The VIP Effect in Medicine: How Patients' Insider Knowledge, Social Ties, and Organizational Rank Shape Clinical Decisions *

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Abstract

Very Important Persons (VIPs) often receive preferential treatment across many settings. We study how patients' privileged traits, including insider knowledge, social ties to physicians, and organizational authority, drive physicians' clinical decision-making. We leverage a policy reform that alters physicians' financial incentives without affecting patient-physician matching. Using 100% insurance claim data from a major Chinese provincial capital city, we separately examine how physicians' responses vary by patients' privileged traits. We show that a policy eliminating physician profits from drug sales reduces drug utilization but increases the use of other forms of care, raising overall costs without improving patient health. These responses are strongest for non-insider patients (those not working in a healthcare institution) and attenuate by comparable magnitudes at each step along the social proximity gradient: from non-insiders to insiders outside the treating hospital and to insiders within the treating hospital. However, the responses diminish only modestly between low-rank and high-rank colleagues within the same hospital. These findings suggest that preferential access to efficient care operates primarily through insider knowledge and social ties, rather than organizational rank.

Keywords: information, social ties, organizational rank, physician behavior, financial incentives

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1 Introduction

Principal-agent problems arise in many domains of society, and principals with different levels of privilege can be treated in strikingly different ways. Differences in insider knowledge, social ties, and authority reflect underlying inequalities among principals, which in turn may shape how agents treat them. In an unequal society, such variation is inevitable, and it can distort resource allocation while deepening disadvantages for vulnerable groups. Despite its importance, however, little is known empirically about how these distinct dimensions of privilege separately shape agents' behavior and which dimension matters most.

These dynamics are especially consequential in healthcare, where patients delegate complex decisions to physicians who hold superior information and control over clinical resources. In this paper, we separately identify the roles of insider knowledge, social ties, and organizational rank in shaping physicians' clinical decision-making.

An empirical challenge in establishing the influence of patients' privileged traits on physicians' decision-making is that direct comparisons of care utilization and health outcomes across patient groups may be confounded by unobserved differences in health status, preferences, and patient-physician matching. We address this challenge by exploiting a policy shock to physicians' financial incentives that does not affect patients' unobserved health risks and provider choice. We then examine how physicians' strategic responses to the policy vary with patients' insider knowledge, social ties to physicians, and organizational rank, leveraging the rich patient characteristics in our data.

We first develop a conceptual framework to describe how physicians adjust treatment recommendations based on patients' privileged traits. In the model, non-insider patients passively follow physicians' recommendations, whereas insider patients are skeptical, Bayesian, and actively update their beliefs before making the final decision. Physicians act more altruistically toward patients with social ties and obtain more precise signals about illness severity for high-rank patients, reflecting career concerns. The model predicts that physicians respond more strongly to financial incentives when treating non-insider patients and those without close social ties or high organizational rank.

We then test these model predictions by examining how physicians' responses to financial incentives, introduced through a drug pricing policy reform in China, vary with patients' privileged traits. Specifically, we make use of the Zero-Markup Drug Policy (ZMDP, hereafter) implemented in public hospitals in the 2010s, which eliminated the previous 15% markup on drugs dispensed by public hospitals but did not apply to private hospitals.[1] By eliminating the 15% drug markup, a key source of hospital revenue that funded physician compensation and thus incentivized over-prescription, ZMDP substantially reshaped physicians' financial incentives in public hospitals, shifting them away from drug prescriptions and toward the provision of other medical services.

Our main data sources are 100% insurance claim data for hospital stays and social security records from Changsha, a major provincial capital city in central China, covering the period from 2010 to 2018. We focus on patients with orthopedic conditions, which account for one-sixth of all hospitalizations in our data. Compared to other specialists, orthopedists typically have greater discretion in choosing between non-invasive (e.g., medications) and invasive (e.g., surgeries) treatment (Ding and Liu 2021). Our main sample consists of workers and retirees covered by the Urban Employee Basic Medical Insurance (UEBMI), the government-provided insurance that primarily covers employees in the formal sector and accounts for about 30% of the population in Changsha (Changsha Municipal Bureau of Statistics, 2024).

The novelty of the data is that it includes unique information on patients' current or pre-retirement workplaces, as well as their administrative rank if they work in the public sector. Such information allows us to separately measure patients' insider knowledge, social ties, and organizational rank, and to disentangle their relative importance. Patients employed in healthcare institutions are classified as insider patients, as they possess more insider knowledge (institutional knowledge and/or general medical knowledge); among them, those working in the same hospital as the treating physician are classified as same-hospital insider patients, who have closer social ties to the treating physician.[2] Within the group of same-hospital insiders, those holding administrative leadership positions are classified as same-hospital high-rank insider patients, reflecting their higher organizational rank. We focus

[1]To compensate public hospitals'/physicians' revenue loss due to ZMDP, the government allowed price increases for non-drug medical services, aiming to cover 80% of the decline in drug revenue.

[2]Hospitals, especially public hospitals, are the main healthcare providers in China, covering primary care, specialty care, inpatient care, drug prescription, and drug dispensing. They are typically large organizations, employing hundreds to thousands of staff members.

on same-hospital high-rank colleagues to ensure a clear hierarchy of power and authority between physicians and their patient-colleagues.

Before conducting our main analysis, we verify that ZMDP does not affect patient-physician matching. We then estimate separate difference-in-differences (DiD) models for each patient group, comparing public and private hospitals before and after ZMDP. We show that while insiders' health care utilization remains largely unchanged, non-insiders experience a decline in drug utilization accompanied by increases in other forms of care, raising total medical costs by 1,578 CNY (28.9%) per claim relative to insiders without corresponding improvement in health outcomes. Such results suggest substantial inefficiency in the treatment of non-insiders.[3]

To disentangle the role of each trait, we conduct sequential pairwise comparisons of physician responses. Comparing physician responses between non-insiders and different-hospital insiders identifies the role of insider knowledge; comparing different-hospital with same-hospital insiders identifies the incremental role of social ties; and comparing high-rank with low-rank same-hospital colleagues isolates the role of organizational rank. We find significant and comparably sized response differences in the first two comparisons, but only a modest and largely insignificant difference between high-rank and low-rank same-hospital insiders. Across all comparisons, changes in health outcomes are not statistically different between any two groups. These results suggest that insider knowledge and social ties play similarly important roles in shaping physicians' decision-making, while organizational rank plays a more limited role.

Moreover, using same-hospital high-rank patients as the benchmark, ZMDP leads to progressively larger cost increases for less privileged groups: insignificant for same-hospital low-rank patients, 1,126 CNY (15.0%) for different-hospital insiders, and 2,260 CNY (30.1%) for non-insiders, with no corresponding changes in health outcomes. This gradient in cost

[3] A related literature documents that expert patients may have better access to care, better adherence to medical guidelines, and better health outcomes than non-experts (Bronnenberg et al., 2015; Frakes et al., 2021; Chen et al., 2022; Finkelstein et al., 2022; Kakani et al., 2025). While such differences may exist, as long as they remain constant over time and do not change simultaneously with ZMDP, our DiD and triple-difference estimates provide causal effects. Moreover, the direction of the estimated effects—reduced drug utilization and increased use of other forms of care—is consistent with physician-driven responses to the elimination of drug markups, and opposite to what patient-side responses would predict. This suggests that the observed differential treatment patterns are predominantly physician-driven.

increases suggests that each dimension of privilege incrementally shields patients from the cost-escalating effects of ZMDP.

Our paper contributes to the rising literature that examines how patient characteristics influence physicians' decision-making. Currie et al. (2024*b*) reviews studies documenting treatment disparities due to patients' demographic and socioeconomic status (Chandra and Staiger 2010; McDevitt and Roberts 2014; Hoffman et al. 2016; Brekke et al. 2018; Angerer et al. 2019; Chen and Lakdawalla 2019; Eli et al. 2019; Fumarco et al. 2020; Singh and Venkataramani 2022; Currie et al. 2024*a*). One strand of this literature examines concordance, assessing whether patients who are more similar to their doctors, along dimensions such as race and gender, receive better treatment (Greenwood et al. 2018, 2020; Alsan et al. 2019; Frakes and Gruber 2022; Wallis et al. 2022; Hill et al. 2023; Ye and Yi 2023; Cabral and Dillender 2024).

Recent studies have made important progress by examining patient characteristics that are typically unobserved in most settings, such as whether patients are physicians themselves or hold high-ranking positions in the military (Johnson and Rehavi 2016; Schwab and Singh 2024; Chen et al. 2025). We advance this literature by separately identifying three distinct channels—insider knowledge, social connections to treating physicians, and organizational rank—that may drive differential treatment. Our paper is closest to Chen et al. (2025), which studies cancer patients and constructs measures of expertise and social connection based on physician-patients' subspecialty codes. We complement their work by exploiting a quasi-experimental setting, using workplace information to separately identify insider knowledge and social connections, and leveraging the administrative ranking system in Chinese public hospitals to isolate the role of organizational hierarchy.

Second, we add to the literature examining how physicians respond to financial incentives (Clemens and Gottlieb 2014; Johnson and Rehavi 2016; Brekke et al. 2019; Alexander and Schnell 2024) and providers' strategic responses to regulations (Coudin et al. 2015; Alexander 2020; Gupta 2021; Wilding et al. 2022; Shi 2024). Prior work has shown that cost-reducing policies can backfire through offsetting provider responses (Alexander, 2020; Luan et al., 2020; Fang et al., 2021; Shi et al., 2023). We go beyond by showing that these unintended cost increases are borne disproportionately by patients without privileges.

Finally, our paper adds to studies on the role of social ties in resource allocation (Fisman, 2001; Hong et al., 2005; Khwaja and Mian, 2005; Faccio, 2006; Cohen et al., 2008, 2010; Fisman et al., 2018). Li (2017) shows that in NIH peer review, social ties and expertise are bundled together in shaping funding decisions. We extend this line of research by examining how insider knowledge, social ties, and organizational rank each shape physician decision-making, in a setting where we can separately identify these channels.

The rest of the paper is structured as follows: Section 2 provides background information on the health care system in China and the ZMDP policy. Section 3 illustrates our stylized model. Section 4 describes the data, sample, and empirical strategy. Section 5 rules out patient sorting. Section 6 presents the heterogeneous effects of ZMDP on insiders and non-insiders and the mechanisms behind the differences. Section 7 conducts various robustness checks, and Section 8 concludes.

2 Institutional Background

This section describes the institutional background of China's healthcare system and ZMDP, with a particular focus on the ZMDP reform in Changsha, our study region.

2.1 China's Healthcare System

Hospitals. Healthcare services in China are predominantly provided by public hospitals. In 2015, public hospitals accounted for 88.0% of outpatient services and 85.3% of inpatient services (National Health Commission of the PRC, 2016), with the remainder provided by private hospitals.

China's healthcare system follows a three-tier hospital structure comprising primary, secondary, and tertiary hospitals, which differ systematically in service scope. Tertiary hospitals provide comprehensive and highly specialized care and are often affiliated with medical schools. Secondary hospitals provide general inpatient and outpatient services and treat common conditions, while primary hospitals, such as urban community health centers and rural township hospitals, focus on basic and preventive care. Unlike in many other healthcare systems, routine outpatient care in China is predominantly delivered through hospital outpatient departments rather than independent clinics.

Hospital Financing. Hospitals are generally reimbursed on a fee-for-service basis, with prices for both medical services and drugs administratively set by the government. Public hospitals derive revenue from service charges, drug sales, and government subsidies. In China, hospital pharmacies, rather than retail pharmacies, serve as the primary channel for drug dispensing, accounting for roughly 80% of all prescription drug sales (IMS Health, 2016). Consequently, drug revenue constitutes an important source of hospital income, with drugs accounting for more than 40% of total hospital expenditures (National Health Commission of the PRC, 2016).

Drug Pricing. Beginning in the 1950s, the government allowed hospitals to apply a 15% markup over procurement prices for drugs, partly to offset revenue losses resulting from declining government subsidies. In 2006, the National Development and Reform Commission (NDRC), which oversees pharmaceutical price regulation, reaffirmed that retail drug prices should be set at the providers' procurement prices plus a 15% profit margin. With government subsidies covering only a limited share of operating costs and service prices tightly regulated, public hospitals have increasingly relied on revenue-generating activities, most notably drug sales and high-tech diagnostic tests, to maintain financial viability (Sun et al., 2008; Milcent, 2018).

Physicians. Physicians in public hospitals are salaried employees whose income consists of a base salary and a bonus. While the base salary is low, bonuses, typically linked to physicians' contributions to hospital revenue, can account for as much as three-quarters of total income (Milcent, 2018). Because hospital revenues are pooled and subsequently distributed to physicians through bonuses, we assume throughout our analysis that hospitals and physicians share aligned financial incentives to increase hospital revenue.

Patient Insurance. China has achieved near-universal health insurance coverage since 2009, with 95% of the population covered by either Urban Employee Basic Medical Insurance (UEBMI) or Urban-Rural Resident Basic Medical Insurance (URRBMI). UEBMI covers employees and retirees with urban hukou, while URRBMI covers the remaining population.[4] Although UEBMI insures only about one-quarter of the population, it accounted for 61.5% of total public health insurance payments as of 2015 (National Health Commission of the PRC, 2016). This is because UEBMI offers significantly more generous reimbursement rate for patients compared to URRBMI. For instance, for inpatient care, UEBMI typically reimburses 70–90% of costs, whereas URRBMI reimburses 50–70%, with rates varying by hospital tier.[5] We focus on workers and retirees covered by UEBMI, as the data provide unique and detailed information on individuals' current and pre-retirement workplaces as well as their administrative rank.

2.2 ZMDP Reform and Its Implementation in Changsha

To reduce hospitals' dependence on drug sales as a revenue source and to improve patients' access to affordable and high-quality essential medicines, the Chinese government introduced ZMDP in all public hospitals nationwide (State Council of the People's Republic of China, 2016). The policy was initially rolled out through pilot programs in 2009 and gradually expanded to cover all public hospitals nationwide by 2017. To offset revenue losses from eliminating drug markups, the government introduced compensation mechanisms for healthcare institutions. These included upward adjustments to regulated prices for medical services and procedures, as well as increased government subsidies, with the aim of maintaining hospitals' financial viability without relying on drug markups (State Council of the People's Republic of China, 2016).

While ZMDP is a nationwide policy, its implementation varies substantially across regions in timing and scope. We study the ZMDP reform in Changsha, the capital city of Hunan Province. Changsha's healthcare system, public health insurance coverage, and drug pricing regime are representative of those in China as a whole. At the time of the large-scale rollout of ZMDP in 2016, Changsha had a population of 8.56 million and a GDP per capita of 18,687 USD.

[4]Hukou is China's household registration system. Based on their registered place of residence, each Chinese citizen holds either a rural or an urban hukou.

[5]Lower-tier hospitals have higher reimbursement rates and lower deductibles.

Figure B1 illustrates the rollout of ZMDP across hospitals in Changsha, in accordance with the central government's implementation timeline. The earliest adoption occurred in October 2012 in rural township hospitals, while 102 out of 125 hospitals implemented the policy in 2016. By the end of 2016, all public hospitals in Changsha had adopted ZMDP. Although detailed documentation on changes in hospital service fees is limited, policy guidelines in Hunan Province, of which Changsha is the capital, aimed to compensate for approximately 80% of revenue losses from prescription drugs through increases in regulated prices of medical services (Xinhua News Agency, 2017).[6] Private hospitals, by contrast, were not subject to ZMDP.

3 A Stylized Framework

This section presents a stylized model of physician–patient interaction, which yields predictions that are tested in the empirical analysis. The model emphasizes how patients' insider knowledge, connection to physicians, and rank influence physicians' treatment recommendations and the way patients process information and make decisions.

3.1 Treatment Decision Process

We consider a single physician and a patient with a specific orthopedic condition. Two treatment options are available: a non-invasive approach involving physical therapy and drugs, denoted by n, and a more invasive approach involving surgery, denoted by v.

Patient Utility. Patient i's utility from non-invasive treatment is normalized to 0. The relative value of invasive surgery v for patient i is

$$U_i^v = \xi_i - \kappa_i, \tag{1}$$

where ξ_i represents patient severity, with more severe cases yielding a larger relative benefit from surgery. Unlike the patient, the physician has the expertise to learn more (though not

[6] During our study period, the payment model in Changsha was fee-for-service for inpatient and outpatient care.

necessarily everything) about ξ_i by examining symptoms and performing laboratory tests. In particular, once the patient enters the physician's office, the physician receives a noisy signal about the severity ξ_i. This is the physician's informational advantage.

κ_i summarizes the common knowledge regarding the unsuitability of invasive treatment. It is assumed to be a function of patient i's demographics and the out-of-pocket price difference between the invasive and non-invasive treatment. The greater the κ_i, the less desirable the surgery is. If the patient observed the true severity ξ_i, they would choose invasive treatment if and only if $\xi_i \geq \kappa_i$.

Physician Utility. A physician's utility from the invasive treatment v is a weighted sum of the patient's utility and the physician's financial incentives:

$$M_i^v = \alpha_i^c \cdot U_i^v + F_i, \tag{2}$$

where F_i is a function of the relative profitability of invasive surgery. It captures the net financial benefit after accounting for the marginal cost differences between the two treatment options. A smaller $|F_i|$ indicates closer alignment between physician and patient incentives, with perfect alignment at $F_i = 0$. The parameter α_i^c captures the altruism weight on the patient's well-being and reputational concerns, reflecting the physician's reluctance to deviate from what is best for the patient. α_i^c increases with the strength of the physician–patient connection, and $\alpha_i^c \geq 0$.

Treatment Decision Process. The physician designs a recommendation strategy, specifically, when to recommend invasive surgery based on their observed signal of patient severity ξ_i and patient characteristics, including the VIP traits. Given the physician's recommendation, the patient decides whether to follow.

In particular, the physician observes a noisy signal s_i of the health benefit of surgery ξ_i by discussing symptoms with the patient and interpreting diagnostic tests,

$$s_i = \xi_i + \epsilon_i, \tag{3}$$

where we assume $\xi_i \sim N(0,1)$, $\epsilon_i \sim \mathcal{N}(0,\sigma_i^2)$, and noise ϵ_i is independent of severity ξ_i.

σ_i^2 measures the precision of the signal; a smaller σ_i^2 indicates a more precise signal. σ_i^2 is assumed to decrease with patient rank. Higher-rank patients are likely to possess greater power, which may earn the physician's respect or prompt more careful considerations due to a credible threat of punishment in the event of misdiagnosis or mistreatment. As a result, physicians may exert greater effort to obtain a more precise signal for higher-rank patients.[7]

Patients differ in how they respond to physicians' recommendations. Non-insider patients, lacking institutional knowledge, passively follow physicians' recommendations. By contrast, insider patients are more sophisticated and active in medical decision-making. We follow a Bayesian persuasion framework as in Xiang (2026) to characterize the interaction between a physician and an insider patient. Insider patients do not observe as much information about severity ξ_i as the attending physician, but share a common prior on ξ_i. In addition, they know the physicians' financial incentives and altruism, enabling them to infer the physicians' recommendation strategy. Upon receiving a recommendation, they can deduce the possible signals the physician might have observed, rationally update their belief about ξ_i accordingly, and decide whether to follow the recommendation.

3.2 Physician's Optimal Recommendation Strategy

Appendix A.1 presents the full derivation and closed-form expressions for the optimal strategies for non-insider and insider patients, respectively. For both patient types, the physician's optimal policy follows a cutoff rule: whenever the signal exceeds a threshold, invasive surgery is recommended; otherwise, drugs.

3.3 Model Properties and Testable Predictions

We examine how physicians' response to ZMDP differs by patient traits. Because ZMDP made surgical treatment relatively more profitable compared to non-surgical treatment, F_i increased due to this policy. As a result, physicians' optimal cutoff became lower, which

[7]In our empirical setting, average diagnostic test and imaging costs are higher for high-rank patients compared to low-rank patients, consistent with the modeling assumption that physicians obtain more precise signals for these patients. We can also allow for greater altruism toward high-rank patients, though this addition does not alter the model's implications.

implies a higher probability of recommending and performing surgery. We provide graphical illustrations here, with derivations and more model properties in Appendix A.2.

Panel (a) of Figure 1 illustrates how physicians' responses to ZMDP (i.e., an increase in F_i) vary with connection level α_i^c. The blue line represents the physician's optimal cutoff response for non-insiders, while the red line corresponds to insiders. It shows that, for non-insiders, stronger patient connections (higher α_i^c) attenuate the cutoff response, leading to a smaller increase in surgery. For insiders, stronger connections similarly reduce the response once α_i^c exceeds a threshold.

Panel (b) illustrates the role of patient rank separately for non-insiders and insiders. For both groups, a higher rank (i.e., lower σ_i^2) dampens the response, resulting in a smaller increase in surgery probability.

Both panels of Figure 1 highlight heterogeneity between insiders and non-insiders. For a given level of altruism α_i^c or patient rank σ_i^2, non-insiders exhibit a weakly larger cutoff response and thus a larger increase in surgery probability than insiders, following ZMDP, holding other factors constant.

Based on these model properties, we propose the following four testable hypotheses:

Hypothesis 1: ZMDP increases the use of invasive surgery and total medical costs.

Hypothesis 2: The increase is greater for non-insider patients than for insider patients (holding connection and rank fixed).

Hypothesis 3: The increase is larger for non-connected insiders than for connected insiders (conditional on rank), once the connection level crosses a threshold.

Hypothesis 4: The increase is larger for low-rank insiders than for high-rank insiders.

4 Data, Sample, and Empirical Strategy

4.1 Data and Sample

We use UEBMI inpatient claims data from Changsha, China, covering November 2010 to December 2018. Our main analysis focuses on orthopedic conditions because their treatment often involves discretionary choices between conservative care (e.g., medications) and invasive interventions (e.g., surgery) (Ding and Liu 2021).[8] In addition, orthopedic conditions are prevalent, accounting for approximately one-sixth of all hospital claims in Changsha. We exclude individuals aged 80 and above, as they are eligible for more generous insurance coverage (Human Resources and Social Security Administration 2011). In addition, we drop hospitalizations exceeding 30 days, as long-term hospitalizations are rare ($< 1\%$) and may differ fundamentally from short-term hospitalizations.

Utilization and Health Outcomes Measures. We observe specific drugs prescribed and services provided during each hospital stay, along with their quantities and costs. We classify healthcare utilization into seven categories: (1) prescription drugs, including both western medicines and proprietary Chinese medicine (traditional Chinese medicine in standardized dosage forms); (2) surgeries and related anesthesia services; (3) diagnostic tests; (4) imaging tests; (5) medical services, such as physician consultations, nursing care, and other ward-based services; (6) materials; and (7) other expenses.[9] Among these categories, we construct quantity measures for categories (1)–(4), which comprise 57% of total costs. These categories are most directly linked to physicians' treatment decisions, whereas the remaining categories primarily capture ancillary services and downstream costs. For category (1), we measure quantity by the number of unique drugs in a claim, and for categories (2)–(4), by the number of services provided.[10] In addition to these quantity measures, we also consider changes in total costs per claim as an additional primary outcome variable. Finally, we examine

[8] In the main analysis, we use 100% of inpatient claims for orthopedic conditions, where sample size is critical for estimating fine-grained treatment effects. For other conditions, we rely on a 10% random sample of patients, which substantially reduces computational burden without sacrificing statistical precision.

[9] Other expenses include blood transfusion, oxygen therapy, and non-specified services, which together account for only 0.59% of total healthcare costs.

[10] We calculate the number of unique western drugs and Chinese patent medicines, excluding Chinese herbal pieces, which consist of raw, unprocessed materials rather than standardized formulations.

patients' health outcomes, including 30-day readmission rates and 30-day mortality rates (Almond and Doyle Jr, 2011; Hoe, 2022; Silber et al., 2019).[11] Due to the relatively low incidence of readmission and mortality, we report readmission rates in percentage points and mortality rates per thousand.

Measures of Insider Knowledge, Social Ties, and Organizational Rank. We supplement UEBMI claims data with social security beneficiary summary files, which provide information on individuals' workplaces, administrative rank within a workplace, and demographics (age and gender). We classify an individual as an "insider" if their workplace is a healthcare institution (hospitals, clinics, sanatoriums, and nursing hospitals) and as a "non-insider" otherwise. Among insiders, we further classify patients as "same-hospital insiders" if they receive medical care at their own workplace and as "different-hospital insiders" otherwise. For patients working in the public sector, we observe their administrative rank. We classify a patient as high-rank if they hold a cadre-level administrative position and as low-rank if they hold a non-cadre (ordinary staff) position.

To examine the role of organizational rank, we focus on same-hospital patients, because the salience and interpretability of administrative rank may differ substantially across patient types. For same-hospital patients, physicians can clearly infer whether patients outrank them within the same organizational hierarchy, making patients' authority directly relevant to the physicians' career concerns. By contrast, for patients from different hospitals or other public sectors, their relative rank is less clearly defined. Even if we observe such patients' administrative titles, it remains unclear whether—and to what extent—their authority could influence the treating physicians' careers. Focusing on same-hospital patients thus ensures that organizational rank is both well-measured and meaningful. Moreover, comparing high-rank and low-rank patients within the same hospital helps mitigate differences in social connections and insider knowledge, thereby better isolating the effect of hierarchical authority within the organization.

[11]The 30-day mortality rates are constructed using the social security beneficiary termination records, which document the timing and cause of individuals' exit from the benefit pool.

Summary Statistics. Table B1 compares claim-level characteristics between public (treated) and private (control) hospitals, with separate panels for insiders and non-insiders. On average, public hospitals are associated with higher health care resource use per case and slightly worse health outcomes, consistent with evidence that they treat more severe and complex cases than private hospitals. Public and private hospitals are well balanced in terms of patient age (58.50 vs. 57.27) and gender composition (0.70 vs. 0.65). Insiders account for 2% of patients treated in private hospitals and 3% of those treated in public hospitals. Moreover, 7% of patients in private hospitals hold cadre-level administrative ranks, compared with 15% in public hospitals. Overall, insiders exhibit less intensive care utilization than non-insiders and achieve better health outcomes. Insiders are younger and more likely to be female. Their choice of hospital tier is broadly comparable to that of non-insiders.

Table B2 compares healthcare utilization and patient characteristics across insider subgroups within public hospitals. The differences between insiders and non-insiders in public hospitals documented in Table B1 are mainly driven by same-hospital insiders, who use fewer health care resources than different-hospital insiders but have better health outcomes. Regarding demographics, different-hospital insiders are the oldest on average (53), followed by same-hospital high-rank insiders (51), while same-hospital low-rank insiders are the youngest (47). Same-hospital high-rank insiders have the highest female share (81%), followed by same-hospital low-rank insiders (78%), whereas 74% of different-hospital insiders are female. Among same-hospital high-rank insiders, 75% work in a Tier 3 hospital, 6% work in a Tier 2 hospital, and the remaining 19% work in a Tier 1 hospital. For same-hospital low-rank insiders, however, 33% work in a Tier 3 hospital, 10% work in a Tier 2 hospital, and 58% work in a Tier 1 hospital. For different-hospital insiders, 37% work in a Tier 3 hospital, 11% work in a Tier 2 hospital, and the remaining work in Tier 1 or below hospitals. With respect to treating hospital tier choices, same-hospital high-rank insiders are most likely to be treated at a Tier 3 hospital (75%), followed by different-hospital insiders (60%), and then same-hospital low-rank insiders (33%). Given these differences in demographics, affiliated hospital tier, and treating hospital choice across insider subgroups, we control for these factors in our econometric specifications.

4.2 Empirical Strategy

4.2.1 The VIP Effect in Medicine: Insiders vs. Non-insiders

To examine whether ZMDP affects VIPs (insiders) and non-VIPs (non-insiders) differently, we estimate the following event-study and DiD equations separately for insiders and non-insiders:

$$y^V_{iht} = \alpha_0 + \sum_{k=-12, k\neq -1}^{k=8} \beta^V_k Pub_h \cdot 1(t_{ih} - t^*_h = k) + X_{it} + \gamma_h + \mu_t + \varepsilon^V_{iht}, \tag{4}$$

$$y^V_{iht} = \alpha_0 + \beta^V ZMDP_{ht} + X_{it} + \gamma_h + \mu_t + \varepsilon^V_{iht}, \tag{5}$$

where y^V_{iht} represents the outcome of admission i in treating hospital h in quarter t for patient group V, with V being VIPs (insiders) or non-VIPs (non-insiders). Both specifications compare patients treated in public versus private hospitals before and after ZMDP implementation, estimated separately for insiders and non-insiders. In specification (4), t^*_h denotes the calendar quarter in which ZMDP was implemented in public hospital h, and k indicates the relative quarter with respect to the implementation. We include 12 relative quarters before and 8 relative quarters after ZMDP, binning quarters with $k < -12$ into $k = -12$ and those with $k > 8$ into $k = 8$. In specification (5), $ZMDP_{ht}$ ($public_h \cdot post_{ht}$) equals 1 if public hospital h has implemented ZMDP in quarter t, and 0 otherwise.

Because some patients are healthcare insiders, we control for the tier of the hospital with which the patient is affiliated to proxy for differences in medical knowledge and insider access. We additionally include treating-hospital fixed effects to absorb time-invariant differences across treating hospitals. Formally, X_{it} includes individual characteristics that may directly affect y_{iht}, including five-year age-cohort fixed effects, an indicator for female, indicators for ICD-10 diagnosis codes (first three digits), and indicators for the tier of the patient's affiliated hospital (coded as zero for non-insiders). γ_h and μ_t denote treating hospital fixed effects and year-quarter fixed effects, respectively.[12]

[12]We do not include individual fixed effects in our main specification because the majority of patients have only one hospital stay for an orthopedic condition during the study period. Specifically, only 12.3% (16200/131237) of patients treated in public hospitals have at least one hospitalization both before and after the policy implementation. Nevertheless, in Section 7, we conduct a robustness check that includes

The identifying assumption here is that, absent ZMDP, insiders (or non-insiders) treated in public and private hospitals would have followed parallel trends in healthcare utilization and patient health outcomes. After the implementation of ZMDP, we expect treated hospitals to reduce prescription drug utilization and increase the use of other forms of care in order to offset lost drug-related revenues. As predicted by the model, these responses should be more pronounced for non-VIPs. Specifically, for drug utilization we expect $\beta_k < 0$ when $k > 0$ while for other forms of healthcare utilization we expect $\beta_k > 0$ when $k > 0$, with $|\beta_k^{nonVIP}| > |\beta_k^{VIP}|$.

In addition, we conduct a triple-difference estimation to examine whether physicians' treatment of VIPs statistically differs from their treatment of non-VIPs under ZMDP:

$$y_{iht} = \alpha_0 + \beta Noninsider_i \cdot ZMDP_{ht} + \delta ZMDP_{ht} + \theta public_h \cdot Noninsider_i + Noninsider_i + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}, \quad (6)$$

where $ZMDP_{ht}$ follows the same definition as in equation (5), and $Noninsider_i$ indicates whether a patient is a non-insider. β is our coefficient of interest, measuring the differential impact of ZMDP on non-insiders relative to insiders.

Under ZMDP, physicians' responses and patients' responses are expected to work in opposite directions. For example, patients may increase drug consumption due to lower drug prices, while physicians may decrease drug prescriptions due to the eliminated profit margins on prescription drugs. Given the unequal power dynamics between patients and physicians, particularly for non-insider patients, the overall effects are likely physician-dominated. Our empirical analysis will provide evidence on whether physician-side responses dominate in practice.

4.2.2 Mechanisms: Insider Knowledge, Social Ties, or Organizational Rank?

We use the analysis above to test whether physicians tend to treat VIP patients and non-VIP patients differently. However, VIP patients differ along multiple dimensions from non-VIPs. To separately identify the roles of insider knowledge, social ties, and organizational rank,

individual fixed effects, and the results remain robust.

we analyze four patient groups: (1) non-insiders, (2) different-hospital insiders, (3) same-hospital low-rank insiders, and (4) same-hospital high-rank insiders. Sequential comparisons between adjacent groups isolate each privilege channel, while comparisons with the most privileged group, the same-hospital high-rank insiders, quantify the cumulative effects. Since administrative rank is only defined for public-sector employees, we restrict the analysis in this section to public hospitals.

We first conduct a sequence of pairwise comparisons to isolate the role of each VIP trait. Specifically, we compare non-insiders with different-hospital insiders to assess the role of insider knowledge; compare different-hospital insiders with same-hospital insiders of all ranks to quantify the role of social ties; and compare same-hospital high-rank insiders with same-hospital low-rank insiders to isolate the effect of organizational rank. To implement these comparisons, we estimate the following specification, restricting the sample to the two groups of interest in each case:

$$y_{iht}^{g} = \alpha_0 + \beta_0 ZMDP_{ht} + \beta^g PatGrp_i * ZMDP_{ht} + \eta^g PatGrp_i + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}^{g}, \quad (7)$$

where $PatGrp_i$ is an indicator for the patient group with fewer VIP traits. When comparing physicians' responses to ZMDP between non-insiders and different-hospital insiders, $PatGrp_i$ indicates the non-insider group; when comparing different-hospital and same-hospital insiders, $PatGrp_i$ indicates the different-hospital insider group; and when comparing same-hospital low-rank and high-rank insiders, $PatGrp_i$ indicates the same-hospital low-rank group. We expect β^g to be negative for drug utilization and positive for outcome capturing the use of other forms of care.

We next compare all four subgroups directly by using the same-hospital high-rank patient group as the benchmark, the premium VIP group who tend to receive the most efficient care.[13] The regression specification (8) is as follows:

$$y_{iht}^{g} = \alpha_0 + \beta_0 ZMDP_{ht} + \sum_{g=1}^{g=3} \beta^g PatGrp_i * ZMDP_{ht} + \sum_{g=1}^{g=3} \eta^g PatGrp_i + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}^{g}, \quad (8)$$

[13] Figure B3 shows that trends for this subgroup are generally flat across all outcomes before and after ZMDP, suggesting minimal effects of physician financial incentives on their care.

where g represents three subgroups of patients: (1) same-hospital low-rank insiders, (2) different-hospital insiders, and (3) non-insiders. The baseline group consists of same-hospital high-rank insiders. The advantage of this specification relative to the pairwise comparisons is that it allows for a straightforward assessment of how physicians adjust treatment intensity across patient groups in response to changes in financial incentives, benchmarked against the most premium VIP group, which is minimally affected by the policy change. We expect $\beta^g < 0$ when y^g_{iht} represents drug utilization, while $\beta^g > 0$ when y^g_{iht} represents utilization of other services. In terms of the magnitude of β^g, we expect it to be smallest for same-hospital low-rank insiders, larger for different-hospital insiders, and largest for non-insiders.

5 Ruling Out Patient Reallocation from ZMDP

Our key identification strategy relies on the assumption that ZMDP changes physicians' financial incentives but does not change patient-physician (hospital) matching. We acknowledge that patient sorting across hospitals based on characteristics and preferences exists at all times. However, our approach requires only that this sorting pattern remains stable around ZMDP implementation. We provide the following evidence in support of this assumption.

First, we test whether there are differential changes in patient volume between public and private hospitals, and among public hospitals with different pre-ZMDP drug shares in total revenue. If a hospital admits more patients in the post-period, the new patients may have different characteristics and thus exhibit different healthcare utilization patterns and health outcomes. We test for sorting using the following specification (9):

$$Y_{ht} = \alpha_0 + \beta Z_h * post_{ht} + \gamma_h + \mu_t + \varepsilon_{ht}, \tag{9}$$

where Y_{ht} represents (i) the number of admissions in hospital h in quarter t and (ii) the share of insider patients. For sorting between public and private hospitals, $Z_h = Public_h$, an indicator for public hospitals. For sorting within public hospitals, $Z_h = preZMDPshareD_h$, an indicator for whether a public hospital's pre-ZMDP drug share in total revenue exceeds the median. $post_{ht}$ equals 1 if a public hospital adopts ZMDP, and 0 otherwise.

Table 1 demonstrates that there is no sorting between public and private hospitals, as there is no significant change in the number of hospitalizations or the share of insiders in either column (1) or (3). Similarly, columns (2) and (4) show no evidence of sorting within public hospitals between those that heavily relied on drug sales before ZMDP and those that did not.

Next, we rule out differential sorting among the four patient subgroups, which is a key threat to identification for heterogeneous effects across subgroups. We estimate equation (8), with hospital characteristics or individual demographics as the dependent variable and without individual-level controls.[14] Specifically, Y_{iht} represents whether patient i in quarter t is hospitalized in (1) a Tier 3, (2) a Tier 2, or (3) a Tier 1 hospital h, or (4) individual characteristics of patient i, such as age and gender. Using these outcome variables, we test for differential changes in hospital choice or patient composition across subgroups. An insignificant β^g would indicate no differential sorting and validate our identifying assumption.

Table 2 confirms that there is no evidence of differential sorting induced by ZMDP. Columns (1)–(3) indicate no differential sorting across patient subgroups in terms of the treating hospital tier, and columns (4)–(5) show no significant changes in patient demographic characteristics before and after ZMDP.

6 Results

6.1 Treatment Intensities and Health Outcomes for Non-insiders vs. Insiders

We first examine whether a patient's insider status affects their treating physicians' responses to ZMDP implementation. Figure 2 panel (a) reveals that the decrease in drug utilization is more pronounced among non-insiders, suggesting that drug over-prescription was a more serious problem for non-insiders than for insider patients prior to ZMDP.[15] On average, as

[14]Similar to equation (8), we only include public hospitals because high- and low-rank patients are only definable for public employees.

[15]The raw trends in panel (a) of Appendix Figure B2 indicate that non-insiders on average have higher prescription drug utilization than insiders before ZMDP in both public and private hospitals. These trends remain unchanged in private hospitals. However, the gap reverses after ZMDP in public hospitals, as non-

shown in column (1) of Table 3 panel A, drug utilization for non-insiders in public hospitals decreases by 3.06 unique drugs per claim (32.5%) relative to their counterparts in private hospitals after ZMDP, while column (1) of panel B reveals that insiders experience no significant change in drug utilization due to ZMDP.

For other forms of healthcare utilization, non-insider patients in public hospitals exhibit larger post-ZMDP increases, consistent with physicians compensating for profit loss from prescription drug sales. As shown in Figure 2 panels (b)–(d) and columns (2)–(4) of Table 3 panel A, ZMDP leads to increases in utilization (number of services per claim) for non-insider patients in surgeries, diagnostic tests, and imaging tests, by 0.14 (74.1%), 6.35 (28.6%), and 2.79 (27.5%), respectively.[16] As a result, Figure 2 panel (e) and column (5) of Table 3 panel A show that non-insiders end up spending more after ZMDP, with total costs increasing by 1,668 CNY (30.5%) per claim. By contrast, insiders' utilization of care and total costs remain almost unchanged after ZMDP.

Despite non-insiders' higher medical costs after ZMDP, we find no improvement in their health outcomes. If anything, column (7) of Table 3 panel A indicates that non-insider patients in public hospitals experience a 0.62 percentage point (19.3%) marginally significant increase in the likelihood of 30-day readmission. As for 30-day mortality rates, we find no significant change for either insiders or non-insiders.

Moreover, the triple-difference results in Table 4 echo the above findings and show that physicians' responses to ZMDP differ significantly between non-insiders and insiders. As a result, column (5) shows that non-insiders' average spending per claim increases by 1,578 CNY more after ZMDP compared to insiders. Overall, non-insider patients' higher utilization of drugs before ZMDP and larger post-ZMDP increases in other forms of care utilization, combined with no meaningful change in health outcomes, suggest that non-insiders receive less efficient care than insiders, both before (in the form of excessive prescription drug use) and after ZMDP (in the form of unnecessary healthcare services).

insiders' utilization of prescription drugs decreases greatly after the policy, whereas insiders' drug utilization increases slightly in public hospitals during the same period.

[16] Panels (b)–(d) in Figure B2 show that prior to ZMDP, non-insiders on average receive similar levels of non-drug treatment as insiders in public hospitals. However, these trends diverge after ZMDP, with insiders continuing to receive a similar amount of other forms of care, while non-insiders receive substantially more. This pattern suggests that physicians change their treatment only for non-insiders.

6.2 Mechanisms: Insider Knowledge, Social Ties, and Organizational Rank

The above section demonstrates that, compared to insiders, physicians' responses to financial incentives are more pronounced for non-insider patients, while health outcomes remain unchanged. This raises the question of what drives such differences in treatment decisions and outcomes. We consider three dimensions of privileges held by insider patient subgroups. First, compared to non-insiders, different-hospital insiders tend to have greater insider knowledge, which could lead to more cogent treatment by physicians. Second, compared to different-hospital insiders, same-hospital insiders additionally have stronger social ties with treating physicians as they are same-hospital colleagues, which may make physicians treat them more altruistically. Third, compared to same-hospital lower-rank patients, same-hospital higher-rank patients may additionally have greater power within their hospital, which may also influence physicians' attitudes and effort towards such patients.

Following this logic, Table 5 shows the two-sample comparisons sequentially. Panel A compares physicians' responses towards non-insiders to different-hospital insiders, and it demonstrates that insider knowledge can explain a 1,123 CNY difference in additional medical costs incurred by non-insider patients. Panel B compares different-hospital insiders to same-hospital insiders, and the greater physician responses among the former group reveal that social ties additionally explain a 890 CNY difference in medical costs. Finally, Panel C compares same-hospital lower-rank insiders to their higher-rank counterparts. Lower-rank insiders experience a larger reduction in drug utilization but a greater increase in other forms of care utilization. However, except for increases in surgery, none of the estimates is statistically significant, nor are total medical costs. This implies that organizational rank plays a more limited role than that of insider knowledge and social ties.

We then compare all three less-privileged groups with the premium VIP group—same-hospital, high-rank patients—to show how, under ZMDP, physicians' differential treatment leads to less favorable utilization and outcomes for the remaining patient groups. Table 6 shows the DiD results. Overall, compared to premium VIP patients, all other patient groups exhibit lower drug utilization and higher utilization of other forms of care following ZMDP.

However, consistent with Table 5, the differences are insignificant between the same-hospital low-rank and the same-hospital high-rank patients.

Specifically, for drug utilization, as shown in column (1) of Table 6, compared to same-hospital high-rank insiders, same-hospital low-rank insiders, different-hospital insiders, and non-insiders all experience a reduction in their drug utilization after ZMDP. The decline is largest for non-insiders (4.6 unique drugs per claim), followed by different-hospital insiders (1.6). The difference between same-hospital low-rank and same-hospital high-rank patients (0.8) is not statistically significant. Similar patterns arise in other forms of care. Column (2) of Table 6 reveals that, compared to same-hospital high-rank patients, all other groups experience an increase in the number of surgeries after ZMDP, with magnitudes mirroring the reductions in drug use. Diagnostic and imaging utilization exhibit the same ordering: largest increases for non-insiders, followed by different-hospital insiders, while changes for same-hospital low-rank patients remain statistically insignificant from premium VIPs, as shown in columns (3)–(4) of Table 6. As a result, column (5) shows that total medical costs rise by an additional 2,260 CNY for non-insiders and 1,126 CNY for different-hospital insiders relative to premium VIPs. As for health outcomes, columns (6)–(9) in Table 6 show no differential changes in readmission or mortality rates across patient groups.

7 Robustness Checks and Additional Results

7.1 Staggered DiD Model

While ZMDP was announced as a uniform policy and most hospitals in our sample implemented it in 2016, the rollout was staggered across hospitals throughout 2016. This staggered rollout raises concerns about treatment effect heterogeneity and potential bias in two-way fixed effects (TWFE) estimators when treatment effects vary over time or across cohorts (Goodman-Bacon, 2021; Sun and Abraham, 2021). In particular, TWFE estimators may inadvertently use already-treated units as controls for later-treated units, leading to contamination bias.

To address this concern, we employ the estimators proposed by De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), and Borusyak et al. (2024). Figure B4–B7 and Table B3 present the results from the staggered DiD specification. The estimated effects remain consistent with our baseline TWFE results: non-insiders experience a reduction of approximately 3.42 drugs and an increase of 3,010 CNY in total medical costs relative to insiders. Parallel pre-trends across cohorts further support our identification assumption. These findings confirm that our main results are not driven by treatment effect heterogeneity or improper comparisons across cohorts with different treatment timing.

7.2 Static DiD Model

Approximately 95% of the observations in our sample received treatment in 2016 Quarter 1 (Q1) or 2016 Q3. To further ensure that staggered timing does not confound our estimates, we implement a "clean" static DiD design by restricting the sample to hospitals treated in these two quarters and assigning 2016 Q1 as the uniform treatment date. This approach trades sample size for a simpler identification environment where all treated units share the same treatment timing, eliminating any concerns about dynamic treatment effects or forbidden comparisons. Tables B4–B5 present the triple-difference and pairwise two-sample comparison results from this restricted sample. Despite the reduction in sample size, the estimated treatment effects remain highly consistent with our main findings.

7.3 Patients with Repeated Hospitalizations

To examine whether our findings hold within individual patients over time, we focus on patients with at least one hospitalization both before and after ZMDP implementation. This within-patient design offers the strongest possible control for the time-invariant patient characteristics, as each patient serves as their own control through the inclusion of patient fixed effects.

This sample, however, has important limitations. First, it represents less than 20% of all patients, raising concerns about generalizability—these patients likely have more chronic or severe conditions. Second, analyzing health outcomes in this sample is problematic: by construction, patients cannot die in the pre-period (since they must survive to appear in the post-period), and they mechanically have higher readmission rates in the pre-period (because their conditions were not fully cured, making subsequent hospitalizations more likely). These features create severe selection bias for health outcome measures. Given these limitations, we focus exclusively on healthcare utilization patterns, where the repeated-observation design provides a clean test of whether physicians systematically adjust treatment intensity for the same patient after ZMDP.

Tables B6–B7 present the results for this repeated-hospitalization sample. The triple-difference estimates in Table B6 remain highly consistent with our main findings, with non-insiders experiencing a 3.31 reduction in drug utilization and a 1,725 CNY increase in total medical costs relative to insiders. The pairwise comparisons in Table B7 also broadly replicate Table 5, with one notable pattern: while the cost difference between non-insiders and different-hospital insiders shrinks substantially and becomes insignificant (206 CNY vs. 1,123 CNY in the full sample), the difference between different-hospital and same-hospital insiders remains significant and, if anything, grows larger (1,288 CNY vs. 890 CNY). This is consistent with the interpretation that repeated hospitalizations allow non-insiders to accumulate institutional knowledge, narrowing their gap with different-hospital insiders (Wang et al., 2026), whereas social ties cannot be acquired through hospital visits and continue to confer significant advantages. The comparison between same-hospital low-rank and high-rank insiders remains insignificant in both samples.

7.4 Alternative Non-insider Group: Teachers

A potential concern with our main specification is that non-insider patients may differ from insider patients along unobservable dimensions beyond hospital affiliation status. To the extent that insiders (physicians and hospital staff) represent a selected, highly educated population, comparisons with the general non-insider population may conflate the effect of insider status with other socioeconomic differences.

To address this concern, we construct an alternative non-insider group consisting of teachers from primary, secondary, and tertiary educational institutions. Teachers share several key characteristics with medical professionals, including similar education levels (typically at least a bachelor's degree, with many holding graduate degrees), stable employment in public institutions, and comparable socioeconomic status. Unlike medical insiders, however, teachers lack insider knowledge, social connections, and organizational authority within hospitals, making them a more appropriate counterfactual for isolating the effects of insider traits.

Tables B8–B9 replicate our main analyses using teachers as the non-insider comparison group. The results show comparable differential reductions in drug prescribing between non-insiders and insiders relative to the baseline results using the general population as the non-insider group. Effects on other forms of care (surgeries, diagnostics, imaging) and total costs remain directionally consistent, though slightly attenuated. These results suggest that although socioeconomic differences between healthcare workers and the general population may account for a portion of the insider advantage, insider knowledge and social connections within healthcare institutions remain the primary drivers of our main findings.

7.5 Other Diseases

Our main analysis focuses on orthopedic patients. To assess the generalizability of our findings, we extend the analysis to four other major ICD-10 disease groups: neoplasms (ICD-10 code: C00–D46), diseases of the circulatory system (ICD-10: I00–I99), diseases of the digestive system (ICD-10: K00–K93), and diseases of the genitourinary system (ICD-10: N00–N99). These categories cover a diverse range of conditions with varying degrees of treatment discretion, disease severity, and clinical protocols, providing a comprehensive test of whether insider effects persist across broad medical contexts.

Figures B8 and B9 show that the results extend consistently across these other disease groups. While the magnitudes vary moderately across disease categories, likely reflecting differences in baseline treatment intensity and the scope for physician discretion, the qualitative pattern of larger adjustments for non-insiders remains consistent. This cross-disease robustness strongly suggests that insider privileges and preferential treatment affect healthcare delivery broadly.

8 Discussion and Conclusion

In this paper, we explore physicians' heterogeneous response to ZMDP, a reform that eliminates drug markup in public hospitals in China, based on patients' characteristics. We first demonstrate that, compared to healthcare insiders, non-insider patients experience a larger reduction in drug utilization and a greater increase in other forms of care, suggesting that they are more vulnerable to inefficient treatment driven by physicians' financial incentives. By further dividing insider patients into three subgroups, we find that physicians' responses are slightly attenuated for different-hospital insiders relative to non-insiders and even more attenuated for same-hospital insiders. Moreover, among insiders, same-hospital high-rank insiders receive the least distorted care. Overall, these differential responses indicate that insider knowledge and social connections play a critical role in ensuring efficient care in China, while higher organizational rank has additional but more limited influence.

Given these findings, implementing medical guidelines that tie physicians' treatment plans to those observed for same-hospital patients, especially high-rank same-hospital insiders, could benefit both different-hospital insiders and non-insider patients, while generating cost savings for the entire healthcare system. One limitation of our study is that our measure of insider knowledge captures both institutional familiarity and general medical knowledge, and it does not isolate disease-specific expertise, leaving the relative importance of these distinct dimensions as an open question for future research.

More broadly, while our findings are most directly informed by the institutional features of China's healthcare system, the underlying mechanisms—information asymmetry, social ties, and organizational hierarchy—are relevant to healthcare systems broadly. That said, the magnitudes may be larger in settings where medical guidelines are less standardized and physician discretion is greater.

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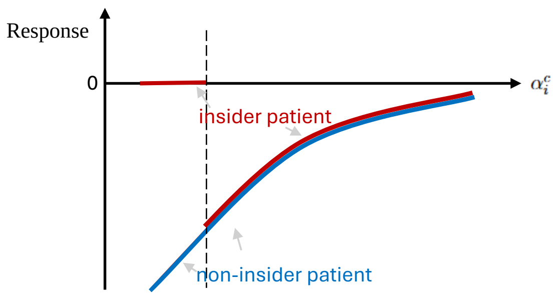
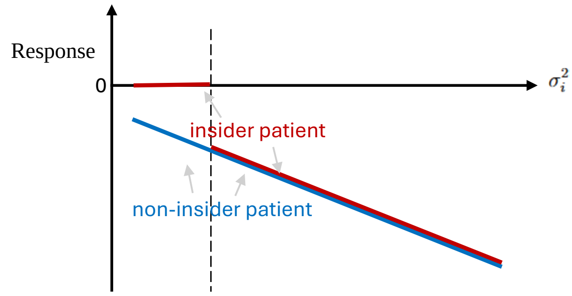
Figures



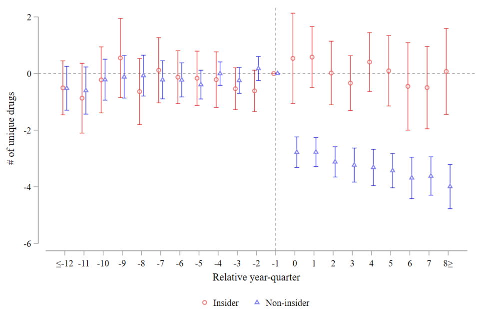
(a) Connection



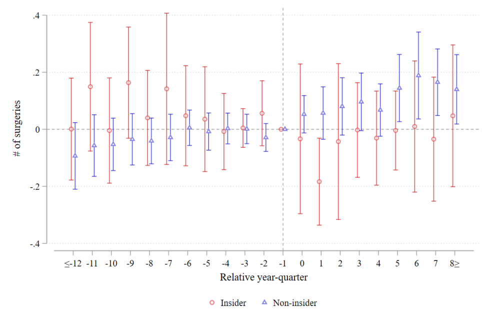
(b) Rank

Figure 1: Cutoff Response to ZMDP Depends on Connection, Rank, and Insider Knowledge

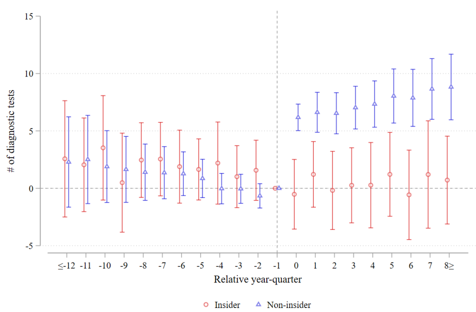
Figure 2: Effects of ZMDP on Health Care Utilization for Insiders vs. Non-Insiders



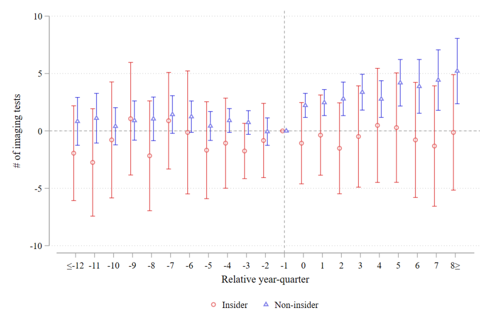
(a) Drug



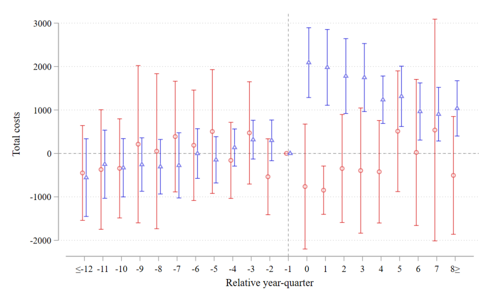
(b) Surgery



(c) Diagnostic test



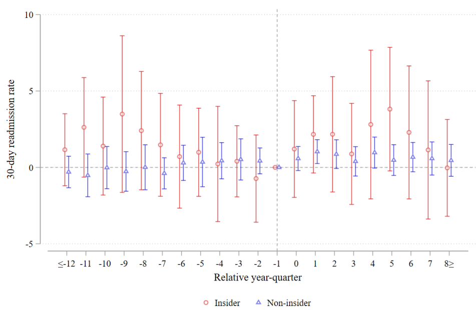
(d) Imaging test



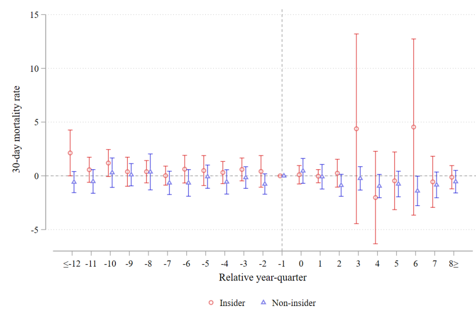
(e) Total costs

Notes: These figures show event study estimates of the effects of ZMDP on health care utilization for orthopedic patients, based on Equation (4). Caps indicate 95% confidence intervals. All specifications control for gender, age-cohort fixed effects, three-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Figure 3: Effects of ZMDP on Health Outcomes for Insiders vs. Non-Insiders



(a) 30-day readmission rate



(b) 30-day mortality rate

Notes: These figures show event study estimates of the effects of ZMDP on health outcomes for orthopedic patients, based on Equation (4). Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (coefficients multiplied by 1,000). Caps indicate 95% confidence intervals. All specifications control for gender, age-cohort fixed effects, three-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Tables

Table 1: Test for Patient Sorting at the Hospital-Quarter Level

	(1) # of hosp.	(2) # of hosp.	(3) Insider share	(4) Insider share
Public*post	-6.70		0.01	
	(9.45)		(0.01)	
High pre-ZMDP shareD*post		-1.04		0.02
		(13.54)		(0.01)
Treating hospital FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	5,078	2,588	5,078	2,588
Mean of Y (Pre-ZMDP)	83.72	92.57	0.03	0.04

Notes: Columns (1) and (3) include all hospitals, and columns (2) and (4) include public hospitals only. Public*post equals 1 if a hospital is a public hospital in the post-ZMDP period, as specified in Equation (9); High pre-ZMDP shareD*post equals 1 for public hospitals with above-median pre-ZMDP drug revenue share (as a proportion of total revenue) in the post-ZMDP period, as specified in Equation (9). Standard errors are clustered at the hospital level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: Test for Patient Sorting at the Individual-Claim Level

	(1) Tier 3	(2) Tier 2	(3) Tier 1	(4) Age	(5) Female
Subgroup*ZMDP					
Same hospital-low rank*ZMDP	-0.07	-0.06	0.12	-0.37	-0.02
	(0.07)	(0.11)	(0.08)	(1.24)	(0.05)
Diff hospital*ZMDP	-0.06	0.02	0.06	-0.27	-0.00
	(0.08)	(0.07)	(0.05)	(1.30)	(0.03)
Non-insider*ZMDP	-0.05	-0.02	0.09	0.03	-0.03
	(0.09)	(0.07)	(0.06)	(0.71)	(0.03)
Subgroup					
Same hospital-low rank	-0.15***	0.15*	0.14	-2.30	-0.06**
	(0.04)	(0.08)	(0.11)	(1.93)	(0.02)
Diff hospital	-0.09	0.08	0.06	2.91**	0.01
	(0.06)	(0.07)	(0.06)	(1.34)	(0.03)
Non-insider	-0.20**	0.20**	0.04	5.83***	0.10**
	(0.09)	(0.08)	(0.05)	(2.12)	(0.05)
ZMDP	0.47***	-0.37***	0.15	0.44	0.03
	(0.14)	(0.12)	(0.13)	(0.71)	(0.03)
Treating hospital FE	No	No	No	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
3-digit ICD FE	Yes	Yes	Yes	Yes	Yes
Affiliated hospital's tier FE	Yes	Yes	Yes	Yes	Yes
Observations	225,385	225,385	225,385	225,385	225,385
Mean of Y (Pre-ZMDP)	0.31	0.55	0.13	57.06	0.66

Notes: Individuals' claim-level data analysis based on Equation (8). Only public hospitals are included because same-hospital high- and low-rank patients can only be defined in public hospitals. Outcome variables are dummy variables in columns (1)–(3) and column (5). Same hospital-low rank*ZMDP equals 1 if a patient is a same-hospital low-rank insider and is hospitalized after ZMDP. Diff hospital*ZMDP equals 1 if a patient is a different-hospital insider admitted after ZMDP. Non-insider*ZMDP equals 1 if a patient is a non-insider admitted after ZMDP. Standard errors are clustered at the hospital level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effects of ZMDP by Patient VIP Status: Non-Insiders vs. Insiders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Non-insider patients							
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
ZMDP	-3.06***	0.14***	6.35***	2.79***	1,668.20***	0.62*	-0.06
	(0.35)	(0.05)	(1.32)	(0.93)	(349.43)	(0.33)	(0.15)
Observations	418,614	418,614	418,614	418,614	418,614	418,614	418,614
Mean of Y (Pre-ZMDP)	9.417	0.189	22.19	10.15	5472	3.215	0.560
Panel B. Insider patients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
ZMDP	0.36	-0.04	-1.62	0.09	-377.75	0.56	-0.15
	(0.36)	(0.04)	(1.27)	(1.12)	(245.52)	(0.53)	(0.36)
Observations	8,897	8,897	8,897	8,897	8,897	8,897	8,897
Mean of Y (Pre-ZMDP)	8.188	0.205	20.35	10.59	5069	1.781	0.281

Notes: Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). ZMDP equals 1 if a hospital is a public hospital in the post-ZMDP period, as specified in Equation (5). All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects of ZMDP: Triple Difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
Non-insider*ZMDP	-3.69***	0.22***	5.43***	5.86***	1,577.79***	0.41	-0.51
	(0.38)	(0.05)	(0.98)	(1.17)	(313.71)	(0.33)	(0.90)
ZMDP	0.62	-0.08*	0.87	-3.00**	86.26	0.21	0.45
	(0.41)	(0.04)	(1.26)	(1.20)	(265.39)	(0.47)	(0.85)
Public*Non-insider	0.67**	0.02	-1.66***	2.77***	393.91**	0.30	0.03
	(0.26)	(0.06)	(0.59)	(0.78)	(192.29)	(0.40)	(0.42)
Observations	427,511	427,511	427,511	427,511	427,511	427,511	427,511
Mean of Y (Pre-ZMDP)	9.392	0.190	22.15	10.16	5464	3.186	0.554

Notes: Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). As specified in Equation (6), Non-insider*ZMDP equals 1 if a patient is a non-insider and is treated in a public hospital after ZMDP; ZMDP equals 1 if a hospital is a public hospital in the post-ZMDP period; Public*Non-insider equals 1 if a hospital is a public hospital and the patient is a non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Mechanisms: Public Hospitals, Two-Group Comparisons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
			Panel A. Non-insider vs. Different hospital insider				
Non-insider*ZMDP	-3.08***	0.15**	4.07***	4.59***	1,122.51***	0.41	-1.07
	(0.34)	(0.07)	(0.96)	(1.63)	(387.09)	(0.62)	(1.70)
Observations	222,736	222,736	222,736	222,736	222,736	222,736	222,736
Mean of Y (Pre-ZMDP)	10.85	0.371	22.66	15.68	7528	3.381	0.980
			Panel B. Different hospital insider vs. Same hospital insider				
Diff hospital*ZMDP	-1.25*	0.12*	3.06**	3.57*	889.99**	0.03	0.13
	(0.68)	(0.07)	(1.28)	(1.99)	(409.42)	(1.15)	(0.97)
Observations	5,450	5,450	5,450	5,450	5,450	5,450	5,450
Mean of Y (Pre-ZMDP)	8.942	0.320	20.52	14.34	6204	1.924	0.542
			Panel C. Same hospital lower-ranked insider vs. Same hospital higher-ranked insider				
Same hospital-low rank*ZMDP	-0.91	0.09***	1.11	-0.32	-346.56	0.25	
	(0.64)	(0.03)	(1.84)	(1.56)	(466.17)	(0.47)	
Observations	2,649	2,649	2,649	2,649	2,649	2,649	
Mean of Y (Pre-ZMDP)	7.668	0.192	19.25	11.16	4960	1.450	

Notes: Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). In Panel C, column (7) is omitted because there is zero mortality among same-hospital insiders. As specified in Equation (7), Non-insider*ZMDP equals 1 if a patient is a non-insider admitted after ZMDP; Diff hospital*ZMDP equals 1 if a patient is a different-hospital insider admitted after ZMDP; Same hospital-low rank*ZMDP equals 1 if a patient is a same-hospital low-rank insider admitted after ZMDP. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Mechanisms: Public Hospitals Only, Relative to Same-Hospital High-Rank Patients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
Subgroup*ZMDP							
Same hospital-low rank*ZMDP	-0.77	0.10	2.58	1.97	442.85	0.36	0.36
	(0.65)	(0.08)	(1.66)	(1.20)	(415.85)	(0.57)	(0.40)
Diff hospital*ZMDP	-1.55**	0.19*	4.18**	3.88*	1,126.38**	0.18	1.47
	(0.71)	(0.11)	(1.89)	(2.14)	(510.40)	(1.02)	(1.72)
Non-insider*ZMDP	-4.62***	0.34***	8.26***	8.50***	2,260.49***	0.60	0.41
	(0.69)	(0.08)	(1.89)	(1.51)	(437.89)	(0.61)	(0.28)
Subgroup							
Same hospital-low rank	1.87***	0.04	0.22	0.74	1,067.77***	0.35	0.69
	(0.27)	(0.04)	(0.86)	(0.67)	(292.22)	(0.36)	(0.44)
Diff hospital	2.11***	0.18*	0.03	3.38**	1,247.27***	0.28	1.17*
	(0.38)	(0.10)	(1.00)	(1.35)	(397.77)	(0.46)	(0.70)
ZMDP	1.65**	-0.28***	-1.35	-5.42***	117.05	-0.68	0.25
	(0.73)	(0.08)	(2.05)	(1.45)	(502.66)	(0.70)	(0.40)
Observations	225,385	225,385	225,385	225,385	225,385	225,385	225,385
Mean of Y (Pre-ZMDP)	10.81	0.369	22.62	15.62	7497	3.357	0.968

Notes: Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). As specified in Equation (8), Same hospital-low rank*ZMDP equals 1 if a patient is a same-hospital low-rank insider admitted after ZMDP; Diff hospital*ZMDP equals 1 if a patient is a different-hospital insider admitted after ZMDP; Non-insider*ZMDP equals 1 if a patient is a non-insider admitted after ZMDP. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Appendix A: Model Details

A.1 Physician's Optimal Recommendation Strategy

A.1.1 Optimal Recommendation Strategy for Non-insider Patients

Since non-insider patients passively follow the physician's recommendation, the physician will recommend invasive surgery for all signals that yield a higher physician expected utility from surgery than non-invasive treatment. Given a signal realization s, the physician's expected payoff from invasive surgery is

$$\alpha_i^c \mathbb{E}_\epsilon(\xi_i|s) - \alpha_i^c \kappa_i + F_i. \tag{A.1}$$

Since $\xi_i \sim N(0,1)$, $\epsilon_i \sim \mathcal{N}(0,\sigma_i^2)$, and noise ϵ_i is independent of severity ξ_i, we have

$$\begin{pmatrix} \xi \\ s \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \mathrm{Var}(\xi) & \mathrm{Cov}(\xi, s) \\ \mathrm{Cov}(s,\xi) & \mathrm{Var}(s) \end{pmatrix} \right),$$

where $\mathrm{Var}(\xi) = 1,\ \mathrm{Var}(s) = \mathrm{Var}(\xi+\varepsilon) = 1+\sigma_i^2,\ \mathrm{Cov}(\xi,s) = \mathrm{Cov}(\xi,\xi+\varepsilon) = \mathrm{Var}(\xi) = 1.$ As a result,

$$\begin{aligned} \mathbb{E}_\epsilon[\xi \mid s] &= \frac{\mathrm{Cov}(\xi,s)}{\mathrm{Var}(s)}\, s \\ &= \frac{1}{1+\sigma_i^2}\, s. \end{aligned} \tag{A.2}$$

The physician's expected payoff from invasive surgery can be written as

$$\begin{aligned} &\alpha_i^c \mathbb{E}_\epsilon(\xi_i|s) - \alpha_i^c \kappa_i + F_i \\ =&\alpha_i^c \frac{s}{1+\sigma_i^2} - \alpha_i^c \kappa_i + F_i. \end{aligned} \tag{A.3}$$

Therefore, any signal s that makes this expected payoff weakly greater than zero (the normalized payoff from non-invasive treatment) will lead to a surgery recommendation for non-insider patients. In equilibrium, for any $s \geq \left(\kappa_i - \frac{F_i}{\alpha_i^c}\right)(1+\sigma_i^2)$, it is optimal for the physician to recommend invasive surgery; otherwise, they recommend non-invasive treatment. Therefore, we denote the physician's optimal cutoff for the signal for the non-insider patient as c_i^{*NI}:

$$c_i^{*NI} = \big(\kappa_i - \frac{F_i}{\alpha_i^c}\big)(1 + \sigma_i^2). \tag{A.4}$$

The non-insider patient follows the physician's recommendation irrespective of the recommendation.

A.1.2 Optimal Recommendation Strategy for Insider Patients

Following the literature on information design (Bergemann and Morris, 2019), we focus on an obedient recommendation strategy: given insider patient i's best response, the physician selects a recommendation rule that maximizes the physician's expected payoff, such that the Bayesian patient is willingness to follow it despite knowing it is biased. Moreover, since the physician's payoff is monotonic in ξ_i, Xiang (2026) shows that the optimal strategy in this case is a cutoff rule: the physician recommends invasive surgery if the observed signal exceeds a threshold, and non-invasive treatment otherwise. Therefore, the physician chooses a threshold c_i for the signal:

$$\begin{aligned} &\max_{c_i} \qquad \int_{c_i}^{\infty} \big[\alpha_i^c\, \mathbb{E}[\xi_i \mid s] - \alpha_i^c\, \kappa_i + F_i\big] f_S(s)\, ds \\ &s.t \textit{ (Obedience constraints)} \\ &\qquad \text{①}\ \mathbb{E}(\xi_i | s_i \geq c_i) - \kappa_i \geq 0 \\ &\qquad \text{②}\ \mathbb{E}(\xi_i | s_i < c_i) - \kappa_i \leq 0. \end{aligned} \tag{A.5}$$

The first obedience constraint states that if the physician recommends invasive surgery, the insider patient, knowing that the physician's signal must be above the threshold, will update their belief about the expected value of surgery and find it weakly optimal to follow the recommendation. Similarly, the second obedience constraint ensures that if non-invasive treatment is recommended, the insider patient will be willing to follow. This formulation shows that a physician's ability to induce treatment for an insider patient is limited not only by altruism, as in the case of a non-insider patient, but also by the patient's skepticism and rational evaluation of the recommendation, as captured by the obedience constraints. The conditional expectations in these constraints imply that the insider patient is aware of the physician's biased recommendation strategy. If the physician always recommends the same treatment, the insider patient's updated expectation will match their prior, rendering the recommendation uninformative and unable to influence the decision.

We first solve for the physician's optimal recommendation strategy for an insider patient.

Interior Solution to Equation (A.5) One can solve for the interior solution (when constraints are slack) using a first-order condition. However, it can also be obtained more simply and intuitively: In the physician's objective function, the integrand is the payoff from surgery given signal s. If it is positive for a given s, it should be included in the integral to maximize the objective; if negative, it should not. Since $\mathbb{E}[\xi_i \mid s] = \frac{s}{1+\sigma_i^2}$ increases with s, the optimal cutoff $c_i^{*I(interior)}$ is the signal at which the integrand equals zero:

$$c_i^{*I(interior)} = \big(\kappa_i - \frac{F_i}{\alpha_i^c}\big)(1 + \sigma_i^2). \tag{A.6}$$

Corner Solution to Equation (A.5) Since we assume $F_i \geq 0$, the physician's financial bias favors invasive surgery. Therefore, whenever the physician recommends non-invasive treatment, the patient's expected utility from that option is strictly greater than from surgery. In other words, the second obedience constraint, $\mathbb{E}(\xi_i|s_i < c_i) - \kappa_i \leq 0$, never binds in our setting. We now consider the case when the first obedience constraint binds, i.e, $\mathbb{E}(\xi_i | s_i \geq c_i^{*I}) - \kappa_i = 0$. Note that by the law of iterated expectation,

$$
\begin{aligned}
&\mathbb{E}(\xi_i \mid s_i \geq c_i^{*I}) \\
=&\mathbb{E}\Big[\mathbb{E}(\xi_i \mid s) \Big| s \geq c_i^{*I}\Big] \\
=&\mathbb{E}\left[\tfrac{1}{1+\sigma_i^2} \cdot s \,\middle|\, s \geq c_i^{*I}\right] \\
=&\tfrac{1}{1+\sigma_i^2} \cdot \sqrt{1+\sigma_i^2} \cdot \mathbb{E}\left[\tfrac{s}{\sqrt{1+\sigma_i^2}} \,\middle|\, \tfrac{s}{\sqrt{1+\sigma_i^2}} \geq \tfrac{c_i^{*I}}{\sqrt{1+\sigma_i^2}}\right] \\
=&\tfrac{1}{\sqrt{1+\sigma_i^2}} \cdot \underbrace{\frac{\phi\Big(\frac{c_i^{*I}}{\sqrt{1+\sigma_i^2}}\Big)}{1-\Phi\Big(\frac{c_i^{*I}}{\sqrt{1+\sigma_i^2}}\Big)}}_{\equiv h\left(\frac{c_i^{*I}}{\sqrt{1+\sigma_i^2}}\right)}.
\end{aligned}
\tag{A.7}
$$

In the last row, we define the inverse mills ratio $\frac{\phi(x)}{1-\Phi(x)} \equiv h(x)$, which is increasing in x. When the first obedience constraint binds, we have

$$
\begin{aligned}
&\frac{1}{\sqrt{1+\sigma_i^2}} \cdot h\left(\frac{c_i^{*I}}{\sqrt{1+\sigma_i^2}}\right) = \kappa_i \\
\Rightarrow \quad & c_i^{*I(corner)} = \sqrt{1+\sigma_i^2}\; h^{-1}\big(\kappa_i \sqrt{1+\sigma_i^2}\big).
\end{aligned}
\tag{A.8}
$$

Combining The Two Cases When the optimal cutoff is the interior solution, we know the first obedience constraint is not binding:

$$
\begin{aligned}
&\mathbb{E}(\xi_i | s_i \geq c_i^{*I(interior)}) > \kappa_i = \mathbb{E}(\xi_i | s_i \geq c_i^{*I(corner)}) \\
\Rightarrow & c_i^{*I(interior)} > c_i^{*I(corner)}.
\end{aligned}
$$

When the optimal cutoff is the corner solution, we know the first obedience constraint will not hold for the interior solution:

$$\begin{aligned}&\mathbb{E}(\xi_i|s_i \geq c_i^{*I(interior)}) < \kappa_i = \mathbb{E}(\xi_i|s_i \geq c_i^{*I(corner)})\\ \Rightarrow & c_i^{*I(interior)} < c_i^{*I(corner)}.\end{aligned}$$

Therefore, the optimal cutoff of the signal for the insider patient can be written as

$$\begin{aligned} c_i^{*I} &= \max\left\{c_i^{*I(interior)},\ c_i^{*I(corner)}\right\} \\ &= \max\left\{\left(\kappa_i - \frac{F_i}{\alpha_i^c}\right)(1+\sigma_i^2),\ \sqrt{1+\sigma_i^2}\ h^{-1}\left(\kappa_i\ \sqrt{1+\sigma_i^2}\right)\right\}, \end{aligned} \tag{A.9}$$

where $h^{-1}(x)$ is the inverse function of the inverse mills ratio $h(x) \equiv \frac{\phi(x)}{1-\Phi(x)}$. In Equation (A.9), $c_i^{*I} = \left(\kappa_i - \frac{F_i}{\alpha_i^c}\right)(1+\sigma_i^2)$ is the interior solution where the constraint does not bind, and it coincides with the non-insider patient's cutoff. $c_i^{*I} = \sqrt{1+\sigma_i^2}\ h^{-1}\left(\kappa_i\ \sqrt{1+\sigma_i^2}\right)$ is the corner solution when the first obedience constraint binds, that is, when the patient is exactly indifferent between the two treatment options when being recommended surgery.

Particularly, when $F_i = 0$, we have the interior solution $c_i^{*I} = \kappa_i(1+\sigma_i^2)$. To see this, by the property of inverse mills ratio, we know $h(x) > x$. Therefore, $h\left(\kappa_i\sqrt{(1+\sigma_i^2)}\right) > \kappa_i\sqrt{(1+\sigma_i^2)}$. This implies $\kappa_i(1+\sigma_i^2) > \sqrt{1+\sigma_i^2}\ h^{-1}\left(\kappa_i\ \sqrt{1+\sigma_i^2}\right)$.

A.2 Model Properties

In this section, we study how physicians' responses to the ZMDP policy and physicians' distortions from the patients' perspectives vary with patient traits.

A.2.1 Responses to ZMDP w.r.t. Connection, Rank, and Insider Knowledge

First, we examine how physicians' response to ZMDP differs by patient connection, rank, and insider information. Because ZMDP made surgical treatment relatively more profitable compared to non-surgical treatment, F_i increases due to this policy. We study how a physician's response to such increased in financial incentives, $\frac{\partial c_i^*}{\partial F_i}$, will depend on α_i^c (connection), σ_i^2 (rank), and patient insider information. An increase in F_i implies a lower cutoff in physicians' recommendation strategy and, consequently, a higher probability of recommending (and performing) invasive surgery. For non-insider patients, the cutoff change with respect to the policy is:

$$\frac{\partial c_i^{*NI}}{\partial F_i} = -\frac{1}{\alpha_i^c}(1+\sigma_i^2). \tag{A.10}$$

For insider patients, the cutoff response is:

$$\frac{\partial c_i^{*I}}{\partial F_i} = \mathbf{1}\{\text{constraint non-binding}\}\big(-\frac{1}{\alpha_i^c}(1+\sigma_i^2)\big) + \mathbf{1}\{\text{constraint binding}\}\ 0. \tag{A.11}$$

Response to ZMDP w.r.t Connection. For non-insider patients,

$$\frac{\partial(\frac{c_i^{*NI}}{F_i})}{\partial \alpha_i^c} = \frac{1+\sigma_i^2}{\alpha_i^{c2}} > 0, \tag{A.12}$$

where the response to financial incentives $\frac{c_i^{*NI}}{F_i} = -\frac{1+\sigma_i^2}{\alpha_i^c} < 0$. Therefore, for non-insider patients, stronger connection reduces the extent to which physicians lower the cutoff in response to increased financial incentives.

For insider patients,

$$\frac{\partial(\frac{c_i^{*I}}{F_i})}{\partial \alpha_i^c} = \mathbf{1}\{\text{constraint binding}\}\cdot 0 + \mathbf{1}\{\text{constraint non-binding}\}\ \frac{1+\sigma_i^2}{\alpha_i^{c2}}. \tag{A.13}$$

Therefore, for insider patients, when the constraint binds, the physician cannot respond to financial incentives regardless of connection. When the constraint is non-binding, stronger connection reduces the extent to which the physician lowers the cutoff in response to increased financial incentives F_i.

Panel (a) of Figure A1 illustrates the role of patient connections in shaping physicians' responses to financial incentives for insiders and non-insiders separately.

Response to ZMDP w.r.t Rank. For non-insider patients,

$$\frac{\partial(\frac{c_i^{*NI}}{F_i})}{\partial \sigma_i^2} = -\frac{1}{\alpha_i^c} < 0. \tag{A.14}$$

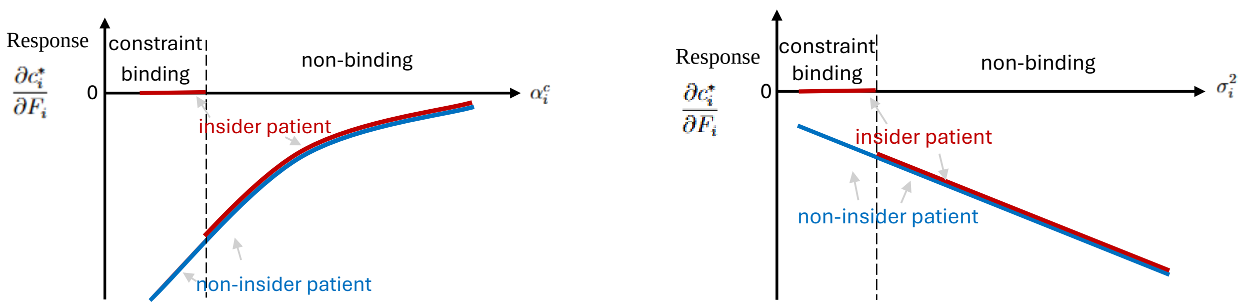
Therefore, for non-insider patients, higher-rank (i.e., lower σ_i^2) reduces the extent to which physicians lower the cutoff in response to increased financial incentives F_i.

For insider patients,

$$\frac{\partial(\frac{c_i^{*I}}{F_i})}{\partial \sigma_i^2} = \mathbf{1}\{\text{constraint binding}\} \cdot 0 + \mathbf{1}\{\text{constraint non-binding}\} \quad (-\frac{1}{\alpha_i^c}). \tag{A.15}$$

Therefore, for insider patients, when the constraint binds, the physician cannot respond to financial incentives regardless of rank. With a non-binding constraint, higher rank dampens their response.

Panel (b) of Figure A1 illustrates the role of patient rank in shaping physicians' responses to financial incentives for insiders and non-insiders separately.



(a) Connection (b) Rank

Figure A1: How Response to ZMDP Depends on Connection, Rank, and Insider Information

Response to ZMDP w.r.t Insider Knowledge. Panel (a) of Figure A1 also suggests that, at a given level of connection α_i^c, physicians' responses to the policy will be weakly greater for non-insider patients. Similarly, Panel (b) of Figure A1 also suggests that at a given level of rank σ_i^2, physicians' responses to the policy will be weakly greater for non-insider patients.

A.2.2 Physicians' Distortions w.r.t. Connection, Rank, and Insider Knowledge

We define a notion of distortion from the patient perspective and show how the distortion varies with patient traits. Note that without any physician financial incentives ($F_i = 0$), the perfect agent would choose $c_i^* = \kappa_i(1+\sigma_i^2)$ (See Appendix A.1 for details). We refer to it as the first-best cutoff from the patient's perspective. If $F_i > 0$, the incentives are not aligned and physician's optimal cutoff will locate to the left of the first-best cutoff; a lower cutoff indicates a higher probability of invasive surgery. Define distortion as the distance between first-best cutoff and the physician's optimal cutoff c_i^*. We then conduct comparative statics analysis.

Distortion w.r.t Connection. The distortion for a non-insider is

$$Distortion^{NI} = \kappa_i(1+\sigma_i^2) - \big(\kappa_i - \frac{F_i}{\alpha_i^c}\big)(1+\sigma_i^2) = \frac{F_i}{\alpha_i^c}(1+\sigma_i^2). \tag{A.16}$$

$$\frac{Distortion^{NI}}{\alpha_i^c} = -\frac{F_i(1+\sigma_i^2)}{\alpha_i^{c2}} < 0. \tag{A.17}$$

Therefore, for non-insider patients, weaker connection (smaller α_i^c) leads to greater distortion.

The distortion for an insider is

$$\begin{aligned} Distortion^{I} = \; & \mathbf{1}\{\text{constraint non-binding}\} \quad \underbrace{\frac{F_i}{\alpha_i^c}(1+\sigma_i^2)}_{Distortion^{(interior)}} \\ & + \mathbf{1}\{\text{constraint binding}\} \underbrace{\Big(\kappa_i(1+\sigma_i^2) - \sqrt{1+\sigma_i^2}\; h^{-1}\big(\kappa_i\, \sqrt{1+\sigma_i^2}\big)\Big)}_{Distortion^{corner}}. \end{aligned} \tag{A.18}$$

$$\frac{Distortion^{I}}{\alpha_i^c} = \mathbf{1}\{\text{constraint binding}\}\cdot 0 + \mathbf{1}\{\text{constraint non-binding}\}\big(-\frac{F_i(1+\sigma_i^2)}{\alpha_i^{c2}}\big). \tag{A.19}$$

As α_i^c increases, $c_i^{*I(\text{interior})}$ rises until the optimal cutoff becomes the interior solution, at which point the constraint no longer binds. Therefore, for insider patients, if the obedience constraint is not binding, weaker connection (smaller α_i^c) also leads to greater distortion. However, once α_i^c decreases to the point where the constraint binds, distortion no longer varies with α_i^c. The role of connections is illustrated in panel (a) of Figure A2.

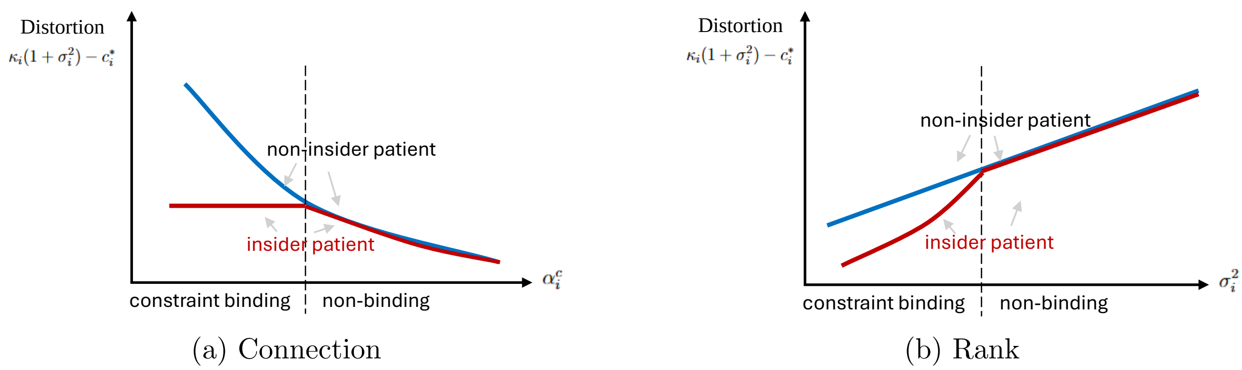


Figure A2: How Distortion Depends on Connection, Rank, and Insider Information

Distortion w.r.t Rank For non-insider patients, and for insider patients when the obedience constraint is slack, the distortion with respect to σ_i^2 is positive. That is, the lower the rank, the greater the distortion.

$$\frac{\partial Distortion^{NI}}{\partial \sigma_i^2} = \frac{Distortion^{(interior)}}{\partial \sigma_i^2} = \frac{F_i}{\alpha_i^c} > 0. \tag{A.20}$$

Next, we show that for insider patients, when the obedience constraint is binding, the distortion with respect to σ_i^2 remains positive as long as $\kappa_i\sqrt{1+\sigma_i^2} > h(0) \approx 0.8$. This holds when the noise in the physician's signal, σ_i^2, and the patient's reluctance toward invasive surgery, κ_i, are sufficiently large. Formally, when the obedience constraint binds, the distortion for insider patients with respect to σ_i^2 is given by:

$$\begin{aligned}
\frac{\partial\, Distortion^{(\text{corner})}}{\partial \sigma_i^2} &= \kappa_i - \frac{h^{-1}\big(\kappa_i\sqrt{1+\sigma_i^2}\big)}{2\sqrt{1+\sigma_i^2}} - \sqrt{1+\sigma_i^2}\,\frac{1}{h'\Big[h^{-1}\big(\kappa_i\sqrt{1+\sigma_i^2}\big)\Big]}\,\frac{\kappa_i}{2\sqrt{1+\sigma_i^2}} \\
&= \kappa_i - \frac{h^{-1}\big(\kappa_i\sqrt{1+\sigma_i^2}\big)}{2\sqrt{1+\sigma_i^2}} - \frac{1}{2\sqrt{1+\sigma_i^2}\Big[\kappa_i\sqrt{1+\sigma_i^2} - h^{-1}\big(\kappa_i\sqrt{1+\sigma_i^2}\big)\Big]} \qquad \text{(use } h'(x)=h(x)[h(x)-x]\text{)} \\
&> \kappa_i - \frac{h^{-1}\big(\kappa_i\sqrt{1+\sigma_i^2}\big)}{2\sqrt{1+\sigma_i^2}} - \frac{h^{-1}\big(\kappa_i\sqrt{1+\sigma_i^2}\big)}{2\sqrt{1+\sigma_i^2}} \qquad \text{(let } x=h^{-1}(\cdot)>0\text{, use } h(x)>x+\tfrac{1}{x}\text{)} \\
&> \kappa_i - \frac{\kappa_i}{2} - \frac{\kappa_i}{2} \qquad \text{(use } h^{-1}(x)<x\text{)} \\
&= 0.
\end{aligned} \tag{A.21}$$

Next, we show that under a stronger assumption, the difference $c_i^{*I(\text{interior})} - c_i^{*I(\text{corner})}$ increases with σ_i^2. Hence, as σ_i^2 rises, $c_i^{*I(\text{interior})}$ becomes relatively larger, and eventually the optimal cutoff switches to the interior solution (constraint non-binding).

$$
\begin{aligned}
\frac{\partial(c_i^{*I(\text{interior})} - c_i^{*I(\text{corner})})}{\partial \sigma_i^2} =& \frac{\partial(Distortion^{(corner)} - Distortion^{(interior)})}{\partial \sigma_i^2} \\
>& \kappa_i - \frac{h^{-1}\left(\kappa_i \sqrt{1+\sigma_i^2}\right)}{\sqrt{1+\sigma_i^2}} - \frac{F_i}{\alpha_i^c} \\
\geq& 0 \quad \text{if} \quad \frac{F_i}{\alpha_i^c} \leq \kappa_i - \frac{h^{-1}\left(\kappa_i \sqrt{1+\sigma_i^2}\right)}{\sqrt{1+\sigma_i^2}} \qquad \text{(A.22)}
\end{aligned}
$$

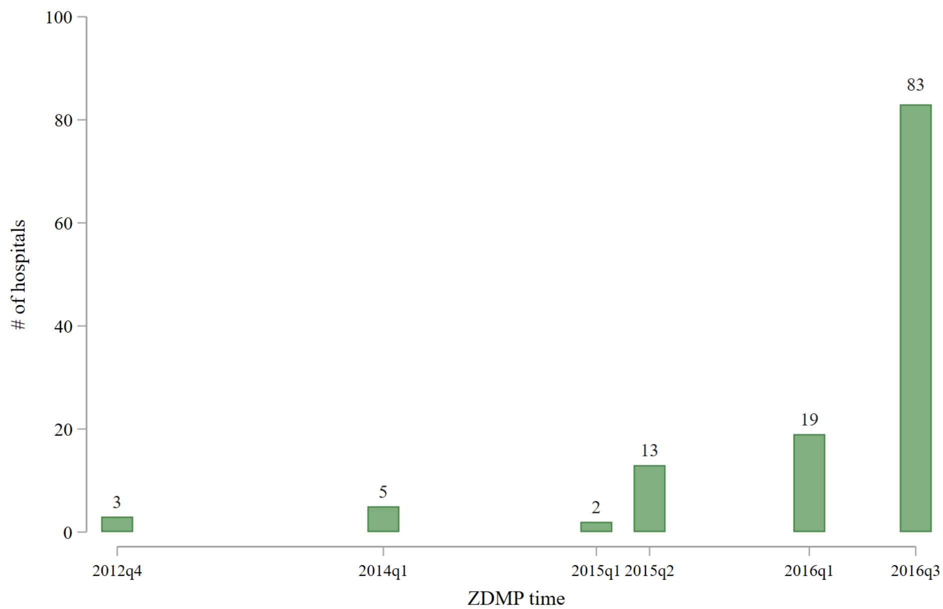
Therefore, when financial incentives are not too large, an increase in σ_i^2 causes the obedience constraint to shift from binding to non-binding.

The role of rank in determining distortion is illustrated in panel (b) of Figure A2. It suggests that for both insiders and non-insiders, distortion decreases with patient ranks.

Distortion w.r.t. Insider Knowledge. For insider patients, when the obedience constraint binds, i.e., $c_i^{*I(\text{interior})} < c_i^{*I(\text{corner})}$, we have $Distortion^{(\text{interior})} > Distortion^{(\text{corner})}$. Therefore, once the constraint binds, the distortion for insider patients remains fixed at a level lower than the interior-solution distortion. Since the interior-solution distortion is the same as that of non-insider patients, the distortion for insider patients is strictly smaller than for non-insider patients. Graphically, for both panels in Figure A2, at a given level of α_i^c or σ_i^2, the red line (insiders) lies strictly below the blue line (non-insiders) for the constraint-binding regions, indicating lower distortion for insider patients.

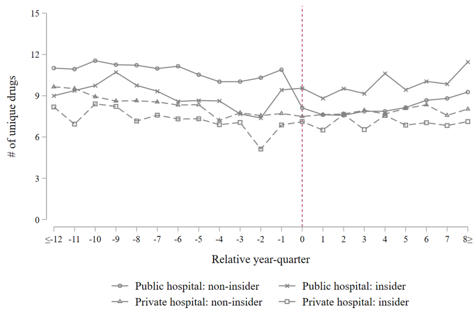
Appendix B: Additional Figures and Tables

Figure B1: ZMDP Implementation Time in Changsha

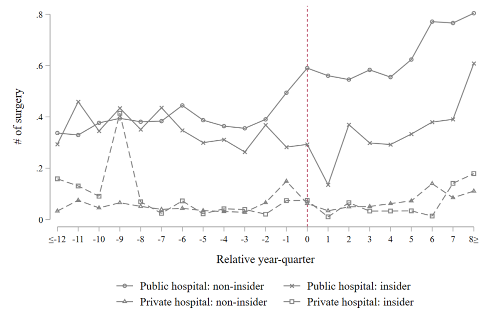


Notes: This figure shows the implementation timing of ZMDP across hospitals in Changsha, the capital city of Hunan Province. The number of hospitals that implemented the policy in each year-quarter is shown above the corresponding bar.

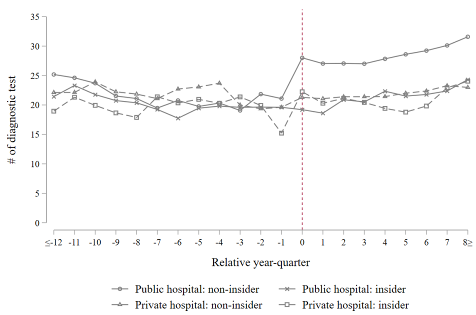
Figure B2: Raw Trends by Insiders and Non-insiders in Public and Private Hospitals: Health Care Utilization



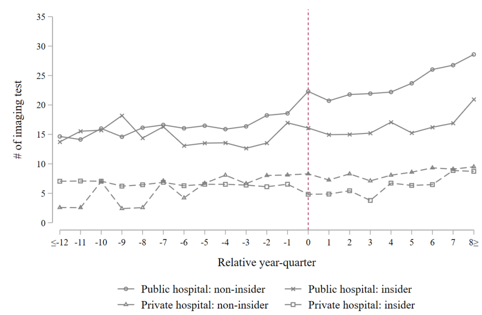
(a) Drug



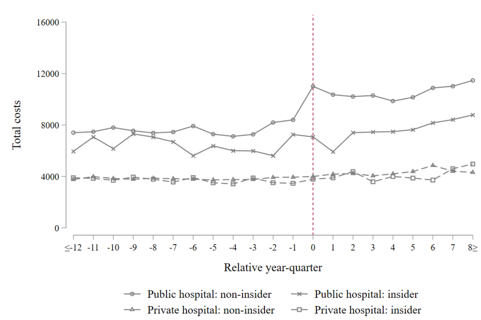
(b) Surgery



(c) Diagnostic test

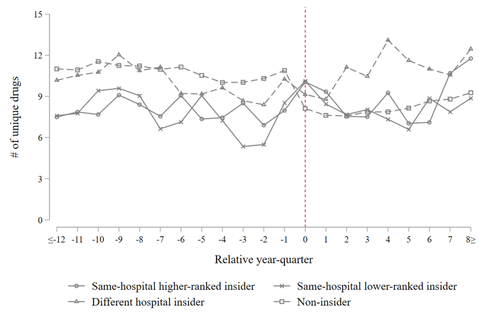


(d) Imaging test

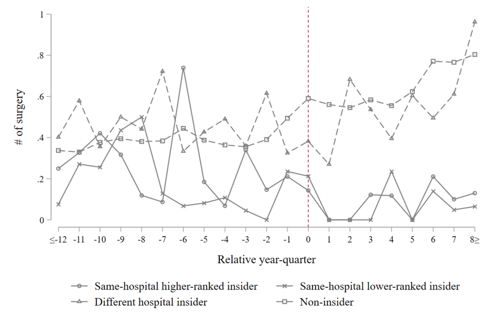


(e) Total costs

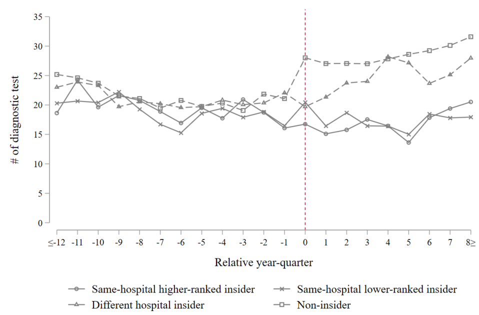
Figure B3: Raw Trends by Subtype of Insiders and Non-insiders in Public Hospitals: Health Care Utilization



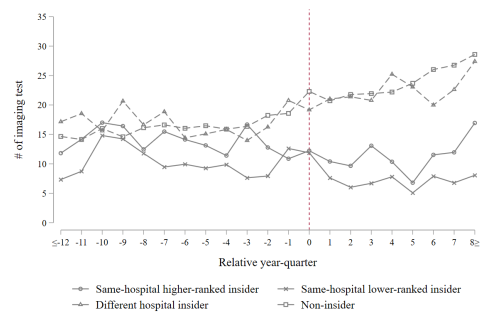
(a) Drug



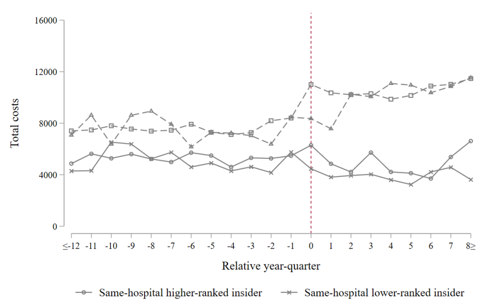
(b) Surgery



(c) Diagnostic test

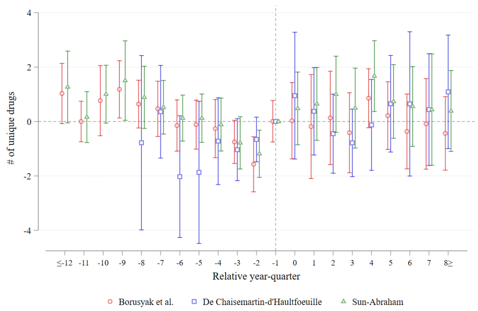


(d) Imaging test

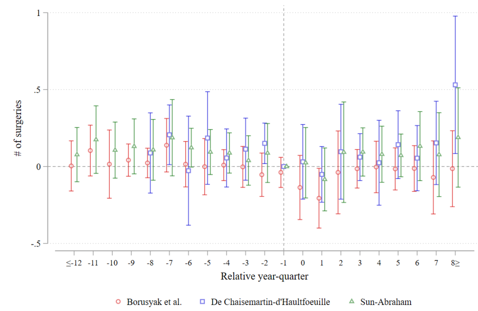


(e) Total costs

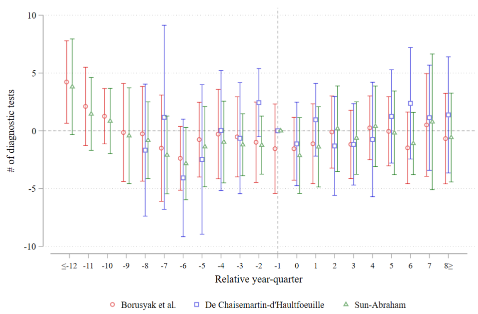
Figure B4: Alternative Event Study Models: Health Care Utilization of Insiders



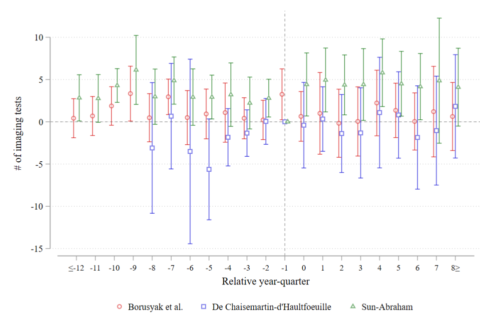
(a) Drug



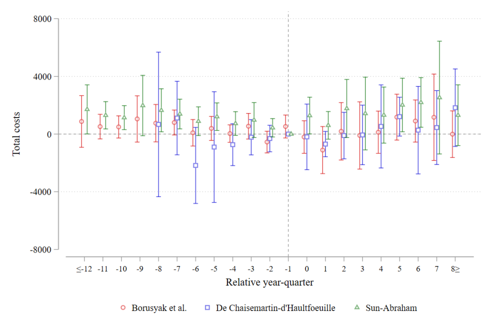
(b) Surgery



(c) Diagnostic test



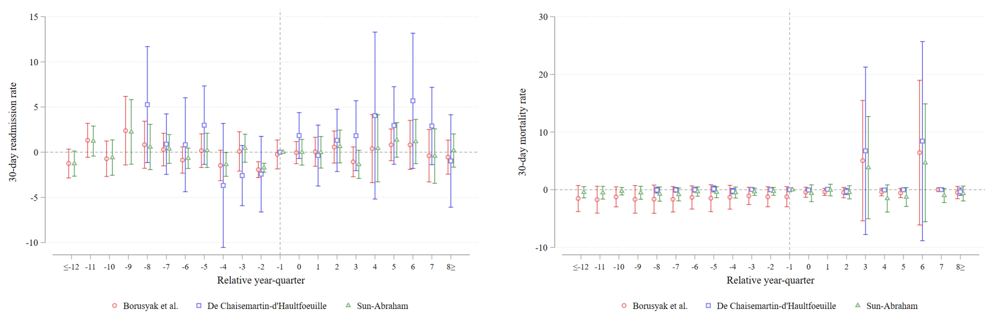
(d) Imaging test



(e) Total costs

Notes: These figures show health care utilization of insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. The event study estimates, obtained using alternative estimators proposed by Borusyak et al. (2024), De Chaisemartin and d'Haultfoeuille (2020), and Sun and Abraham (2021), are shown in the figures. Dots represent point estimates, and caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

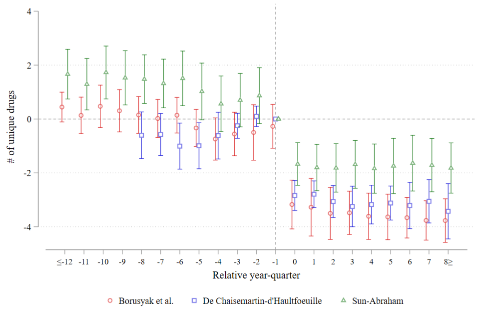
Figure B5: Alternative Event Study Models: Health Outcomes of Insiders



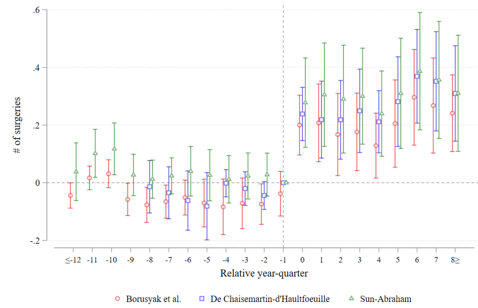
(a) 30-day readmission rate (b) 30-day mortality rate

Notes: These figures show health outcomes of insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. The event study estimates, obtained using alternative estimators proposed by Borusyak et al. (2024), De Chaisemartin and d'Haultfoeuille (2020), and Sun and Abraham (2021), are shown in the figures. Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). Dots represent point estimates, and caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

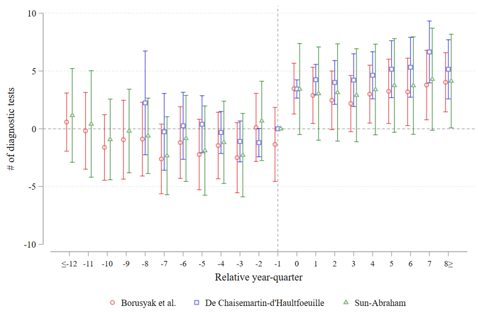
Figure B6: Alternative Event Study Models: Health Care Utilization of Non-Insiders



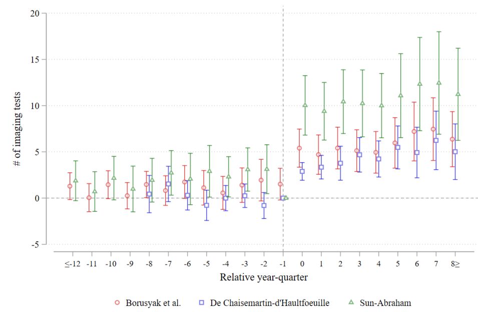
(a) Drug



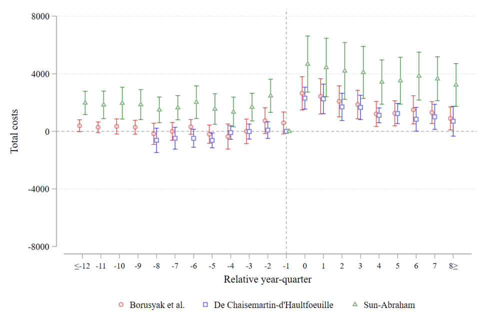
(b) Surgery



(c) Diagnostic test



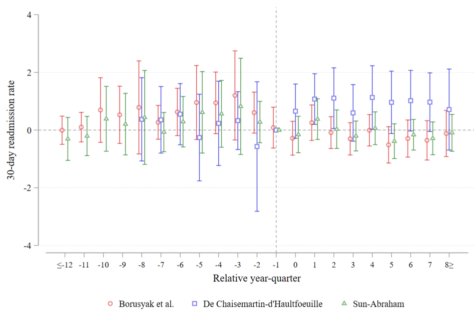
(d) Imaging test



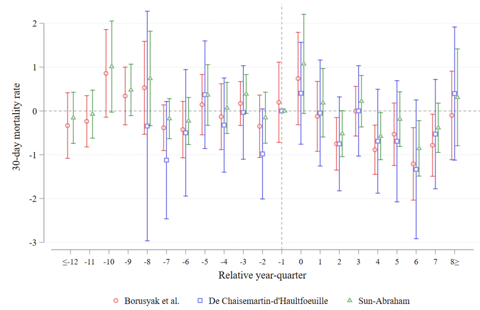
(e) Total costs

Notes: These figures show health care utilization of non-insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. The event study estimates, obtained using alternative estimators proposed by Borusyak et al. (2024), De Chaisemartin and d'Haultfoeuille (2020), and Sun and Abraham (2021), are shown in the figures. Dots represent point estimates, and caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Figure B7: Alternative Event Study Models: Health Outcomes of Non-Insiders



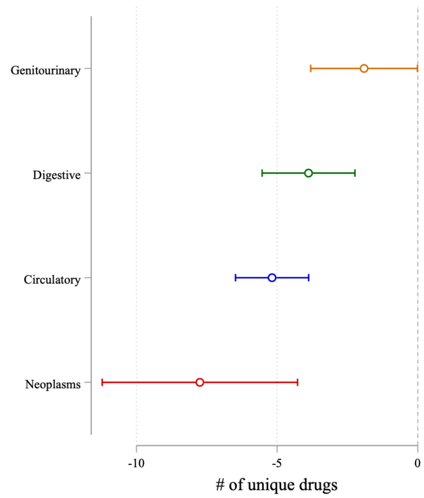
(a) 30-day readmission rate



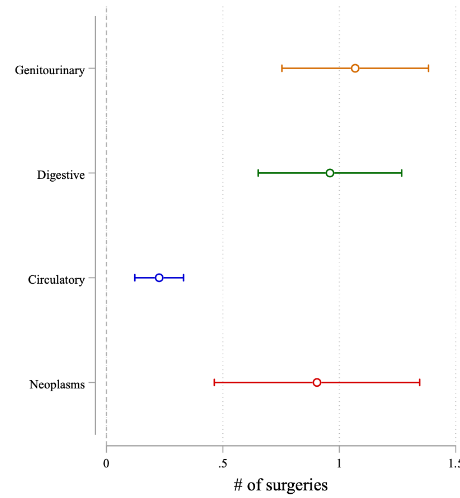
(b) 30-day mortality rate

Notes: These figures show health outcomes of non-insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. The event study estimates, obtained using alternative estimators proposed by Borusyak et al. (2024), De Chaisemartin and d'Haultfoeuille (2020), and Sun and Abraham (2021), are shown in the figures. Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). Dots represent point estimates, and caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

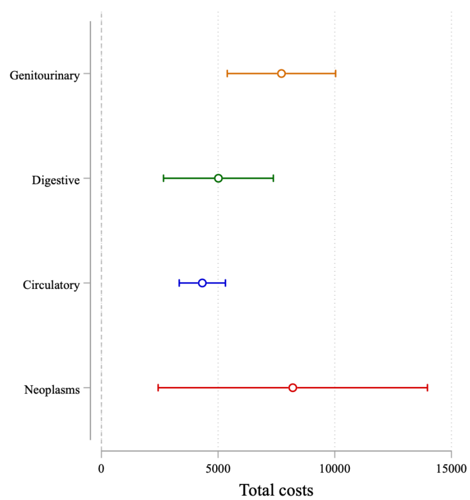
Figure B8: ZMDP Effects on Other Medical Conditions: Care Utilization and Health Outcomes



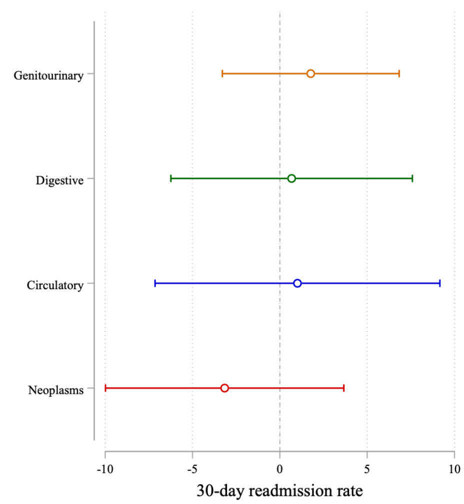
(a) Drug quantity



(b) Surgery quantity



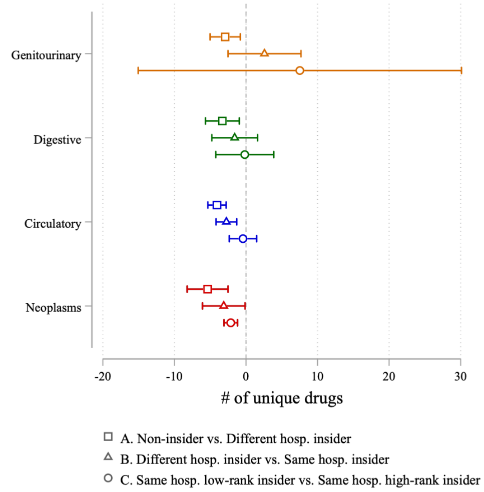
(c) Total costs



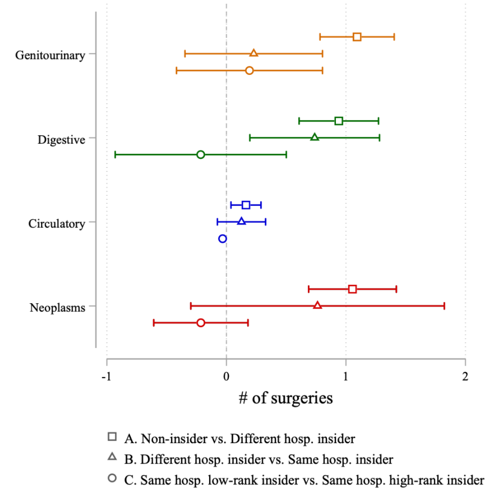
(d) 30-day readmission rate

Notes: These figures show the effects of ZMDP on health care utilization and health outcomes for four disease categories, separately for non-insiders and insiders, based on Equation (6). The disease categories are: neoplasms (ICD-10: C00–D46), diseases of the circulatory system (ICD-10: I00-I99), diseases of the digestive System (ICD-10: K00–K93), and diseases of the genitourinary System (ICD-10: N00–N99). Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). Dots represent point estimates. Solid lines indicate 90% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

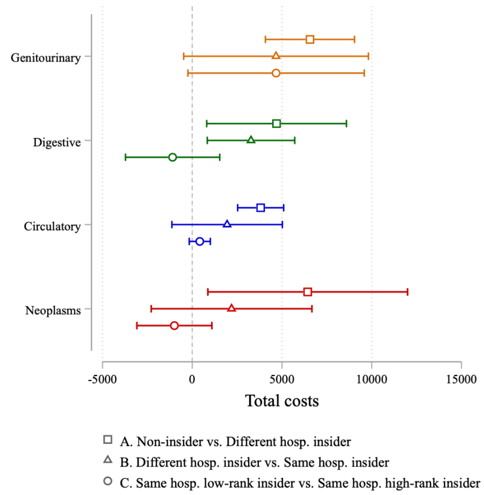
Figure B9: ZMDP Effects on Other Medical Conditions, Two-Group Comparisons: Care Utilization and Health Outcomes



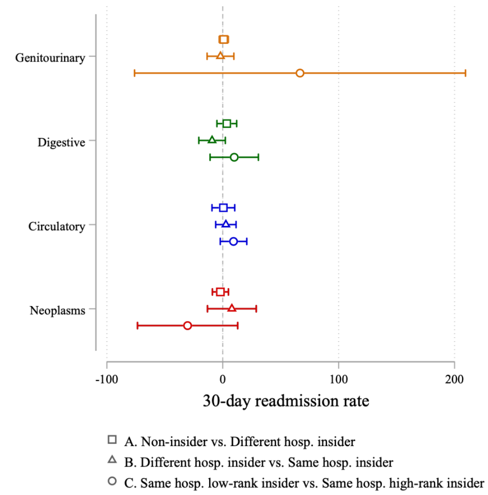
(a) Drug quantity



(b) Surgery quantity



(c) Total costs



(d) 30-day readmission rate

Notes: These figures compare the effects of ZMDP on health care utilization outcomes for four disease categories based on Equation (7). Each estimate presents a pairwise comparison: non-insiders vs. insiders, different-hospital insiders vs. same-hospital insiders, and low-rank vs. high-rank same-hospital insiders. The disease categories are: neoplasms (ICD-10: C00–D46), diseases of the circulatory system (ICD-10: I00-I99), diseases of the digestive System (ICD-10: K00–K93), and diseases of the genitourinary System (ICD-10: N00–N99). Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). Dots represent point estimates. Solid lines indicate 90% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Table B1: Descriptive Statistics: Public vs Private Hospitals, Insiders vs Non-Insiders

	All		Non-insider		Insider	
	(1) Public	(2) Private	(3) Public	(4) Private	(5) Public	(6) Private
	Panel A. Outcome variables					
Health care utilization						
# of unique drugs	10.04	8.34	10.06	8.36	9.35	7.36
	(8.37)	(4.68)	(8.38)	(4.69)	(7.95)	(4.30)
# of surgeries	0.47	0.06	0.47	0.06	0.34	0.10
	(1.47)	(0.58)	(1.48)	(0.57)	(1.28)	(1.01)
# of diagnostic tests	24.74	21.80	24.84	21.83	20.97	20.16
	(18.74)	(14.51)	(18.80)	(14.53)	(16.09)	(13.29)
# of imaging tests	18.61	6.12	18.70	6.11	15.27	6.55
	(25.76)	(7.17)	(25.84)	(7.18)	(22.29)	(6.89)
Total costs	8,510.75	3,966.17	8,557.73	3,960.65	6,742.87	3,905.01
	(12,554.12)	(2,711.59)	(12,622.35)	(2,692.86)	(9,475.05)	(2,616.25)
Health outcomes						
30-day readmission rate (%)	3.39	3.05	3.43	3.08	2.05	1.66
	(18.11)	(17.21)	(18.20)	(17.28)	(14.17)	(12.80)
30-day mortality rate (‰)	1.03	0.25	1.04	0.25	0.68	0
	(32.14)	(17.21)	(32.28)	(15.87)	(26.14)	(0)
	Panel B. Individual and hospital characteristics					
Demographic characteristics						
Age (in years)	57.25	58.49	57.39	58.71	51.31	45.92
	(12.37)	(10.45)	(12.24)	(10.21)	(15.57)	(15.16)
Gender (1 = female)	0.65	0.70	0.65	0.70	0.77	0.75
	(0.48)	(0.46)	(0.48)	(0.46)	(0.42)	(0.43)
Insider (1 = health related employment)	0.02	0.02	-	-	-	-
	(0.15)	(0.13)	-	-	-	-
Rank (1 = Cadre)	0.15	0.07	0.15	0.07	0.46	0.21
	(0.36)	(0.26)	(0.35)	(0.25)	(0.50)	(0.41)
Treating Hospital tier						
Share of Tier 1	0.15	0.67	0.15	0.67	0.17	0.58
	(0.35)	(0.47)	(0.35)	(0.47)	(0.37)	(0.49)
Share of Tier 2	0.27	0.32	0.27	0.32	0.25	0.40
	(0.44)	(0.47)	(0.44)	(0.46)	(0.43)	(0.49)
Share of Tier 3	0.59	0.02	0.59	0.02	0.58	0.02
	(0.49)	(0.13)	(0.49)	(0.13)	(0.49)	(0.15)
Observation	225,385	202,126	219,935	198,679	5,450	3,447

Notes: Means of the variables are reported, with standard deviations in parentheses. The number of unique drugs is the count of distinct medications prescribed during the admission. The number of surgeries is the total number of surgical procedures performed. The numbers of diagnostic tests and imaging tests are the counts of diagnostic and imaging procedures, respectively. Total costs represent total inpatient medical expenditures per admission, measured in RMB. The 30-day readmission rate indicates whether a patient is readmitted within 30 days after discharge, reported as a percentage (%). The 30-day mortality rate indicates whether a patient dies within 30 since admission, reported per thousand (‰).

Table B2: Descriptive Statistics: Subgroups of Insider Patients in Public Hospitals

	(1) Same-hospital high-rank insider	(2) Same-hospital low-rank insider	(3) Different-hospital insider
	Panel A. Outcome variables		
Health care utilization			
# of unique drugs	8.22	7.79	10.46
	(6.62)	(6.11)	(8.90)
# of surgeries	0.21	0.11	0.50
	(0.94)	(0.69)	(1.55)
# of diagnostic tests	18.79	18.53	22.88
	(14.44)	(12.20)	(17.85)
# of imaging tests	13.00	8.47	19.11
	(18.14)	(12.96)	(25.86)
Total costs	5,163.64	4,496.56	8,335.44
	(4,581.23)	(4,275.88)	(11,916.95)
Health outcomes			
30-day readmission rate (%)	1.04	1.36	2.75
	(10.14)	(11.60)	(16.34)
30-day mortality rate (‰)	0	0	1.25
	(0)	(0)	(35.31)
	Panel B. Individual and hospital characteristics		
Demographic characteristics			
Age (in years)	49.98	46.51	54.30
	(13.31)	(14.92)	(16.13)
Gender (1 = female)	0.81	0.77	0.74
	(0.39)	(0.42)	(0.44)
Rank (1 = Cadre)	-	-	0.44
	-	-	(0.50)
Hospital tier			
Share of Tier 1	0.08	0.27	0.16
	(0.27)	(0.44)	(0.37)
Share of Tier 2	0.12	0.37	0.25
	(0.33)	(0.48)	(0.43)
Share of Tier 3	0.80	0.36	0.59
	(0.40)	(0.48)	(0.49)
Working/Affiliated Hospital tier			
Share of Tier 1	0.19	0.58	0.52
	(0.39)	(0.49)	(0.45)
Share of Tier 2	0.06	0.10	0.11
	(0.24)	(0.30)	(0.30)
Share of Tier 3	0.75	0.33	0.37
	(0.43)	(0.47)	(0.47)
Observation	1,252	1,397	2,801

Notes: Means of the variables are reported, with standard deviations in parentheses. The number of unique drugs is the count of distinct medications prescribed during the admission. The number of surgeries is the total number of surgical procedures performed. The Numbers of diagnostic tests and imaging tests refer to the counts of diagnostic and imaging procedures, respectively. Total costs represent total inpatient medical expenditures per admission, measured in RMB. The 30-day readmission rate indicates whether a patient is readmitted within 30 days after discharge, reported as a percentage (%). The 30-day mortality rate indicates whether a patient dies within 30 since admission, reported per thousand (‰).

Table B3: Effects of ZMDP: Triple Difference Using Borusyak et al. (2024)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
Non-insider*ZMDP	-3.42***	0.11*	8.47***	5.20***	3,010.19***	0.01	0.52
	(0.33)	(0.06)	(1.55)	(0.81)	(573.17)	(0.26)	(0.39)
Observations	362,488	362,488	362,488	362,488	362,488	362,488	362,488
Mean of Y (Pre-ZMDP)	9.392	0.190	22.15	10.16	5464	3.186	0.554

Notes: Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). As specified in Equation (6), Non-insider*ZMDP equals 1 if a patient is a non-insider and is treated in a public hospital after ZMDP. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. The number of observations is smaller than in the Table 4 because the imputation estimator restricts the sample to observations with valid untreated outcome imputations. *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Static DDD: Triple Difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
Public*Non-insider*Post	-3.06***	0.09*	7.97***	3.57**	1,395.61***	0.34	-0.41
	(0.49)	(0.05)	(1.17)	(1.42)	(338.09)	(0.66)	(0.90)
Public*Post	0.32	0.05	-2.55	0.93	169.64	0.48	0.25
	(0.45)	(0.06)	(1.56)	(1.52)	(287.41)	(0.70)	(0.84)
Non-insider*Post	-0.22	0.13***	-3.21***	4.15***	127.70	0.23	-0.09
	(0.25)	(0.04)	(0.68)	(0.67)	(121.15)	(0.55)	(0.16)
Public*Non-insider	0.60**	0.06	-2.79***	4.40***	436.43**	0.31	0.01
	(0.28)	(0.07)	(0.69)	(0.88)	(210.73)	(0.48)	(0.42)
Observations	417,095	417,095	417,095	417,095	417,095	417,095	417,095
Mean of Y (Pre-ZMDP)	9.964	0.230	22.62	10.87	5960	3.499	0.654

Notes: Hospitals that implemented the policy before 2016 Q1 are excluded from the sample. Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). As specified in Equation (6), Public*Non-insider*Post equals 1 if a patient is a non-insider and is treated in a public hospital after 2016 Q1; Public*Post equals 1 if a hospital is a public hospital in the post period of 2016 Q1; Non-insider*Post equals 1 if the patient is a non-insider and is treated after 2016 Q1; Public*Non-insider equals 1 if a hospital is a public hospital and the patient is a non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table B5: Static DD: Public Hospitals Only, Two-Group Comparisons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
	Panel A. Non-insider vs. Different hospital insider						
Non-insider*Post	-2.81***	0.17**	3.33***	4.78**	1,098.79***	0.49	-0.98
	(0.34)	(0.07)	(0.95)	(1.89)	(382.47)	(0.67)	(1.67)
Observations	212,397	212,397	212,397	212,397	212,397	212,397	212,397
Mean of Y (Pre-ZMDP)	10.96	0.387	23.12	16.17	7779	3.384	0.991
	Panel B. Different hospital insider vs. Same hospital insider						
Diff hospital*Post	-1.21*	0.11*	3.24**	2.83	832.05**	0.26	0.12
	(0.69)	(0.06)	(1.30)	(2.19)	(417.47)	(1.15)	(0.93)
Observations	5,340	5,340	5,340	5,340	5,340	5,340	5,340
Mean of Y (Pre-ZMDP)	9.065	0.334	20.71	14.62	6327	1.981	0.566
	Panel C. Same hospital lower-ranked insider vs. Same hospital higher-ranked insider						
Same hospital-low rank*Post	-1.11	0.08***	1.43	0.09	-336.59	0.13	
	(0.67)	(0.03)	(1.81)	(1.55)	(461.15)	(0.46)	
Observations	2,572	2,572	2,572	2,572	2,572	2,572	
Mean of Y (Pre-ZMDP)	7.757	0.203	19.46	11.37	5054	1.531	

Notes: Hospitals that implemented the policy before 2016 Q1 are excluded from the sample. Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). In Panel C, column (7) is omitted because there is zero mortality among same-hospital insiders. As specified in Equation (7), Non-insider*Post equals 1 if a patient is a non-insider admitted after 2016 Q1; Diff hospital*Post equals 1 if a patient is a different-hospital insider admitted after 2016 Q1; Same hospital-low rank*Post equals 1 if a patient is a same-hospital low-rank insider admitted after 2016 Q1. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Effects of ZMDP: Triple Difference with Individual Effects

	(1)	(2)	(3)	(4)	(5)
		No. of services			Costs
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs
Non-insider*ZMDP	-3.31***	0.23***	6.32***	5.73***	1,724.72***
	(0.35)	(0.08)	(1.00)	(1.35)	(378.04)
ZMDP	0.67*	-0.13*	-0.03	-2.94**	-4.21
	(0.37)	(0.07)	(1.51)	(1.49)	(403.34)
Public*Non-insider	0.33	0.04	1.31	3.00***	596.66**
	(0.35)	(0.05)	(0.96)	(1.08)	(283.47)
Observations	190,593	190,593	190,593	190,593	190,593
Mean of Y (Pre-ZMDP)	8.596	0.0953	21.01	8.294	4752

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a triple difference model. As specified in Equation (6), Non-insider*ZMDP takes 1 if a patient is a non-insider, a hospital is a public hospital, and the time is after ZMDP; ZMDP takes 1 if a hospital is a public hospital and the time is after ZMDP; Public*Non-insider takes 1 if a hospital is a public hospital and the patient is a non-insider. All specifications include individual fixed effects, age-cohort fixed effects, 3-digit ICD code fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Mechanisms: Public Hospitals, Two-Group Comparisons with Individual Fixed Effects

	(1)	(2)	(3)	(4)	(5)
		No. of services			Costs
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs
	Panel A. Non-insider vs. Different hospital insider				
Non-insider*ZMDP	-3.15***	0.09	3.33**	2.11	206.03
	(0.38)	(0.09)	(1.28)	(3.31)	(523.52)
Observations	62,119	62,119	62,119	62,119	62,119
Mean of Y (Pre-ZMDP)	10.01	0.219	21.01	13.02	6705
	Panel B. Different hospital insider vs. Same hospital insider				
Diff hospital*ZMDP	-1.42**	0.24	3.77**	5.23	1,287.54**
	(0.68)	(0.18)	(1.72)	(4.14)	(585.91)
Observations	1,691	1,691	1,691	1,691	1,691
Mean of Y (Pre-ZMDP)	7.886	0.264	19.43	11.66	5368
	Panel C. Same hospital lower-ranked insider vs. Same hospital higher-ranked insider				
Same hospital-low rank*ZMDP	-0.61	0.01	-0.70	-1.44	-601.60
	(1.05)	(0.09)	(1.45)	(1.15)	(722.48)
Observations	927	927	927	927	927
Mean of Y (Pre-ZMDP)	6.814	0.146	18.67	8.623	4442

Notes: Only individuals with at least one observation treated in public hospitals before and after the implementation of the ZMDP are included in analysis. As specified in Equation (7), Non-insider*ZMDP equals 1 if a patient is a non-insider admitted after ZMDP; Diff hospital*ZMDP equals 1 if a patient is a different-hospital insider admitted after ZMDP; Same hospital-low rank*ZMDP equals 1 if a patient is a same-hospital low-rank insider admitted after ZMDP. All specifications include indiviudal fixed effects, age-cohort fixed effects, 3-digit ICD code fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Effects of ZMDP: Triple Difference, Alternative Definition of Non-insiders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
Non-insider*ZMDP	-3.68***	0.19***	4.05***	4.84***	1,228.22***	0.02	-0.37
	(0.40)	(0.05)	(0.92)	(1.34)	(285.67)	(0.48)	(0.85)
ZMDP	0.54	-0.04	0.12	-1.50	-11.50	-0.43	0.47
	(0.37)	(0.05)	(1.18)	(1.20)	(258.28)	(0.57)	(0.74)
Public*Non-insider	0.55**	-0.00	-1.84***	1.03	230.61	0.77	-1.34**
	(0.22)	(0.05)	(0.59)	(0.90)	(167.02)	(0.47)	(0.66)
Observations	26,056	26,056	26,056	26,056	26,056	26,056	26,056
Mean of Y (Pre-ZMDP)	9.276	0.230	20.88	11.45	6011	2.911	0.152

Notes: Non-insider group consists of teachers from primary schools, secondary schools (middle and high schools), and tertiary institutions (colleges and universities). Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). As specified in Equation (6), Non-insider*ZMDP equals 1 if a patient is a non-insider and is treated in a public hospital after ZMDP; ZMDP equals 1 if a hospital is a public hospital in the post-ZMDP period; Public*Non-insider equals 1 if a hospital is a public hospital and the patient is a non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table B9: Mechanisms: Public Hospitals, Two-Group Comparisons , Alternative Definition of Non-Insiders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. of services			Costs	Health outcomes	
	Unique drugs	Surgeries	Diagnostic tests	Imaging tests	Total costs	30-day readm.	30-day mortality
Non-insider*ZMDP	-3.11***	0.14*	2.39***	3.36*	682.83*	0.09	-0.75
	(0.38)	(0.07)	(0.81)	(1.73)	(344.9)	(0.75)	(1.52)
Observations	15,135	15,135	15,135	15,135	15,135	15,135	15,135
Mean of Y (Pre-ZMDP)	10.68	0.350	21.49	15.70	7834	3.634	0.206

Notes: Non-insider group consists of teachers from primary schools, secondary schools (middle and high schools), and tertiary institutions (colleges and universities). Readmission rates are expressed in percentage points. Mortality rates are expressed per thousand patients (i.e., coefficients are multiplied by 1,000). As specified in Equation (7), Non-insider*ZMDP equals 1 if a patient is a non-insider admitted after ZMDP. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, affiliated hospital's tier fixed effects, treating hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.