and other health care providers eligible to receive payments from the public health insurance system. See <https://www.nhsa.gov.cn/col/col7/index.html> for details.

⁷ Hospitals inspected during the first and second waves were mutually exclusive, whereas the third-wave inspections partially overlapped with hospitals targeted in earlier rounds.

⁸ Examples of suspicious practices included fabricated admissions or medical records; duplicate, unbundled, or otherwise improper billing; and, most commonly, medically unnecessary testing, treatment, or prescribing.

decisions and reimbursement practices. They also examined the treatment of current inpatients for suspicious utilization patterns. Long inpatient stays and high expenditures received particular attention as potential indicators of unnecessary care. When doing so, inspectors could make audio and video recordings and take photographs as supporting evidence.

Following the inspection, the teams summarized their findings and submitted formal reports to the regulatory authorities. When violations were identified, regulators could require hospitals to repay improperly claimed insurance funds and impose administrative sanctions depending on the severity of the violation. These sanctions included fines and suspension or revocation of reimbursement eligibility. Such sanctions may carry particular weight in China, given the close administrative relationship between public hospitals and government health authorities. Physicians associated with confirmed violations could also face adverse consequences in internal performance evaluations and compensation assessments. Together, these financial and professional penalties created strong short-run compliance pressure. Physicians must devote effort to complying with inspections while meeting easily observable regulatory targets, which might lead them to discharge patients earlier.

3. Data and sample

3.1 Data

Our analysis is based on an administrative dataset comprising health insurance claims for beneficiaries enrolled in the Urban Employee Basic Medical Insurance (UEBMI) and Urban-Rural Resident Basic Medical Insurance (URRBMI) programs in the city. The sample is drawn using a stratified random sampling strategy that selects 5% of the insured population each year. The data track all inpatient utilization for each individual within a given year, but individuals cannot be tracked across years. As a result, for the third inspection wave, conducted in late 2015, we cannot fully observe patient outcomes over longer post-discharge horizons. We therefore focus our baseline analysis on the first two inspection waves, and include the third inspection wave as a robustness check.

The data contain all inpatient and outpatient healthcare records in the city for sampled individuals. We restrict the analysis to inpatient claims, which were the primary focus of the regulatory inspections during this period. This yields more than 36,000 inpatient claims in 2014. Each claim record contains detailed information on admission and discharge dates, hospital and department identifiers, length of stay, and medical expenditures. These allow us to examine how on-site inspections affect hospital discharge decisions, healthcare utilization, and subsequent patient outcomes.

3.2 Sample and summary statistics

We construct two primary analytical samples. First, we aggregate claim-level records into a balanced hospital-level panel measured at 10-day intervals. For each hospital-by-interval observation, we calculate the number of inpatient discharges and admissions. We use the start of the on-site inspection as the treatment date because hospitals were generally unaware that they were under review during the pre-inspection stage, making the on-site inspection the first point at which they could respond to the investigation. Moreover, the on-site inspection itself directly affected hospital operations.⁹ Time intervals are defined relative to this treatment date and span from 40 days before the inspection to 90 days afterward. These event windows do not overlap in calendar time across inspection waves.

To implement our stacked difference-in-differences approach, we construct separate samples for the first and second inspection waves. In each wave-specific sample, hospitals inspected during that wave are defined as the treatment group, while hospitals that had not yet been inspected or were never inspected serve as the control group.¹⁰ We then stack the two wave-specific samples into a pooled dataset for estimation. This design ensures that the average treatment effect is identified using appropriate control groups and addresses the bias that can arise from treatment-effect heterogeneity (Layton and Politzer, 2025).

The second sample is constructed at the claim-level for analyses of patient outcomes and healthcare quality. Each patient claim is assigned to a hospital-by-10-day interval based on the discharging hospital and the patient's discharge date. The time window also spans from 40 days before to 90 days after the start of an on-site inspection. To avoid patients already exposed to the inspection re-entering the sample as untreated observations, we drop all subsequent claims of a patient if that patient was discharged from an inspected hospital during the on-site inspection period.¹¹ Similarly, we stack the two wave-specific patient samples into a pooled dataset for estimation.

Table 2 presents descriptive statistics for the two analytical samples. The final hospital-level sample contains 7,631 hospital-interval observations, while the claim-level sample includes 19,549 inpatient claims. Panel A reports summary statistics for the hospital-level dataset. On average, each hospital-by-interval observation contains approximately 2.7 inpatient discharges and a similar number of admissions. Treated hospitals account for about 20 percent of observations in the hospital-level sample. Panel B presents descriptive statistics for the claim-level sample. The average patient is approximately 61 years old; 39 percent are female, and 97 percent are enrolled in the UEBMI program. Average inpatient length of stay is

⁹ As a robustness check, we alternatively redefine the treatment date using the beginning of the pre-inspection stage.

¹⁰ Specifically, hospitals inspected in the second wave serve as not-yet-treated controls in the first-wave sample, whereas those inspected in the first wave are excluded from the second-wave sample. Hospitals not inspected in either of the first two waves serve as controls in both wave-specific samples.

¹¹ For example, suppose a patient is discharged from an inspected hospital during the on-site inspection period and subsequently has one or more additional inpatient claims. All such subsequent claims are excluded from the analytical sample as new index observations. However, this exclusion does not affect the measurement of readmissions: these claims are still used, where relevant, to determine whether the original discharge is followed by a readmission within the specified follow-up window.

9.6 days, with mean inpatient expenditures of approximately RMB 12,000 per hospitalization episode. Notably, the 30-day readmission rate is about 20 percent, suggesting a substantial level of post-discharge inpatient utilization.

[Insert Table 2 here]

Figure 1 presents the raw trends in inpatient discharges and admissions for treated and control hospitals around the timing of the on-site inspections. On average, treated hospitals have a larger number of admissions and discharges than control hospitals. This may reflect the inspection program's greater focus on larger hospitals, although as noted in the background section, it indeed covered hospitals of all tiers. More importantly, treated and control hospitals exhibit broadly similar trends before the inspections in both outcomes. During the on-site inspection period, inpatient discharges increase noticeably among treated hospitals relative to control hospitals, with the difference narrowing after the inspections end. By contrast, inpatient admissions at treated hospitals remain largely unchanged during the inspection period and show only a modest increase shortly thereafter. Throughout the event window, the corresponding trends for control hospitals remain relatively stable. These raw patterns provide an initial descriptive picture of hospital responses to the inspections, which we examine formally using the stacked DID framework in the following section.

[Insert Figure 1 here]

4. Hospital-level analysis

4.1 Econometric framework

We first conduct hospital-level analyses to examine the effects of on-site inspections on inpatient discharges and admissions. Using the hospital-level analytical sample described above, we estimate a stacked DID event-study specification that compares hospitals inspected during a given wave with hospitals that had not yet been inspected or were never inspected. Our estimation equation for the hospital-level analysis is specified as follows:

$$Y_{h,j,t,w} = \alpha_0 + \sum_{\substack{\eta=-4 \\ \eta \neq -1}}^8 \gamma_\eta D_{h,j,t,w}^\eta + \delta_{h,w} + \theta_{j,t,w} + \mathbf{G}'_{h,2013} \times \mathbf{t} + \varepsilon_{h,j,t,w} \quad (1)$$

where $Y_{h,j,t,w}$ denotes the number of discharged or admitted patients at hospital h in district j of the city at time t (measured in 10-day intervals relative to the start of the on-site inspection) relative to inspection

wave w . $D_{h,j,t,w}^\eta$ is an indicator equaling 1 if and only if hospital h at time t is in the $\eta \times 10$ -day interval relative to the start of the on-site inspection in wave w . Hospital fixed effects and district-by-time fixed effects are included. In the most restrictive specification of the stacked DID design, these fixed effects are allowed to vary across inspection waves. We therefore interact both sets of fixed effects with inspection-wave indicators, yielding hospital-by-wave fixed effects $\delta_{h,w}$ and district-by-time-by-wave fixed effects $\theta_{j,t,w}$, respectively. We additionally control for linear time trends interacted with a vector of baseline hospital characteristics measured in 2013, $\mathbf{G}_{h,2013}$, including average inpatient and outpatient expenditures per visit. The standard errors are clustered at the hospital level.

The causal identification of this empirical strategy relies on the assumption that, in the absence of the inspections, treated and control hospitals would have exhibited similar trends in the outcomes of interest. Several aspects of our empirical design help strengthen the plausibility of this identifying assumption. First, our analysis focuses on a relatively short event window, spanning from 40 days before to 90 days after the inspection. Within such a narrow time frame, it is less likely that other confounding shocks would differentially affect treated and control hospitals and generate diverging outcome trends. Second, we include district-by-time fixed effects interacted with inspection-wave indicators, which absorb time-varying shocks common to hospitals within the same district such as short-term fluctuations in local healthcare demand (Shi, 2024). Third, we additionally control for linear time trends interacted with baseline hospital characteristics, including average inpatient and outpatient expenditures per visit in 2013 for each hospital, to account for the possibility that hospitals with different pre-inspection spending patterns may have followed systematically different trajectories over time.

We further assess the validity of the identification assumption using both event-study evidence and placebo exercises. The event-study results reveal no discernible differential pre-treatment trends between treated and control hospitals. As we show later, the estimates are economically small and statistically insignificant throughout the pre-inspection period, and we also fail to reject the null hypothesis that they are jointly equal to zero. Additionally, we conduct a placebo exercise using data from 2013, the year before the inspections. Specifically, we replicate the baseline empirical strategy using the same treated and control groups, the same inspection timeline, and the same stacked DID event-study specification. Reassuringly, the placebo estimates shown in Appendix Figure A1 and Table A1 yield no significant effects and exhibit no systematic dynamic patterns. This finding provides additional support for the validity of our identification strategy and alleviates concerns that the estimated effects are driven by differential trends or other factors correlated with the inspection schedule.

In addition to the event-study specification, we also estimate parsimonious stacked DID specifications

to summarize the average treatment effects of the inspections. Specifically, as shown in Equation (2), we first replace the event-time indicators with a single indicator function, $\mathbf{1}_{\{Insp_{h,j,t,w}\}}$, which equals 1 for treated hospitals during days 1–90 following the start of the on-site inspection. This specification captures the overall average effect of the inspections across the entire post-inspection event window. We then estimate Equation (3), which simultaneously includes two indicators. The first, $\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$, equals 1 for treated hospitals during the on-site inspection window used in our analysis (i.e., days 1–40), while the second, $\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$, equals 1 for treated hospitals during the subsequent post-inspection period (i.e., days 41–90). This specification allows us to separately summarize responses during the on-site inspection period and subsequent adjustments after the completion of the inspections.

$$Y_{h,j,t,w} = \alpha_0 + \alpha_1 \mathbf{1}_{\{Insp_{h,j,t,w}\}} + \delta_{h,w} + \theta_{j,t,w} + \mathbf{G}'_{h,2013} \times \mathbf{t} + \varepsilon_{h,j,t,w} \quad (2)$$

$$Y_{h,j,t,w} = \alpha_0 + \alpha_2 \mathbf{1}_{\{DuringInsp_{h,j,t,w}\}} + \alpha_3 \mathbf{1}_{\{PostInsp_{h,j,t,w}\}} + \delta_{h,w} + \theta_{j,t,w} + \mathbf{G}'_{h,2013} \times \mathbf{t} + \varepsilon_{h,j,t,w} \quad (3)$$

4.2 Effects on inpatient discharges and admissions

Figure 2 plots the dynamic effects of on-site inspections on inpatient discharges and admissions based on Equation (1). Consistent with the raw patterns shown in panel A of Figure 1, inpatient discharges increase significantly following the onset of the inspections, while the effect attenuates after the inspections conclude. Moreover, the results for admissions reported in panel B of Figure 2 indicate that the increase in discharges is unlikely to be driven by a contemporaneous increase in patient inflows, as inpatient admissions remain broadly stable during the on-site inspection period. Following the completion of the inspections, inpatient admissions exhibit a modest short-term increase, potentially reflecting hospitals' efforts to restore inpatient volume after the temporary increase in discharges during the inspection period. Finally, the p -values for the joint significance of the pre-event coefficients are 0.771 and 0.981 for discharges and admissions, respectively, providing no evidence of differential pre-treatment trends between treatment and control hospitals for either outcome.

[Insert Figure 2 here]

Table 3 reports the average treatment effects of on-site inspections on inpatient discharges and admissions. Column (1) of Table 3 reports an average increase of 0.397 inpatient discharges per 10-day interval, equivalent to roughly 9% relative to the pre-treatment mean of treated hospitals. When we separately distinguish the inspection period from the post-inspection period in column (2), the increase in discharges is concentrated entirely during the active enforcement stage. Specifically, inpatient discharges increase by 0.753 per 10-day interval during the inspection period, or approximately 17% relative to the

pre-treatment mean of the treated hospitals, whereas the estimated effect becomes small and statistically insignificant after the inspections conclude. By contrast, column (4) of Table 3 shows no evidence of a contemporaneous increase in inpatient admissions during the inspection period. Instead, inpatient admissions exhibit an increase of 0.391 per 10-day interval, or 8.5% relative to the pre-treatment mean of the treated hospitals, only after the on-site inspections conclude, consistent with the dynamic patterns documented in panel B of Figure 2.

[Insert Table 3 here]

We conduct a series of robustness checks to assess the sensitivity of the hospital-level results to alternative sample constructions and model specifications. Figure 3 summarizes the corresponding estimates, while Appendix Tables A2 and A3 report the underlying coefficient estimates for completeness.

First, primary hospitals, which focus on primary care and preventive services, differ substantially from secondary and tertiary hospitals in the volume of inpatient services, raising the possibility that their inclusion may affect the baseline estimates. We therefore exclude primary hospitals from the sample. The results remain largely unchanged, consistent with the fact that the majority (about 95%) of inpatient admissions and discharges occur in secondary and tertiary hospitals. Second, to assess whether the findings are specific to the first two inspection rounds used in the baseline analysis, we extend the sample to include all three rounds and find that the estimates are highly comparable to the baseline results. Third, if hospitals anticipated the inspection and began adjusting their behavior before the formal start of the on-site inspection, the baseline treatment date could miss these early responses. Although the event-study estimates provide no evidence of anticipatory responses during the pre-inspection period, we nevertheless redefine the treatment date using the beginning of the pre-inspection stage and obtain quantitatively similar estimates. Finally, because the estimated dynamic patterns may depend on the choice of 10-day event-time intervals, we reconstruct the analysis using 7-day intervals (from 42 days pre-event to 91 days post-event) and 15-day intervals (from 45 days pre-event to 90 days post-event), respectively. The estimated effects remain stable in both sign and magnitude across these alternative interval definitions.

[Insert Figure 3 here]

Overall, the results suggest that hospitals respond to on-site inspections primarily by accelerating inpatient discharges during the active inspection period. The absence of a contemporaneous increase in admissions suggests that the rise in discharges is driven mainly by changes in the management of existing inpatients. While this may reflect reductions in unnecessary inpatient utilization, it could also raise concerns that some patients may be discharged before fully completing necessary treatment, with potential consequences for subsequent healthcare utilization and quality of care. This motivates our subsequent

analysis of patient-level outcomes.

5. Claim-level analysis

5.1 Econometric framework

We next turn to claim-level analyses to investigate whether the changes in hospital discharge behavior induced by the on-site inspections lead to any adverse consequences for healthcare quality. Building on the claim-level analytical sample, we implement a stacked DID framework similar to the hospital-level analysis, comparing patients discharged from hospitals inspected during a given wave with patients discharged from hospitals that had not yet been inspected or were never inspected. Event time is defined by the discharge date of the index hospitalization to capture post-discharge outcomes associated with discharge decisions around the inspections. Our baseline claim-level estimation equation is specified as Equation (4):

$$Y_{i,h,j,t,w} = \beta_0 + \sum_{\substack{\eta=-4 \\ \eta \neq -1}}^8 \mu_\eta D_{h,j,t,w}^\eta + X_{i,w} + \tau_{h,w} + \sigma_{j,t,w} + \mathbf{G}'_{h,2013} \times \mathbf{t} + \xi_{i,h,j,t,w} \quad (4)$$

where $Y_{i,h,j,t,w}$ denotes the outcome of interest, for example, readmission within 30 days, for patients associated with claim i discharged by hospital h in district j at time t (measured in 10-day intervals) during inspection wave w . $D_{h,j,t,w}^\eta$ is an indicator equaling 1 if and only if the discharge of claim i from an inspected hospital occurs in the $\eta \times 10$ -day interval relative to the start of the on-site inspection in wave w . Hospital, department, and district-by-time differences are controlled with wave-specific fixed effect, namely hospital-by-wave and department-by-wave fixed effects $\tau_{h,w}$, and district-by-time-by-wave fixed effects $\sigma_{j,t,w}$. To further account for potential differences in patient composition, we consider age, gender, and insurance-type, and interact them with inspection-wave indicators, yielding age-by-wave, gender-by-wave, and insurance-by-wave fixed effects included in $X_{i,w}$. We additionally control for linear time trends interacted with a vector of baseline hospital characteristics measured in 2013, $\mathbf{G}'_{h,2013}$, including average inpatient and outpatient expenditures per visit. The standard errors are again clustered at the hospital level.

The causal interpretation of the claim-level estimates also relies on the assumption that, absent the inspections, outcomes for patients discharged from treated and control hospitals would have followed similar trajectories. An additional concern in the claim-level analysis is that hospitals may selectively admit patients during the inspection period, thereby altering the composition of observed claims. In this case, estimated effects on patient outcomes could partly reflect changes in patient composition rather than changes in healthcare quality induced by the inspections. To account for this possibility, our baseline

specification includes age-by-wave, gender-by-wave, and insurance-by-wave fixed effects. As a further robustness check, we restrict the sample to patients admitted before the onset of the inspections and re-estimate the baseline specifications. The results remain qualitatively unchanged, suggesting that our findings are unlikely to be driven by selective patient admissions during the inspection period. Consistent with the hospital-level analysis, the event-study estimates reveal no evidence of differential pre-treatment trends, and placebo exercises based on the 2013 data yield no significant dynamic effects (see Appendix Figure A2 and Table A4).

Parsimonious stacked DID models are also estimated to summarize the average treatment effects of the inspections on patient outcomes. Similar to the hospital-level analysis, Equation (5) estimates the average effect across the full post-inspection period, while Equation (6) distinguishes between effects during the inspection period and those after the inspections conclude.

$$Y_{i,h,j,t,w} = \beta_0 + \beta_1 \mathbf{1}_{\{Insp_{h,j,t,w}\}} + X_{i,w} + \tau_{h,w} + \sigma_{j,t,w} + \mathbf{G}'_{h,2013} \times \mathbf{t} + \xi_{i,h,j,t,w} \quad (5)$$

$$Y_{i,h,j,t,w} = \beta_0 + \beta_2 \mathbf{1}_{\{DuringInsp_{h,j,t,w}\}} + \beta_3 \mathbf{1}_{\{PostInsp_{h,j,t,w}\}} + X_{i,w} + \tau_{h,w} + \sigma_{j,t,w} + \mathbf{G}'_{h,2013} \times \mathbf{t} + \xi_{i,h,j,t,w} \quad (6)$$

5.2 Effects on readmissions

Figure 4 presents the event-study estimates for the effect of on-site inspections on 30-day readmission rates. The pre-inspection coefficients are small and jointly insignificant (p -value of 0.871), lending support to the parallel trends assumption. For patients discharged during the active inspection period, the probability of readmission rises significantly. This increase dissipates once inspections conclude. This pattern closely mirrors the surge in inpatient discharges documented at the hospital level, suggesting that the accelerated discharges induced by regulatory scrutiny may have come at the expense of healthcare quality.

[Insert Figure 4 here]

Table 4 reports the corresponding average treatment effects estimated from Equations (5) and (6). Over the full event window, column (1) shows an average increase of approximately 3.45 percentage points in readmission rates, corresponding to a 15% rise relative to the pre-treatment mean of the treated hospitals. Once the inspection and post-inspection periods are distinguished in column (2), the increase is concentrated during the active on-site inspection phase, when readmission rates rise by 5.65 percentage points, or 24.6% relative to the pre-treatment mean of the treated hospitals. The post-inspection estimate, by contrast, is small and statistically insignificant.

[Insert Table 4 here]

The concentration of the readmission effect during the active enforcement period, together with the

contemporaneous surge in inpatient discharges, provides supporting evidence for the interpretation that the observed acceleration in discharges worsened post-discharge outcomes for patients. The magnitude of the effect is also sizable and economically meaningful. For comparison, Evans et al. (2008) study policies that encouraged longer postpartum hospital stays and find that reducing early discharge by 16–30 percentage points lowers 28-day readmission rates by only 0.3 percentage points among c-section deliveries, with no detectable effect for vaginal births. Gupta (2021) similarly finds that a performance-based payment policy directly targeting readmissions reduces them by about 1 percentage point. However, note that the settings examined in these studies involve changes in the opposite direction from ours. While extending inpatient care may have limited scope to further reduce readmissions if the existing level of care is already adequate, shortening inpatient stays could pose greater risks if patients are discharged before completing necessary treatment.

Several robustness checks are conducted to assess the sensitivity of the claim-level results. Figure 5 summarizes the estimates, with the corresponding coefficients reported in Appendix Table A5. We first replicate the robustness exercises from the hospital-level analysis by excluding discharges from primary hospitals, including all three inspection rounds, using an alternative treatment date, and grouping event-time windows into 7- or 15-day intervals. The resulting estimates remain close to the baseline results.

[Insert Figure 5 here]

We further examine several issues specific to the claim-level analysis. To address potential changes in patient composition, we restrict the sample to patients admitted before the start of the on-site inspection. The estimated effects become larger but less precise because of the smaller sample. The results also remain quantitatively similar when readmissions are measured over 15- or 60-day windows rather than the baseline 30-day window, and when the baseline patient-characteristic controls are replaced with age-by-gender-by-insurance-type fixed effects. Overall, these exercises indicate that the increase in readmissions is not driven by selective admissions, the choice of the readmission window, or the specification of patient characteristics.

We next examine where the additional readmissions occur. In our main analysis above, readmissions are identified regardless of where the subsequent admission occurs. Panel A of Figure 6 and Appendix Table A6 distinguish between readmissions to the index hospital and those to a different hospital. The increase is concentrated in readmissions to a different hospital, whereas readmissions to the index hospital remain relatively stable or even decline slightly during the inspection period. The shift toward other hospitals may reflect additional behavioral responses to ongoing regulatory scrutiny. Hospitals under inspection may be reluctant to readmit patients whom they have recently discharged, as such rapid returns could make unusual discharge patterns more visible to regulators and increase the risk of being detected and penalized. On the

patient side, those whose conditions remain unresolved after discharge may lose confidence in the index hospital and become less willing to return there, leading them to seek subsequent care elsewhere.

[Insert Figure 6 here]

Panels B and C of Figure 6 and Appendix Tables A7 and A8 further distinguish these readmissions by department of care. These estimates show that the increase in cross-hospital readmissions occurs primarily among patients readmitted to the same department at another hospital, while readmissions to different departments change little. Readmissions to the index hospital show a flipped pattern, with a decline in readmissions in the same department and little change in readmissions involving different departments. These patterns suggest that patients continue to require inpatient treatment, likely for the same underlying condition, after the initial discharge rather than being readmitted for unrelated medical problems. Notably, these responses are also concentrated among cases discharged during the active inspection period and disappear once the inspections conclude. Together with the contemporaneous surge in discharges, the continued need for same-department inpatient care provides further evidence that the inspections induce premature discharges.

5.3 Mechanisms

5.3.1 Treatment compression

The results above show that on-site inspections increase discharges but also lead to higher readmission rates. One possible explanation for this pattern is that inspections induce hospitals to compress treatment episodes by shortening inpatient stays and discharging patients earlier than they otherwise would (Kosecoff et al., 1990). If so, we would expect reduced length of stay and expenditures among inpatients discharged during the inspection period.

[Insert Figure 7 here]

Figure 7 and Table 5 provide evidence for this mechanism. Patients discharged during the active on-site inspection period have stays that are 0.963 days shorter, a reduction of approximately 10% relative to the pre-treatment mean of the treated hospitals. Their inpatient expenditures are also RMB 1,613 (or 13%) lower. Consistent with the discharge pattern, these reductions are concentrated during the active inspection period and largely dissipate once inspections conclude. These findings suggest that hospitals compress treatment episodes when regulatory scrutiny is most intensive, which may result in some patients being discharged before completing necessary treatment, thereby increasing their risk of readmission.

[Insert Table 5 here]

5.3.2 Administrative burden and provider capacity

Treatment compression may arise because hospitals seek to avoid practices that could be viewed as unnecessary utilization or because inspections impose additional administrative burdens on providers. During on-site inspections, physicians and other medical staff have to devote additional time and attention to responding to inspectors, preparing documentation, and explaining clinical decisions. These demands can divert scarce provider time and attention away from patient care, especially in hospitals where providers already face heavy workloads. If this channel contributes to the increase in readmissions, the effect should be more pronounced in hospitals with less spare capacity (Aiken et al., 2002).

To assess this prediction, we examine heterogeneity in the effects of inspections on the 30-day readmission by provider workload measured before the inspections. Specifically, we calculate the number of discharged patients per medical staff member in 2013. Staffing information is obtained from the Annual Statistical Reports of Public Hospitals published by the National Health Commission.¹² Because workload differs systematically across hospital tiers, we classify hospitals as having high or low provider workload relative to the median within the corresponding hospital-tier group. Results are shown in panel A of Figure 8 and Appendix Table A9. The increase in readmissions is concentrated among hospitals with higher provider workloads, while the response is substantially weaker among hospitals with lower workloads. These findings support the idea that inspection-related administrative demands may adversely affect patient outcomes, warranting particular caution when providers already operate under heavy workloads.

[Insert Figure 8 here]

5.3.3 Treatment standardization and individualized care

Regulatory scrutiny may also affect the degree of discretion that providers exercise in treatment and discharge decisions. To reduce the risk that their decisions are viewed as inappropriate, providers may adopt more standardized practices during inspections. The implications for patient outcomes are ambiguous. If pre-inspection variation reflects unnecessary or ineffective treatment use, greater standardization may improve care quality or leave outcomes unchanged. If this variation instead reflects appropriate tailoring to heterogeneous patient needs, more uniform decisions may worsen outcomes, particularly in departments where treatment is ordinarily more individualized (Chandra and Staiger, 2007; Finkelstein et al., 2016). We examine these possibilities by testing whether the readmission response varies with baseline treatment heterogeneity across departments.

Specifically, we use the coefficient of variation (CV) of inpatient expenditures within each department

¹² Staff counts are unavailable for approximately 10% of hospitals, so this analysis covers about 90% of the baseline sample.

in 2013 as a measure of baseline treatment variation.¹³ Departments with greater expenditure variation are likely to exhibit greater heterogeneity in treatment intensity across patients, while lower variation is more consistent with relatively standardized treatment practices. We classify departments according to whether their expenditure variation is above the sample median. Panel B of Figure 8 and Appendix Table A9 show that the increase in 30-day readmissions is more pronounced in departments with above-median expenditure variation, whereas departments with lower variation exhibit little response. This pattern is consistent with the possibility that pressure to comply with regulatory requirements encourages more uniform treatment and discharge decisions that may not adequately accommodate heterogeneous patient needs. It therefore motivates further consideration of the potential trade-off in regulatory enforcement between limiting questionable utilization and preserving appropriate clinical discretion.

5.3.4 Composition of discharged patients

Another possible explanation for the increase in readmissions is that inspections change the composition of discharged patients. For example, under time constraints or in an effort to avoid intensive treatment, hospitals may be more likely to discharge patients with greater care needs, who may also face a higher underlying risk of readmission. We examine this possibility using age as a simple proxy for differences in clinical severity and classify patients into three mutually exclusive groups: below 50, 50–74, and 75 and above.¹⁴ We first examine whether inspections change the age composition of discharged patients and then assess whether the corresponding readmission effects differ across these groups. When using patient age categories as the outcome variable, patient-characteristic controls are excluded from the specifications. Figure 9 summarizes the results, with the corresponding estimates reported in Appendix Table A10.

[Insert Figure 9 here]

Panel A of Figure 9 shows substantial changes in the age composition of discharged patients. The shares of discharged patients below age 50 and those aged 50–74 increase by 2.68 and 3.60 percentage points, respectively, whereas the share of patients aged 75 and above declines by 6.27 percentage points. Thus, inspections shift the composition of discharged patients toward the two younger groups and away from the oldest group.

Panel B further shows that the subsequent increase in readmissions is concentrated among patients aged 50–74. For this group, inspections increase the 30-day readmission rate by approximately 23% relative

¹³ The coefficient of variation is calculated as the within-department standard deviation divided by the within-department mean of inpatient expenditures in 2013.

¹⁴ The baseline classification uses age 50 as the cutoff to preserve sufficient sample size in the group below this age. Appendix Figure A3 uses age 45 as an alternative cutoff and yields qualitatively similar results. Appendix Table A11 examines whether inspections also alter the gender and insurance composition of discharged patients. We find no significant changes along either dimension, suggesting that the compositional response is concentrated primarily along the age margin rather than reflecting a broader reshuffling across observable patient characteristics.

to the pre-treatment mean of the treated hospitals. By contrast, the estimated effects for patients below age 50 and those aged 75 and above are small and statistically insignificant. The absence of a readmission increase among younger patients, despite their higher discharge share, may reflect their relatively lower clinical severity and greater ability to recover outside the hospital following an earlier discharge. Patients aged 50–74, however, may lie closer to the margin of discharge decisions: they appear sufficiently stable to be discharged earlier, yet remain more susceptible than younger patients to incomplete treatment and subsequent rehospitalization. For the oldest patients, whose clinical risks are likely to be more apparent, hospitals may have less scope or willingness to accelerate discharge decisions in the first place. This suggests that the increased readmissions cannot be explained by a simple compositional change in which hospitals discharge more of the oldest, plausibly highest-risk patients. Instead, it is patients in the intermediate age group, those aged 50–74, who become particularly vulnerable to inspection-induced changes in discharge behavior.

5.4 Do inspections generate savings in healthcare spending?

The evidence above suggests that inspections reduce treatment during the index hospitalization but generate additional inpatient utilization after discharge. This raises a natural policy question: whether the initial reductions in healthcare utilization translate into net savings once subsequent inpatient care is taken into account. To answer this question, we examine the impact of inspections on cumulative measures of inpatient utilization following discharge. For each patient, we calculate the inpatient days and expenditures incurred after the index discharge within follow-up horizons ranging from 10 to 90 days in 10-day increments. When a subsequent hospitalization extends beyond the endpoint of a follow-up window, we count only the inpatient days falling within that window and allocate expenditures evenly across the days of the hospitalization.¹⁵ We then add utilization during the index hospitalization to each cumulative post-discharge measure to construct total inpatient utilization over the corresponding horizon.

We estimate Equation (5) separately for each follow-up horizon, using cumulative inpatient utilization as the outcome. Each coefficient therefore captures the effect of inspections on the utilization accumulated over a specified number of days following the index discharge. Figure 10 plots these estimates against the length of the follow-up window, with the corresponding coefficient estimates reported in Appendix Tables A12–A13. Note that this figure differs from the event-study analysis above. In the event-study figure, the horizontal axis indicates the timing of the index discharge relative to the onset of the inspection. In Figure 10, by contrast, all coefficients estimate the effect of inspections for an average post-inspection discharge,

¹⁵ For example, for a seven-day hospitalization beginning 28 days after the index discharge, the 30-day measure includes two inpatient days and the corresponding share of expenditures, whereas the 40-day measure includes all seven inpatient days and the full expenditure.

and the horizontal axis indicates the number of post-discharge days over which subsequent utilization is accumulated.

[Insert Figure 10 here]

The green solid markers in Figure 10 show the estimates for cumulative post-discharge utilization. The effects on both inpatient days and expenditures increase as the follow-up window expands and then stabilize after about 60 days. By 60–90 days after discharge, inspections are associated with roughly 0.8 additional inpatient days and RMB 1,100 in additional post-discharge expenditures. The yellow hollow markers show total utilization, including both the index hospitalization and subsequent inpatient care. The leftmost yellow marker reproduces the reduction in utilization during the index hospitalization documented above. As additional post-discharge utilization accumulates, it increasingly offsets this initial reduction. At longer horizons, the net effects on both total length of stay and expenditures approach zero and even become slightly positive, although statistically insignificant. Taken together, these findings show that the utilization reductions during the index hospitalization do not translate into detectable overall savings over the 90-day follow-up period. Instead, the apparent short-run savings are largely offset by additional inpatient utilization after discharge.

6. Conclusion

Enforcement against improper billing and utilization has become an increasingly important policy tool for governments seeking to contain wasteful healthcare spending and protect the sustainability of public health insurance funds. Yet the effectiveness of such enforcement depends not only on the form and intensity of monitoring itself, but also on how providers adapt their behavior in response to regulatory scrutiny. This paper examines these issues through an on-site hospital inspection program implemented in China.

Using administrative health insurance claims and a stacked DID design, we find that on-site inspections induce hospitals to increase inpatient discharges without a comparable increase in admissions. At the claim level, inspections lead to a significant increase in 30-day readmission rates. Both responses are concentrated during the active inspection period and largely disappear once inspections conclude, suggesting that providers adjust their behavior strategically in response to temporary regulatory pressure. Further analysis reveals a clear shift in the location of follow-up care: readmissions to the same department at different hospitals increase substantially, while readmissions to the same department at the index hospital decline. This pattern suggests that patients continue to require treatment for likely related conditions after the initial discharge, but seek subsequent care at alternative providers.

We provide several pieces of evidence regarding the potential mechanisms underlying these effects.

Length of stay and inpatient expenditures decline significantly during the inspection period, indicating that hospitals compress treatment during inspections. Provider capacity constraints and a shift toward more standardized treatment and discharge decisions are particularly important, as the increase in readmissions is more pronounced in hospitals facing higher provider workloads and in departments with greater baseline treatment variation. We also find changes in discharge composition: inspections increase the discharge shares of patients younger than 50 and those aged 50–74, while the resulting increase in readmissions is concentrated among patients aged 50–74.

Finally, reductions in healthcare utilization during the index hospitalization are gradually offset by increases in subsequent inpatient utilization. As a result, the initial reductions do not translate into detectable overall savings over the 90-day follow-up period.

Our findings highlight a central challenge in the design of regulatory policies. While hospital inspections are intended to reduce inappropriate utilization and improve the efficiency of public spending, providers may respond strategically by altering observable behaviors in ways that are not fully anticipated by regulators. We show that such behavioral responses can have important consequences for healthcare quality and the ultimate effectiveness of enforcement. Therefore, assessing the effectiveness of such enforcement requires considering not only immediate changes in healthcare utilization and spending, but also downstream patient outcomes and subsequent healthcare resource use.

More broadly, our study speaks to the design of regulatory enforcement when regulated agents can respond along multiple margins. Monitoring that targets a narrow set of observable outcomes may improve measured performance while inducing behavioral adjustments along less closely monitored dimensions, without reducing the underlying social costs. Effective enforcement therefore requires accounting for such behavioral substitution and designing incentive-compatible monitoring systems in which regulated agents have less incentive to improve monitored outcomes by shifting costs or risks elsewhere.

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Tables and Figures

Table 1 Overview of hospital inspections in City A, 2014–2015

Waves	Inspection Process			Inspected institutions
	Pre-inspection	On-site Inspection	Post-inspection	
First	February 28, 2014 – March 2, 2014	March 3, 2014 – April 11, 2014	April 14, 2014 – April 25, 2014	89 hospitals (18 tertiary hospitals, 35 secondary hospitals, 36 primary hospitals)
Second	July 7, 2014 – July 13, 2014	July 14, 2014 – August 22, 2014	August 25, 2014 – September 5, 2014	90 hospitals (7 tertiary hospitals, 45 secondary hospitals, 38 primary hospitals)
Third	September 14, 2015 – October 18, 2015	October 19, 2015 – December 8, 2015	December 9, 2015 – December 21, 2015	90 hospitals (16 tertiary hospitals, 42 secondary hospitals, 32 primary hospitals)

Notes: This table summarizes the timeline and inspected institutions for the three rounds of on-site hospital inspections conducted between 2014 and 2015 in City A. Information is sourced from local government administrative records.

Table 2 Descriptive statistics

Variable	N	Mean	SD
Panel A: Hospital-level sample			
Number of discharged patients (10-day interval)	7,631	2.709	4.554
Number of admitted patients (10-day interval)	7,631	2.705	4.581
Indicator for treatment	7,631	0.199	0.400
Average inpatient expenditure per visit in 2013	7,631	11.934	8.265
Panel B: Claim-level sample			
Gender (% Female)	19,549	0.390	0.488
Age	19,549	61.392	19.771
Insurance type (% UEBMI)	19,549	0.971	0.168
Indicator for treatment	19,549	0.360	0.480
Length of stay	19,549	9.608	11.433
Expenditure	19,549	11.984	12.889
30-day readmission rate	19,549	0.201	0.401

Notes: The table reports the descriptive statistics of key variables in the final analytical samples. Panel A presents the results for the hospital-level dataset, while panel B presents the results for the claim-level dataset. All the expenditure outcomes are measured in RMB, thousands.

Table 3 Effects of on-site inspections on inpatient discharges and admissions

	Number of inpatient discharges		Number of inpatient admissions	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.397** (0.154)		0.202 (0.158)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.753*** (0.166)		−0.0316 (0.182)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0968 (0.177)		0.391** (0.167)
Pre-treatment mean of the treated	4.489	4.489	4.573	4.573
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes
Number of observations	7,631	7,631	7,631	7,631

Notes: This table reports estimates of the effects of on-site inspections on inpatient discharges and admissions. Columns (1) and (2) report estimates for inpatient discharges, while columns (3) and (4) report estimates for inpatient admissions. For each outcome, the first column reports the pooled post-inspection effect based on Equation (2), while the second column separately reports the effects during and after the inspection based on Equation (3). Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$

Table 4 Effects of on-site inspections on 30-day readmission rates

	30-day readmission rates	
	(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0345** (0.0148)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0565*** (0.0158)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0138 (0.0174)
Pre-treatment mean of the treated	0.230	0.230
Patient characteristics	Yes	Yes
Department-Wave FE	Yes	Yes
Hospital-Wave FE	Yes	Yes
District-Time-Wave FE	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes
Number of observations	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on 30-day readmission rates. Column (1) reports the pooled post-inspection effect based on Equation (5), while column (2) separately reports the effects during and after the inspection based on Equation (6). Standard errors are clustered at the hospital level and reported in parentheses.

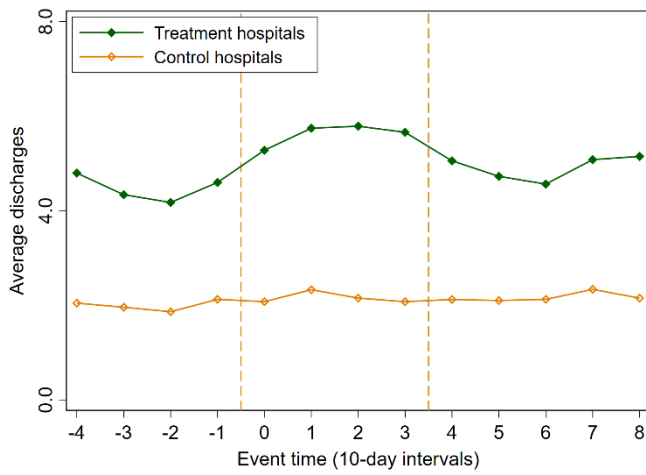
*** $p < 0.01$; ** $p < 0.05$

Table 5 Effect of on-site inspections on length of stay and inpatient expenditure

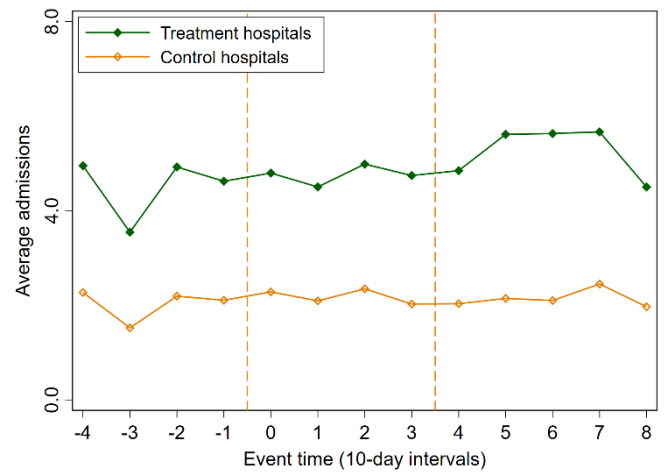
	Length of stay		Expenditure (RMB, thousands)	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	-0.669** (0.308)		-0.964** (0.418)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.963*** (0.337)		-1.613*** (0.490)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		-0.392 (0.337)		-0.352 (0.444)
Pre-treatment mean of the treated	9.381	9.381	12.435	12.435
Patient characteristics	Yes	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on inpatient length of stay and expenditure. Columns (1) and (3) report the pooled post-inspection effects based on Equation (5), while columns (2) and (4) separately report the effects during and after the inspection based on Equation (6). Columns (1) and (2) report results for length of stay, while columns (3) and (4) report results for inpatient expenditure. Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$



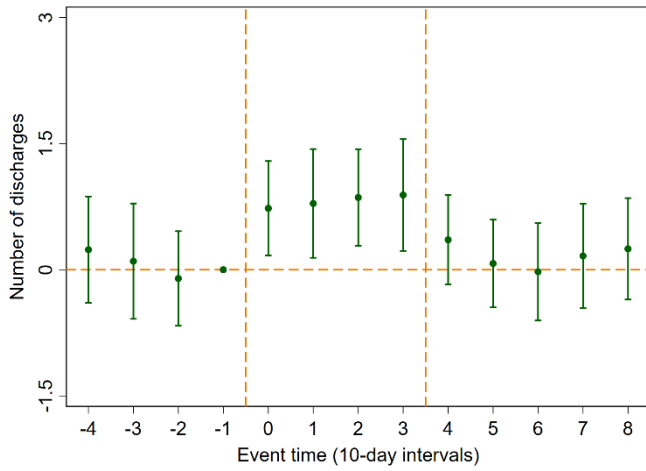
(A) Average number of inpatient discharges



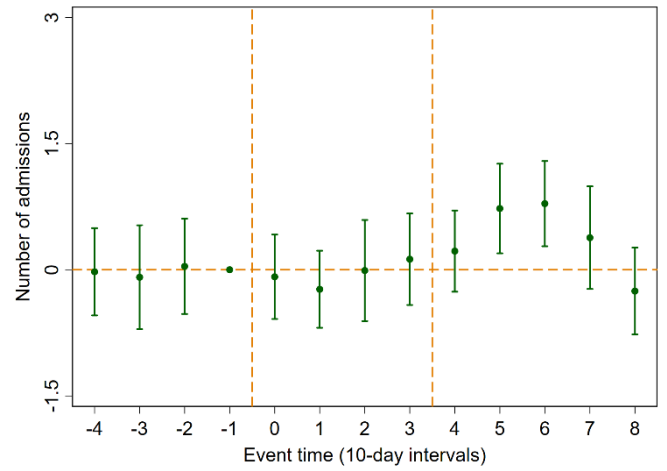
(B) Average number of inpatient admissions

Figure 1 Raw trends in inpatient discharges and admissions around the timing of on-site inspections

Notes: This figure presents raw trends in inpatient discharges and admissions around the timing of the on-site inspections. Panel A plots the average number of inpatient discharges for treatment and control hospitals, while panel B reports the corresponding trends in inpatient admissions. In both panels, solid markers represent treatment hospitals and hollow markers represent control hospitals. The vertical dashed line between -1 and 0 indicates the start of the on-site inspection, while the vertical dashed line between 3 and 4 represents the end of the inspection.



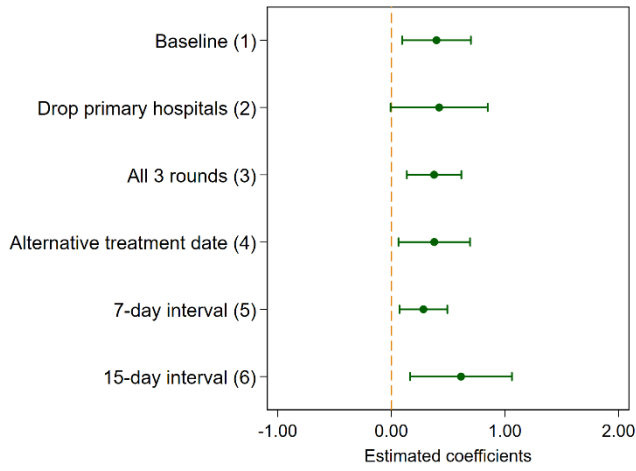
(A) Number of discharges



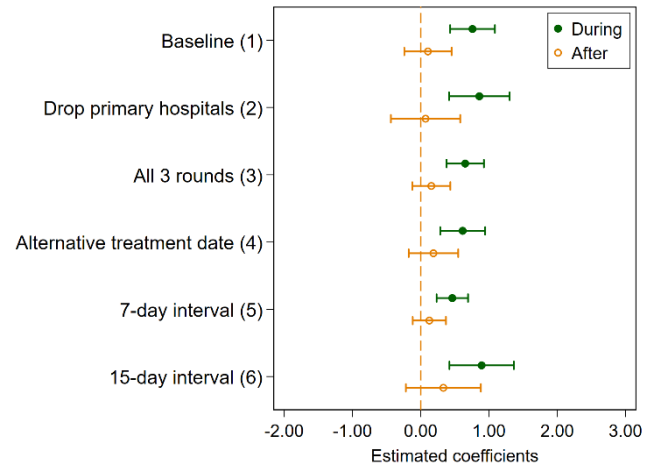
(B) Number of admissions

Figure 2 Event study estimates of the effect on inpatient discharges and admissions

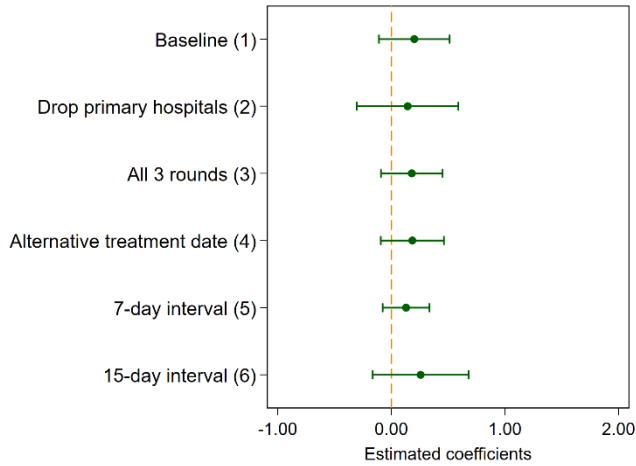
Notes: This figure reports the dynamic effects of on-site inspections on the number of discharges (panel A) and admissions (panel B) estimated using the specification of Equation (1). Each data point represents the estimated coefficient for a time interval relative to the start of the on-site inspection, capturing the effect of inspection relative to the baseline period (10 days before the start of the inspection). Vertical bars around each data point show 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 indicates the start of the on-site inspection while the vertical dashed line between 3 and 4 represents the end of the inspection. The horizontal dashed line at 0 marks the null effect.



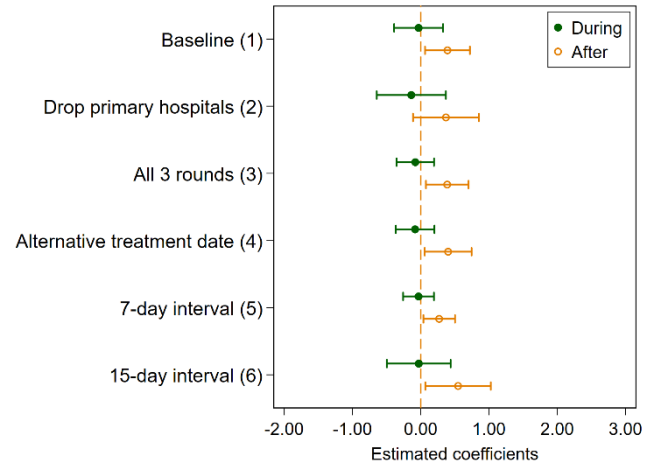
(A) Discharges: pooled effect



(B) Discharges: during vs. after



(C) Admissions: pooled effect



(D) Admissions: during vs. after

Figure 3 Hospital-level robustness checks

Notes: This figure presents robustness checks for the hospital-level analysis under alternative specifications. Panels A and C report the estimates from Equation (2), which pools both the inspection period and the post-inspection period into a single indicator. Panels B and D report the estimates from specifications that separately identify effects during the inspection period and after inspections conclude, corresponding to Equation (3). In panels A and B, the outcome is inpatient discharges, while in panels C and D, the outcome is inpatient admissions. In all panels, points represent coefficient estimates, and horizontal bars indicate 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line at zero marks the null effect.

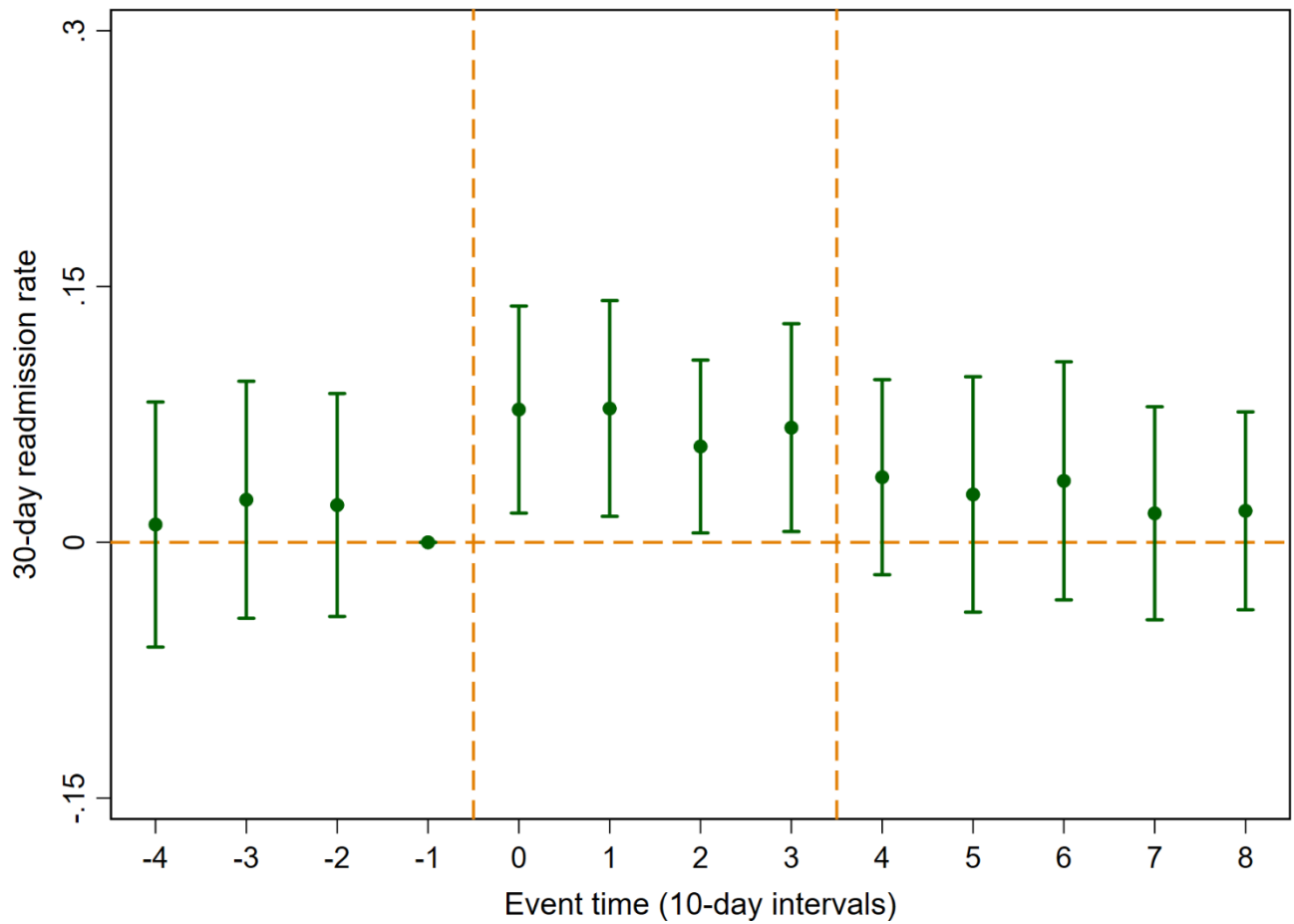
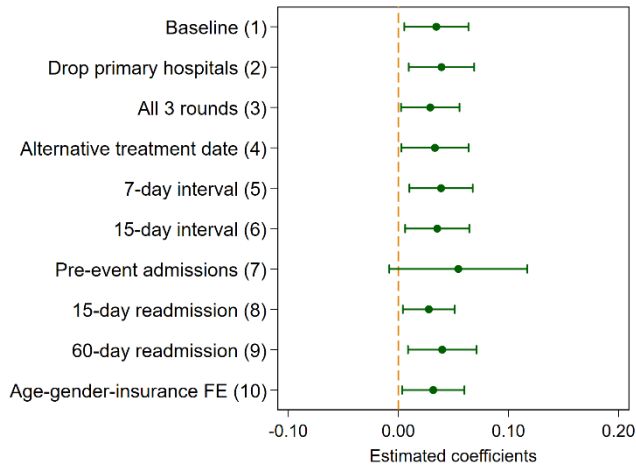
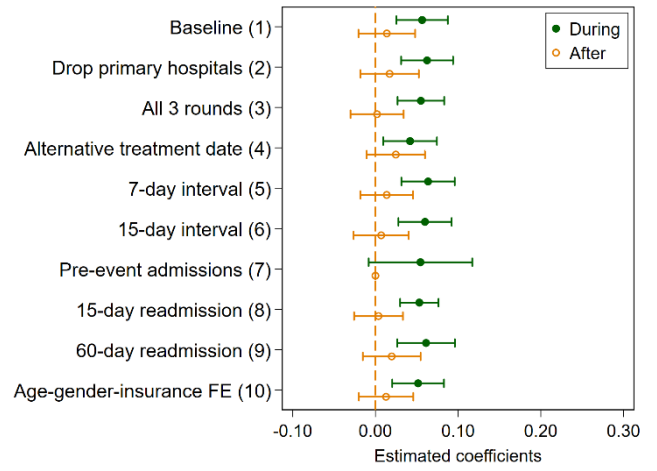


Figure 4 Event study estimates of the effect on 30-day readmission rates

Notes: This figure reports the dynamic effects of on-site inspections on 30-day readmission rates under the specification of Equation (4). Each data point represents the estimated coefficient for a time interval relative to the start of the on-site inspection, capturing the effect of inspection relative to the baseline period (10 days before the start of the inspection). Vertical bars around each data point show 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 indicates the start of the on-site inspection, while the vertical dashed line between 3 and 4 represents the end of the inspection. The horizontal dashed line at 0 marks the null effect.



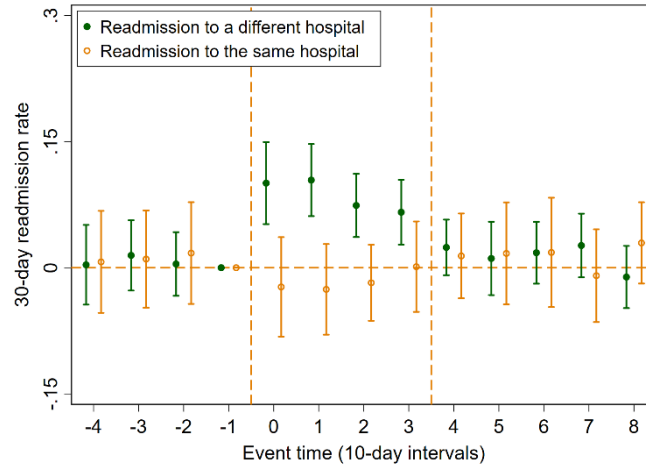
(A) Pooled effect



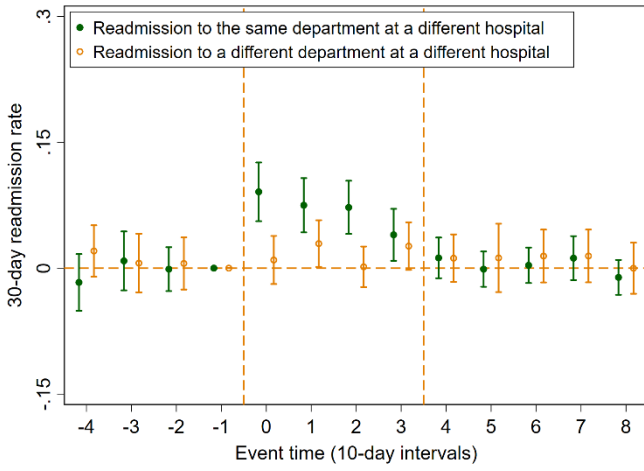
(B) During vs. after

Figure 5 Claim-level robustness checks

Notes: This figure presents robustness checks for the claim-level analysis under alternative specifications. Panel A reports the estimates from specifications using a single indicator for the entire post-inspection-onset period, corresponding to Equation (5), which pools both the inspection period and the post-inspection period. Panel B reports the estimates from specifications that separately identify effects during the inspection period and after inspections conclude, corresponding to Equation (6). Points represent coefficient estimates, and horizontal bars indicate 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line at zero marks the null effect.



(A) Readmissions by hospital



(B) Different-hospital readmissions by department



(C) Same-hospital readmissions by department

Figure 6 Event study estimates of the effect on 30-day readmission rates by hospital and department

Notes: This figure reports the dynamic effects of on-site inspections on 30-day readmission rates by hospital of readmission and department of care. Panel A distinguishes readmissions to a different hospital from those to the same hospital, while panels B and C further distinguish whether readmissions occur in the same or a different department. The estimates are based on Equation (4), with the 10 days before the start of the on-site inspection as the reference period. Vertical bars indicate 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 indicates the start of the on-site inspection while the vertical dashed line between 3 and 4 represents the end of the inspection. The horizontal dashed line at zero marks the null effect.

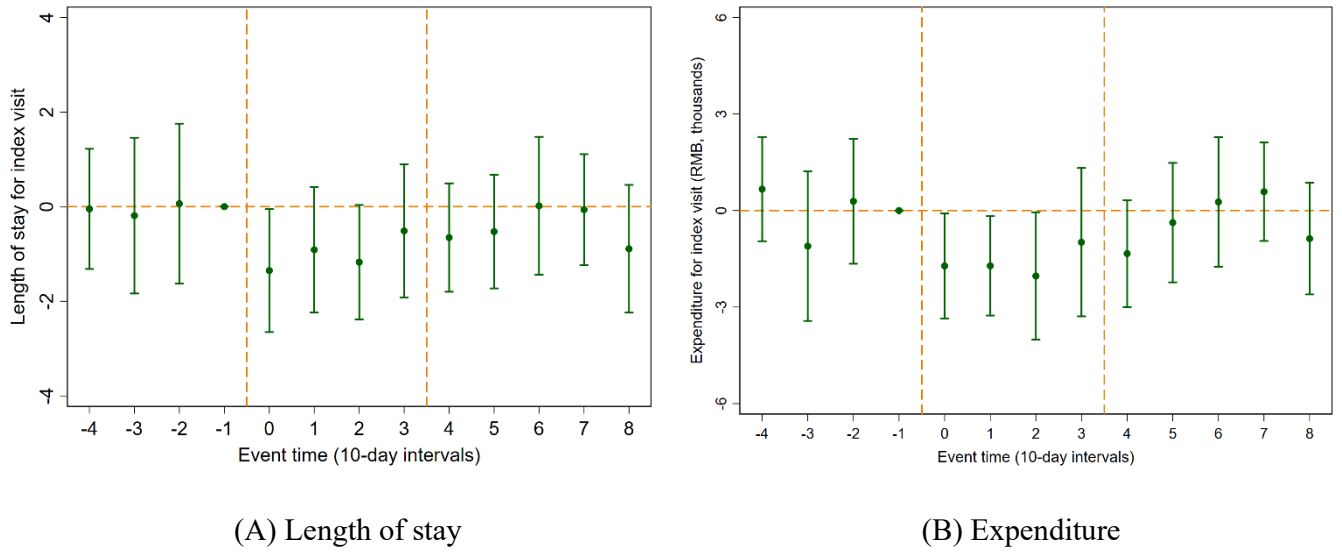
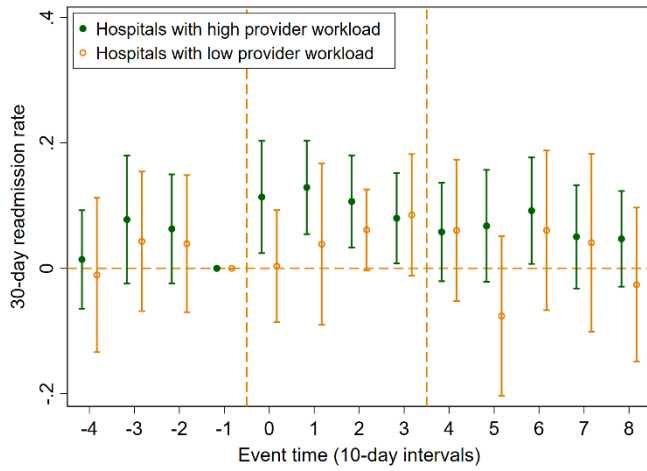
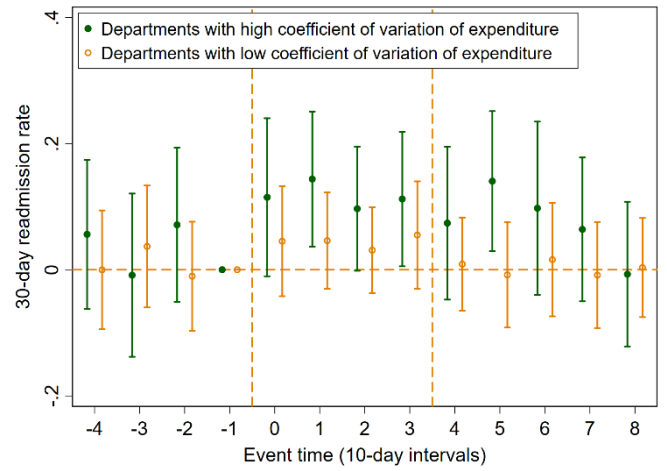


Figure 7 Event-study estimates of the effect on inpatient length of stay and expenditure

Notes: This figure reports the dynamic effects of on-site inspections on treatment intensity for the index visit under the specification of Equation (4). Panel A reports the effect on length of stay, while panel B reports the effect on expenditure. In both panels, each data point represents the estimated coefficient for a time interval relative to the start of the on-site inspection, capturing the effect of inspection relative to the baseline period (10 days before the start of the inspection). Vertical bars around each data point show 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 indicates the start of the on-site inspection, while the vertical dashed line between 3 and 4 represents the end of the inspection. The horizontal dashed line at 0 marks the null effect.



(A) Heterogeneity by provider workload



(B) Heterogeneity by department expenditure variation

Figure 8 Heterogeneity in the effects of on-site inspections on 30-day readmission rates

Notes: This figure reports the dynamic effects of on-site inspections on 30-day readmission rates by provider workload and department expenditure variation. Panel A reports heterogeneity by provider workload, measured as the number of discharged patients per medical staff member in 2013. Hospitals are classified as having high provider workload according to whether this measure is above the median within the corresponding hospital-tier group. Panel B reports heterogeneity by department expenditure variation, measured by the coefficient of variation of inpatient expenditures in 2013. Departments are classified as having high expenditure variation according to whether this measure is above the sample median. The estimates are based on Equation (4), with the 10 days before the start of the on-site inspection as the reference period. Solid markers denote the high-workload or high-variation group, while hollow markers denote the corresponding low group. Vertical bars indicate 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 indicates the start of the on-site inspection, while the vertical dashed line between 3 and 4 represents the end of the inspection. The horizontal dashed line at zero marks the null effect.

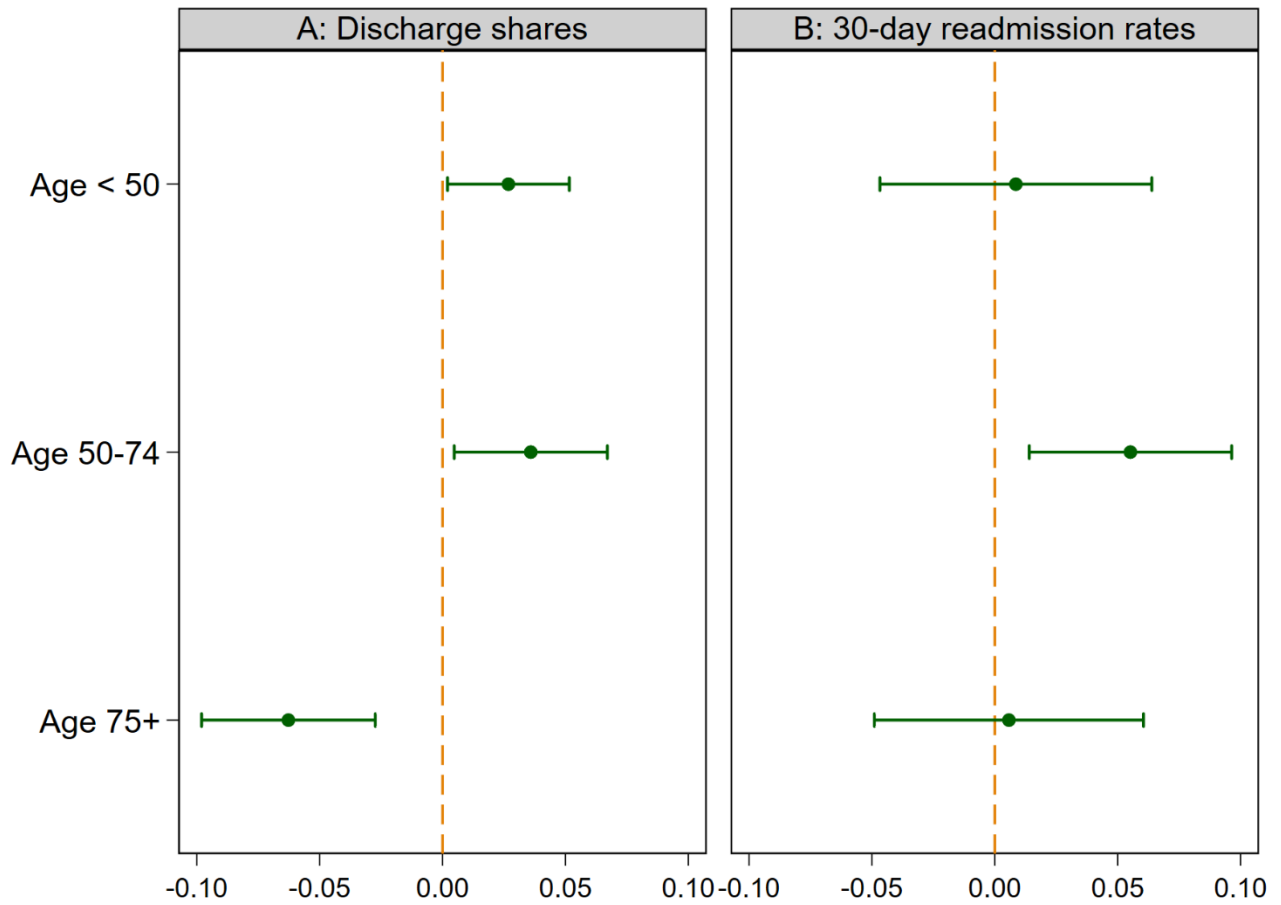
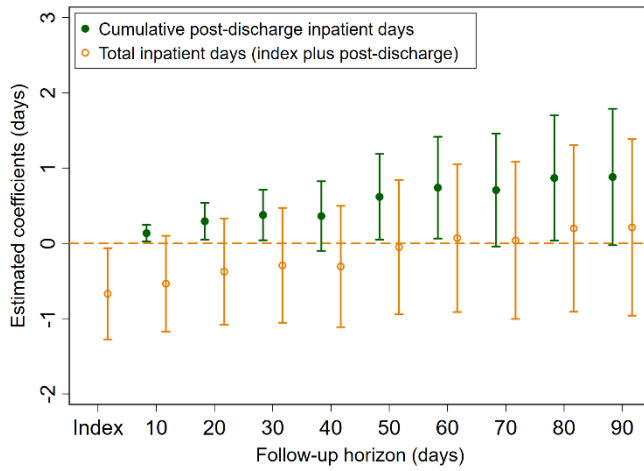
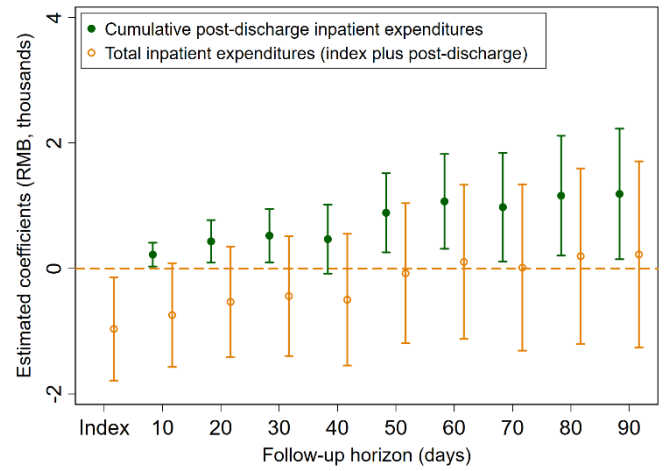


Figure 9 Effects of on-site inspections on discharge shares and 30-day readmission rates by age group

Notes: This figure presents the effects of on-site inspections on discharge shares and 30-day readmission rates across age groups under the specification of Equation (5). Panel A reports the effects on discharge shares, while panel B reports the effects on 30-day readmission rates. Patients are classified into three age groups: below 50, 50–74, and 75 and above. Points represent coefficient estimates, and horizontal bars indicate 95% confidence intervals based on standard errors clustered at the hospital level. Patient-characteristic controls are excluded in panel A because the outcomes are defined by patient age categories. The vertical dashed line at zero marks the null effect.



(A) Inpatient days



(B) Inpatient expenditure

Figure 10 Effects of on-site inspections on post-discharge and total inpatient utilization

Notes: This figure reports the effects of on-site inspections on cumulative inpatient utilization under the specification of Equation (5). Panel A reports effects on inpatient days, while panel B reports effects on inpatient expenditure. Each point represents the estimated effect for the corresponding follow-up horizon, with vertical bars indicating 95% confidence intervals based on standard errors clustered at the hospital level. At the index hospitalization, the hollow marker reports the estimated effect on utilization during the index stay. From the 10-day horizon onward, solid markers denote cumulative post-discharge utilization, while hollow markers denote total utilization including both the index hospitalization and subsequent inpatient care. The horizontal dashed line at zero marks the null effect.

Appendix

Table A1 Placebo estimates for inpatient discharges and admissions using 2013 data

	Number of inpatient discharges		Number of inpatient admissions	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0296 (0.150)		0.0500 (0.156)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		−0.000121 (0.171)		0.162 (0.163)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0534 (0.166)		−0.0396 (0.180)
Pre-treatment mean of the treated	6.071	6.071	6.232	6.232
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	No	No	No	No
Number of observations	7,891	7,891	7,891	7,891

Notes: This table reports placebo estimates for inpatient discharges and admissions using 2013 data. Columns (1) and (2) report estimates for inpatient discharges, while columns (3) and (4) report estimates for inpatient admissions. For each outcome, the first column reports the pooled post-inspection effect based on Equation (2), while the second column separately reports the effects during and after the placebo inspection period based on Equation (3). The placebo exercise replicates the baseline empirical design using the same treatment and control groups and inspection timing structure, but omits the linear time trends interacted with baseline hospital characteristics. Standard errors are clustered at the hospital level and reported in parentheses.

Table A2 Estimates for hospital-level robustness checks I: inpatient discharges

A: Baseline	Inpatient discharges		D: Alternative date	Inpatient discharges	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.397** (0.154)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.378** (0.160)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.758*** (0.167)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.615*** (0.167)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.105 (0.176)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.186 (0.185)
Observations	7,631	7,631	Observations	7,631	7,631
B: Drop primary hospitals	Inpatient discharges		E: 7-day interval	Inpatient discharges	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.421* (0.217)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.282*** (0.107)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.859*** (0.225)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.462*** (0.117)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0705 (0.258)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.126 (0.124)
Observations	3,627	3,627	Observations	11,191	11,191
C: All 3 rounds	Inpatient discharges		F: 15-day interval	Inpatient discharges	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.376*** (0.122)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.613*** (0.228)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.652*** (0.139)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.892*** (0.240)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.155 (0.142)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.331 (0.279)
Observations	11,583	11,583	Observations	5,301	5,301

Notes: This table reports robustness estimates of the effects of on-site inspections on inpatient discharges. In each panel, column (1) reports the estimates from specifications using a single indicator for the entire post-inspection period, corresponding to Equation (2), which pools both the inspection period and the post-inspection period. Column (2) reports the estimates from specifications that separately identify effects during the inspection period and after inspections conclude, corresponding to Equation (3). Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Table A3 Estimates for hospital-level robustness checks II: inpatient admissions

A: Baseline	Inpatient admissions		D: Alternative date	Inpatient admissions	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.202 (0.158)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.185 (0.141)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.0316 (0.182)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.0823 (0.144)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.391** (0.167)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.401** (0.175)
Observations	7,631	7,631	Observations	7,631	7,631
B: Drop primary hospitals	Inpatient admissions		E: 7-day interval	Inpatient admissions	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.143 (0.227)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.129 (0.105)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.138 (0.257)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.0326 (0.115)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.369 (0.245)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.270** (0.118)
Observations	3,627	3,627	Observations	11,191	11,191
C: All 3 rounds	Inpatient admissions		F: 15-day interval	Inpatient admissions	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.180 (0.138)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.258 (0.215)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.0794 (0.140)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		-0.0290 (0.238)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.388** (0.159)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.547** (0.244)
Observations	11,583	11,583	Observations	5,301	5,301

Notes: This table reports robustness estimates of the effects of on-site inspections on inpatient admissions. In each panel, column (1) reports the estimates from specifications using a single indicator for the entire post-inspection period, corresponding to Equation (2), which pools both the inspection period and the post-inspection period. Column (2) reports the estimates from specifications that separately identify effects during the inspection period and after inspections conclude, corresponding to Equation (3). Standard errors are clustered at the hospital level and reported in parentheses.

** $p < 0.05$

Table A4 Placebo estimates for 30-day readmission rates using 2013 data

	30-day readmission rates	
	(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	−0.00919 (0.0119)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		−0.00921 (0.0128)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		−0.00918 (0.0141)
Pre-treatment mean of the treated	0.225	0.225
Patient characteristics	Yes	Yes
Department-Wave FE	Yes	Yes
Hospital-Wave FE	Yes	Yes
District-Time-Wave FE	Yes	Yes
Baseline-characteristic linear trends	No	No
Number of observations	25,590	25,590

Notes: This table reports placebo estimates for 30-day readmission rates using 2013 data. Column (1) reports the pooled post-inspection effect based on Equation (5), while column (2) separately reports the effects during and after the placebo inspection period based on Equation (6). The placebo exercise replicates the baseline empirical design using the same treatment and control groups and inspection timing structure, but omits the linear time trends interacted with baseline hospital characteristics. Standard errors are clustered at the hospital level and reported in parentheses.

Table A5 Estimates for claim-level robustness checks

A: Baseline	30-day readmission		D: Alternative date	30-day readmission	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0345** (0.0148)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0332** (0.0155)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0565*** (0.0158)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0419** (0.0165)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0138 (0.0174)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0246 (0.0179)
Observations	19,549	19,549	Observations	19,404	19,404
B: Drop primary hospitals	30-day readmission		E: 7-day interval	30-day readmission	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0392** (0.0151)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0388*** (0.0146)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0625*** (0.0159)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0637*** (0.0164)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0171 (0.0179)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0137 (0.0162)
Observations	18,658	18,658	Observations	19,896	19,896
C: All 3 rounds	30-day readmission		F: 15-day interval	30-day readmission	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0290** (0.0135)		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0353** (0.0148)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0550*** (0.0143)	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0600*** (0.0163)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.00201 (0.0163)	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.00700 (0.0169)
Observations	23,966	23,966	Observations	20,045	20,045

Notes: This table reports robustness estimates for the claim-level analysis of the effects of on-site inspections on readmission rates. In each panel, column (1) reports the estimates from specifications using a single indicator for the entire post-inspection period, corresponding to Equation (5), which pools both the inspection period and the post-inspection period. Column (2) reports the estimates from specifications that separately identify effects during the inspection period and after inspections conclude, corresponding to Equation (6). Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$

Table A5 Estimates for claim-level robustness checks, continued

G: Pre-event admissions	30-day readmission		I: 60-day readmission	60-day readmission	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0545*		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0338**	
	(0.0318)			(0.0157)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0545*	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0612***
		(0.0318)			(0.0177)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		-	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0197
		-			(0.0177)
Observations	6,433	6,433	Observations	19,549	19,549
H: 15-day readmission	15-day readmission		J: Age-gender-insurance FE	30-day readmission	
	(1)	(2)		(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0277**		$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0317**	
	(0.0120)			(0.0144)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0531***	$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0516***
		(0.0118)			(0.0159)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.00372	$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0128
		(0.0150)			(0.0167)
Observations	19,549	19,549	Observations	19,549	19,549

Notes: This table reports robustness estimates for the claim-level analysis of the effects of on-site inspections on readmission rates. In each panel, column (1) reports the estimates from specifications using a single indicator for the entire post-inspection period, corresponding to Equation (5), which pools both the inspection period and the post-inspection period. Column (2) reports the estimates from specifications that separately identify effects during the inspection period and after inspections conclude, corresponding to Equation (6). Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Table A6 Effects of on-site inspections on 30-day readmission rates by hospital

	30-day readmission rate			
	A different hospital		The same hospital	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0439*** (0.00949)		−0.00937 (0.0130)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.0813*** (0.0119)		−0.0248* (0.0149)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.00857 (0.00962)		0.00522 (0.0145)
Pre-treatment mean of the treated	0.0527	0.0527	0.178	0.178
Patient characteristics	Yes	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on 30-day readmission rates by hospital of readmission. Columns (1) and (3) report the pooled post-inspection effects based on Equation (5), while columns (2) and (4) separately report the effects during and after the inspection period based on Equation (6). Columns (1)–(2) examine readmissions to a different hospital, while columns (3)–(4) examine readmissions to the same hospital. Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; * $p < 0.10$

Table A7 Effects of on-site inspections on 30-day readmission rates to a different hospital by department

	30-day readmission to a different hospital			
	A different department		The same department	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.00529 (0.00711)		0.0386*** (0.00700)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.00824 (0.00737)		0.0731*** (0.00947)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.00251 (0.00858)		0.00606 (0.00634)
Pre-treatment mean of the treated	0.0332	0.0332	0.0195	0.0195
Patient characteristics	Yes	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on 30-day readmission rates to a different hospital by department of care. Columns (1) and (3) report the pooled post-inspection effects based on Equation (5), while columns (2) and (4) separately report the effects during and after the inspection period based on Equation (6). Columns (1)–(2) examine readmissions to a different department, and columns (3)–(4) examine readmissions to the same department. Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$

Table A8 Effects of on-site inspections on 30-day readmission rates to the same hospital by department

	30-day readmission to the same hospital			
	A different department		The same department	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.00850 (0.00600)		−0.0179 (0.0133)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		0.00651 (0.00549)		−0.0313** (0.0151)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		0.0104 (0.00728)		−0.00515 (0.0148)
Pre-treatment mean of the treated	0.0178	0.0178	0.160	0.160
Patient characteristics	Yes	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on 30-day readmission rates to the same hospital by department of care. Columns (1) and (3) report the pooled post-inspection effects based on Equation (5), while columns (2) and (4) separately report the effects during and after the inspection period based on Equation (6). Columns (1)–(2) examine readmissions to a different department, and columns (3)–(4) examine readmissions to the same department. Standard errors are clustered at the hospital level and reported in parentheses.

** $p < 0.05$

Table A9 Effects of on-site inspections on readmission rates by provider workload and department expenditure variation

A: By provider workload	High provider workload	Low provider workload
	(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0489** (0.0187)	0.0133 (0.0255)
Pre-treatment mean of the treated	0.219	0.246
Patient characteristics	Yes	Yes
Department-Wave FE	Yes	Yes
Hospital-Wave FE	Yes	Yes
District-Time-Wave FE	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes
Number of observations	10,808	6,576
B: By department expenditure variation	High CV	Low CV
	(1)	(2)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0660** (0.0284)	0.0174 (0.0195)
Pre-treatment mean of the treated	0.229	0.231
Patient characteristics	Yes	Yes
Department-Wave FE	Yes	Yes
Hospital-Wave FE	Yes	Yes
District-Time-Wave FE	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes
Number of observations	6,676	12,841

Notes: This table reports heterogeneity estimates of the effects of on-site inspections on 30-day readmission rates. Panel A reports heterogeneity by provider workload, measured as the number of discharged patients per medical staff member in 2013. Hospitals are classified as having high provider workload according to whether this measure is above the median within the corresponding hospital-tier group. Panel B reports heterogeneity by department expenditure variation, measured by the coefficient of variation of inpatient expenditures in 2013. Departments are classified as having high expenditure variation according to whether this measure is above the sample median. In each panel, columns (1) and (2) report the pooled post-inspection effects based on Equation (5) for the high and low groups, respectively. In panel A, the smaller sample size reflects missing staffing information for approximately 10% of hospitals. In panel B, the slight difference between the sum of the two subgroup sample sizes and the baseline sample size arises because some observations become singletons after splitting the sample and are excluded by the fixed-effects estimation. Standard errors are clustered at the hospital level and reported in parentheses.

** $p < 0.05$

Table A10 Effects of on-site inspections on discharge shares and readmission rates by age group

A: Discharge shares	Aged < 50	Age 50–74	Age 75+
	(1)	(2)	(3)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.0268** (0.0126)	0.0360** (0.0158)	–0.0627*** (0.0180)
Pre-treatment mean of the treated	0.259	0.379	0.363
Patient characteristics	No	No	No
Department-Wave FE	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549
B: 30-day readmission rates	Aged < 50	Age 50–74	Age 75+
	(1)	(2)	(3)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	0.00856 (0.0280)	0.0552*** (0.0209)	0.00575 (0.0278)
Pre-treatment mean of the treated	0.135	0.239	0.289
Patient characteristics	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes
Number of observations	5,343	7,349	6,645

Notes: This table reports estimates of the effects of on-site inspections on discharge shares and 30-day readmission rates by age group. Panel A reports the effects on discharge shares, while panel B reports the effects on 30-day readmission rates. In each panel, columns (1)–(3) report the pooled post-inspection effects based on Equation (5) for patients aged below 50, 50–74, and 75 and above, respectively. Patient-characteristic controls are excluded in panel A because the outcomes are defined by patient age categories. In panel B, the slight difference between the sum of the three age-group sample sizes and the baseline sample size arises because some observations become singletons after splitting the sample by age group and are excluded by the fixed-effects estimation. Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$

Table A11 Effects of on-site inspections on discharge composition by gender and insurance

	Gender (1: Female)		Insurance (1: UEBMI)	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	−0.0142 (0.0145)		0.00542 (0.00605)	
$\mathbf{1}_{\{DuringInsp_{h,j,t,w}\}}$		−0.0167 (0.0170)		0.00377 (0.00635)
$\mathbf{1}_{\{PostInsp_{h,j,t,w}\}}$		−0.0119 (0.0172)		0.00697 (0.00736)
Pre-treatment mean of the treated	0.412	0.412	0.980	0.980
Patient characteristics	No	No	No	No
Department-Wave FE	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on the gender and insurance composition of discharged patients. Columns (1) and (3) report the pooled post-inspection effects based on Equation (5), while columns (2) and (4) separately report the effects during and after the inspection period based on Equation (6). Columns (1)–(2) examine the share of female patients, while columns (3)–(4) examine the share of patients enrolled in UEBMI. Patient-characteristic controls are excluded because the outcomes are defined by patient gender or insurance status. Standard errors are clustered at the hospital level and reported in parentheses.

Table A12 Effects of on-site inspections on cumulative and total inpatient days

A: Cumulative inpatient days	Index	10-day	20-day	30-day	40-day	50-day	60-day	70-day	80-day	90-day
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	–	0.135**	0.294**	0.377**	0.362	0.618**	0.740**	0.707*	0.868**	0.881*
	–	(0.0557)	(0.124)	(0.171)	(0.235)	(0.289)	(0.343)	(0.381)	(0.422)	(0.460)
Patient characteristics	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department-Wave FE	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital-Wave FE	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Time-Wave FE	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	–	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549
B: Plus index visit	Index	10-day	20-day	30-day	40-day	50-day	60-day	70-day	80-day	90-day
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	–0.669**	–0.535*	–0.375	–0.292	–0.307	–0.0511	0.0704	0.0382	0.199	0.212
	(0.308)	(0.323)	(0.358)	(0.388)	(0.409)	(0.453)	(0.499)	(0.530)	(0.562)	(0.595)
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on cumulative and total inpatient days over follow-up horizons from 10 to 90 days. Panel A reports cumulative post-discharge inpatient days from the 10-day horizon onward, while panel B reports total inpatient days including both the index hospitalization and post-discharge inpatient care. Columns (1)–(10) report estimates for the index hospitalization and follow-up horizons from 10 to 90 days, respectively, based on Equation (5). Standard errors are clustered at the hospital level and reported in parentheses.

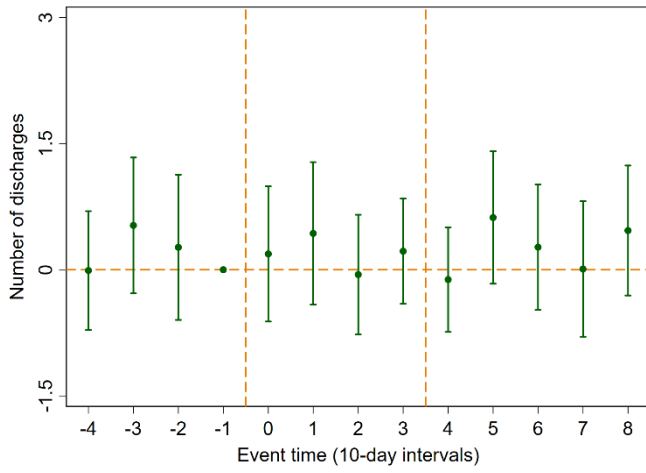
** $p < 0.05$; * $p < 0.10$

Table A13 Effects of on-site inspections on cumulative and total inpatient expenditures

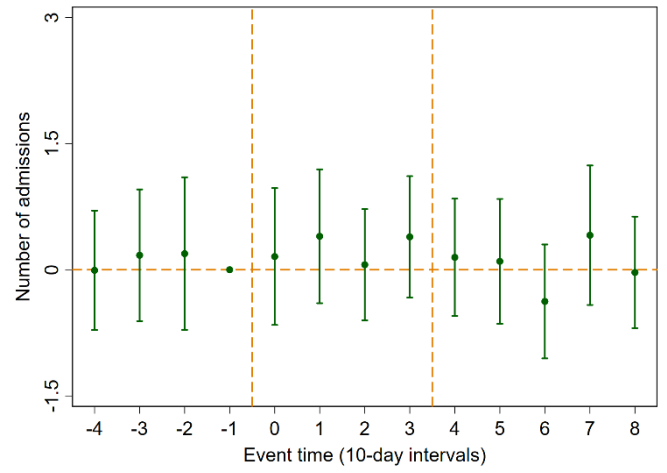
A: Cumulative expenditures	Index	10-day	20-day	30-day	40-day	50-day	60-day	70-day	80-day	90-day
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	–	0.221**	0.432**	0.523**	0.467*	0.887***	1.068***	0.977**	1.160**	1.187**
	–	(0.0961)	(0.172)	(0.217)	(0.279)	(0.321)	(0.384)	(0.440)	(0.485)	(0.529)
Patient characteristics	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department-Wave FE	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital-Wave FE	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Time-Wave FE	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	–	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549
B: Plus index visit	Index	10-day	20-day	30-day	40-day	50-day	60-day	70-day	80-day	90-day
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbf{1}_{\{Insp_{h,j,t,w}\}}$	–0.964**	–0.743*	–0.532	–0.441	–0.497	–0.0765	0.104	0.0129	0.196	0.223
	(0.418)	(0.420)	(0.447)	(0.485)	(0.533)	(0.568)	(0.625)	(0.673)	(0.711)	(0.754)
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Time-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline-characteristic linear trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549	19,549

Notes: This table reports estimates of the effects of on-site inspections on cumulative and total inpatient expenditures over follow-up horizons from 10 to 90 days. Panel A reports cumulative post-discharge inpatient expenditure from the 10-day horizon onward, while panel B reports total inpatient expenditure including both the index hospitalization and post-discharge inpatient care. Columns (1)–(10) report estimates for the index hospitalization and follow-up horizons from 10 to 90 days, respectively, based on Equation (5). All estimates are measured in RMB, thousands. Standard errors are clustered at the hospital level and reported in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$



(A) Number of discharges



(B) Number of admissions

Figure A1 Placebo event-study estimates for inpatient discharges and admissions using 2013 data

Notes: This figure plots the placebo estimates for the dynamic effects of on-site inspections on the number of discharges (panel A) and admissions (panel B) under the specification of Equation (1). The placebo exercise replicates the baseline empirical design, except that hospital-specific linear trends based on baseline covariates are excluded. Each data point represents the estimated coefficient for a time interval relative to the start of the on-site inspection, capturing the effect of inspection relative to the baseline period (10 days before the start of the inspection). Vertical bars around each data point show 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 denotes the placebo inspection start, while the vertical dashed line between 3 and 4 denotes the placebo inspection end. The horizontal dashed line at zero marks the null effect.

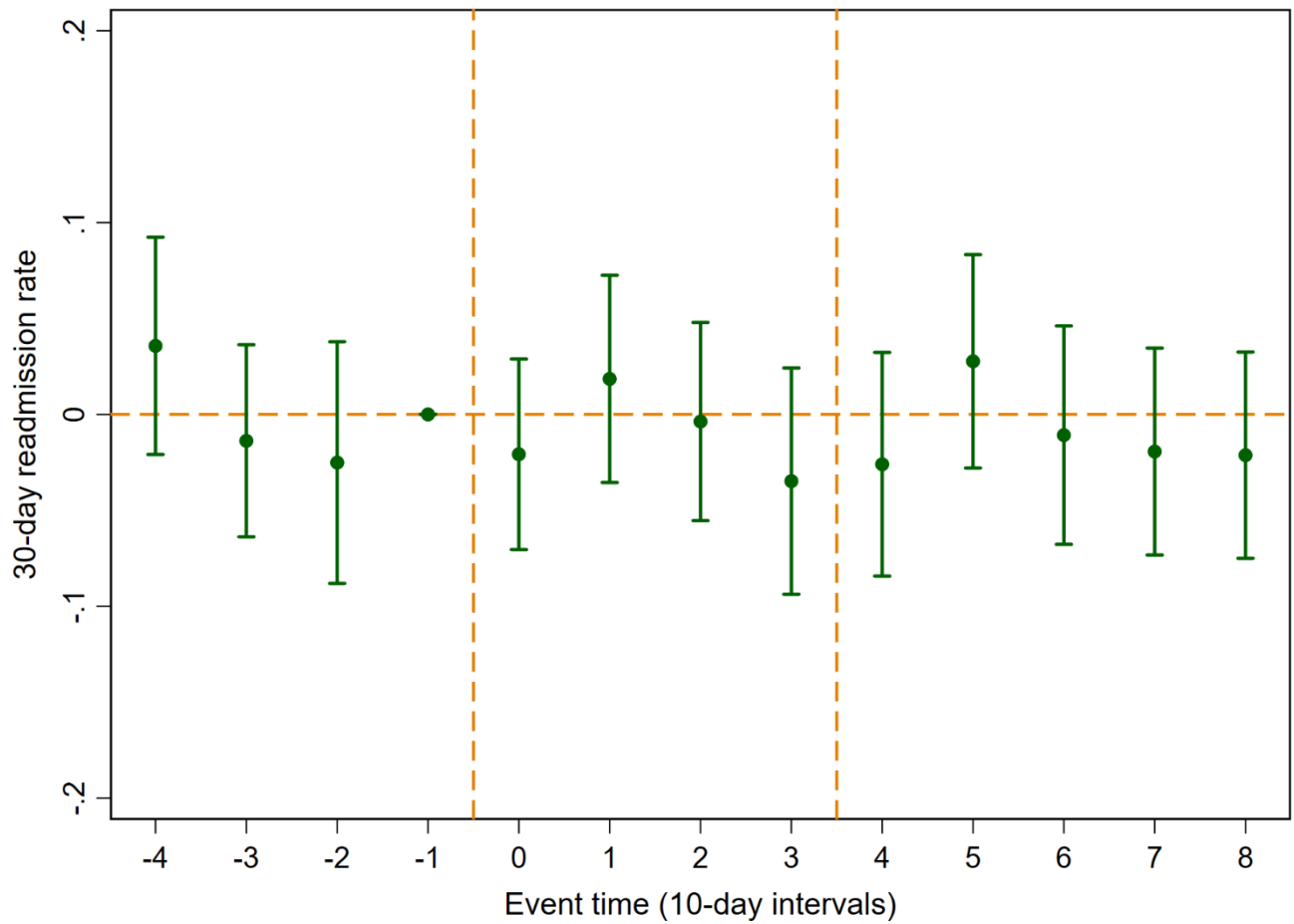


Figure A2 Placebo event-study estimates for 30-day readmission rates using 2013 data

Notes: This figure plots the placebo estimates for the dynamic effects of on-site inspections on 30-day readmission rates under the specification of Equation (4). The placebo exercise replicates the baseline empirical design, except that hospital-specific linear trends based on baseline covariates are excluded. Each data point represents the estimated coefficient for a time interval relative to the start of the on-site inspection, capturing the effect of inspection relative to the baseline period (10 days before the start of the inspection). Vertical bars around each data point show 95% confidence intervals based on standard errors clustered at the hospital level. The vertical dashed line between -1 and 0 denotes the placebo inspection start, while the vertical dashed line between 3 and 4 denotes the placebo inspection end. The horizontal dashed line at zero marks the null effect.

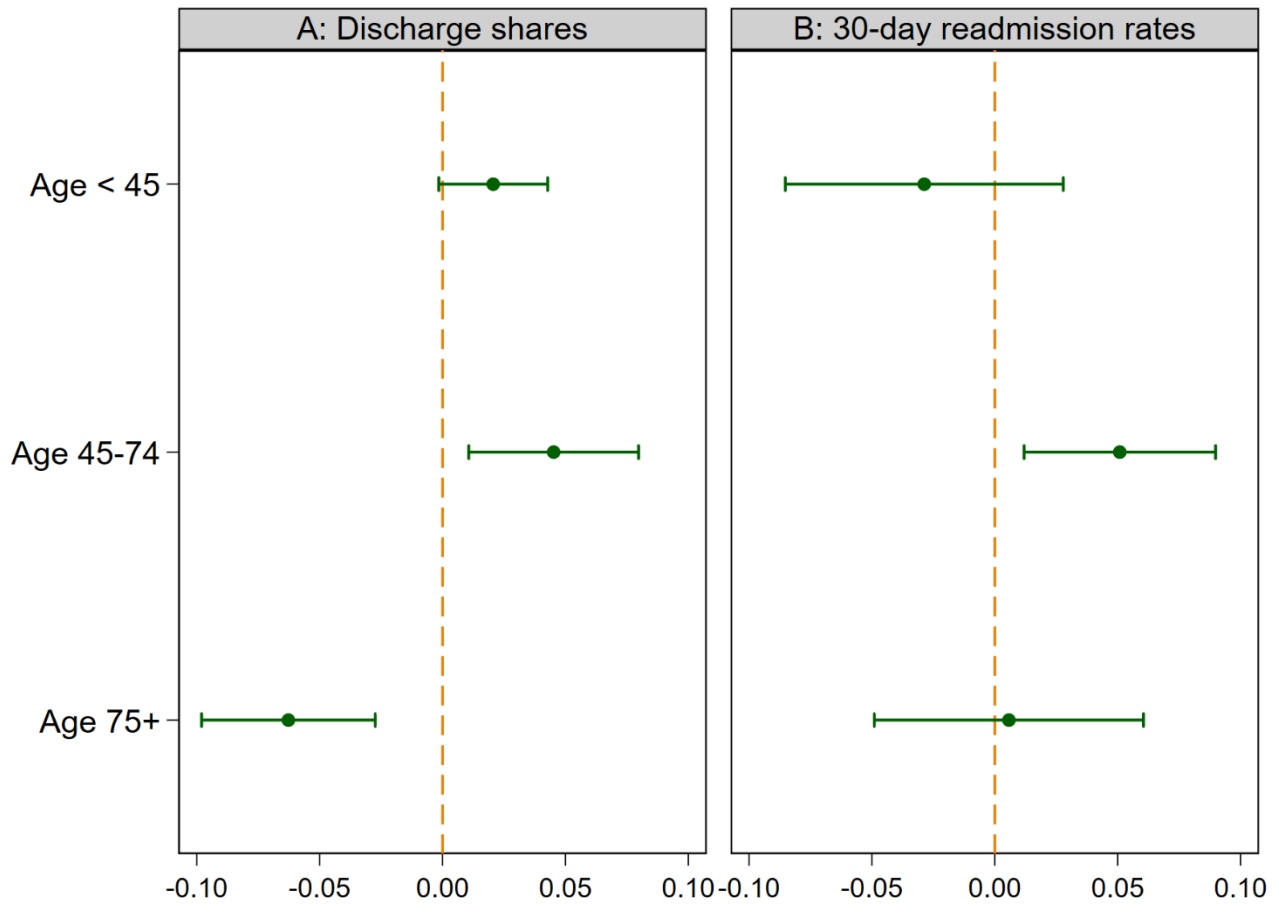


Figure A3 Effects by age group using an alternative cutoff

Notes: This figure presents the effects of on-site inspections on discharge shares and 30-day readmission rates across age groups using an alternative age cutoff under the specification of Equation (5). Panel A reports the effects on discharge shares, while panel B reports the effects on 30-day readmission rates. Patients are classified into three age groups: below 45, 45–74, and 75 and above. Points represent coefficient estimates, and horizontal bars indicate 95% confidence intervals based on standard errors clustered at the hospital level. Patient-characteristic controls are excluded in panel A because the outcomes are defined by patient age categories. The vertical dashed line at zero marks the null effect.