

The VIP Effect in Medicine: How Patients' Insider Knowledge, Social Ties, and Organizational Rank Shapes 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 authority, drive physicians' clinical decision making. We leverage a policy reform that alters physicians' financial incentives but does not alter patient-physician matching and using 100% insurance claim data from a Chinese city, we separately examine how physicians' responses vary by patients' insider knowledge, social ties, and authority. We show that a policy eliminating physician profits from drug sales reduced drug utilization but increased the use of other forms of care, raising overall costs without improving patient health. This policy response is strongest for non-insider patients, weaker for insiders, further attenuated for insiders who are direct colleagues of treating physicians, and almost absent for high-ranking colleagues within the organization, because these most privileged patients always receive closest-to-optimal care.

Keywords: information, social ties, authority, physician behavior, financial incentives

JEL Codes: I11, I18, J44, J70

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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 shape whether agents treat them efficiently and fairly. In an unequal society, such variation is inevitable, and it can distort resource allocation while deepening disadvantages for vulnerable groups. Despite its importance, we still know relatively little about the extent to which these traits influence agents’ behavior.

In this paper, we separately study the role of insider information, social ties, and authority in shaping agents’ behavior, in the context of medical service provision. These dynamics are especially consequential in healthcare, where patients must navigate decisions with physicians who hold superior access to information and clinical resources. Inequality in patient traits can lead to inequitable clinical decisions and worse outcomes for less privileged patients, for example, when they lack the institutional knowledge to critically evaluate physicians’ recommendations, have their preferences overlooked due to systematic bias, or receive less attention. Yet we know little empirically about how important these traits are in shaping physicians’ behavior. Moreover, identifying the relative importance of each trait is critical for policy. If physicians defer to patients with administrative authority, interventions should aim to insulate clinical decisions from hierarchical pressure. If insider knowledge constrains physicians’ discretion, broader patient education and greater transparency can help reduce inequities.

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 physician financial incentives that is orthogonal to patients’ unobserved health risks and preference.¹ We then examine how physicians’ strategic responses to the policy vary with patient insider knowledge, ties to physicians, and administrative authority, leveraging the

¹We also provide arguments and evidence that this policy does not alter how patients sort into providers

rich patient characteristics in the data.

We first develop a conceptual framework to describe how physicians adjust treatment recommendations based on patients' privileged traits, and use it to generate testable predictions about physician heterogeneous responses to financial incentives. 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 those with social ties, and they obtain more precise signals of severity for high-rank patients, reflecting career concerns. The model predicts that physicians respond more strongly to financial incentives for non-insider patients and for those without close ties or high ranks.

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 drug prices.² This reform substantially altered financial incentives for physicians in public hospitals, from prescribing drugs to prescribing other medical services.

Our main data sources are 100% insurance claim data for hospital stays and social security data from Changsha, a large capital city in central China with a population of approximately 10 million, covering the period from 2010 to 2018. We focus on patients with orthopedic diseases, who account for 1/6 of all hospitalizations in our data. Orthopedists, compared to other specialists, typically have greater discretionary power in choosing between non-invasive (e.g., medications) and invasive treatment (e.g., surgeries) (Ding and Liu 2021). Our main sample consists of workers and retirees covered by the Urban Employee Basic Medical Insurance (UEBMI), which is the government-provided insurance that covers over 95% of workers.

The data contains unique information on patients' current or pre-retirement workplaces and administrative ranking. Such information allows us to have unique measures of patients' privileged traits and disentangle the relative importance of each trait. Patients employed

²To compensate public hospitals'/physicians' revenue loss, the policy allows price increases for non-drug medical services, aiming to cover 80% of the decrease in drug costs. Private hospitals are exempt from the policy.

in the healthcare sector are classified as insider patients as they possess more institutional knowledge (though not necessarily condition-specific medical knowledge); among them, those working in the same hospital as the treating physician are classified as same-hospital insider patients, who have closer ties to the treating physicians compared with different-hospital insider patients.³ Within the same-hospital insiders, those holding hospital administrative leadership positions are classified as same-hospital high-rank insider patients, capturing strong authority. We focus on same-hospital high-rank colleagues to ensure a clear hierarchy of power and authority between physicians and their patient colleagues. Therefore, comparing physician responses to ZMDP between non-insiders and different-hospital insider patients highlights the role of insider knowledge. Conditional on being insider patients, physician response differences between same-hospital and different-hospital insiders inform the role of social ties. Lastly, response differences between same-hospital high-rank and same-hospital low-rank insiders reveal the importance of authority.

Before conducting our main analysis, we show that ZMDP does not affect patient-physician matching, as there is no change in differential utilization of public vs. private hospitals by either insiders or non-insiders. The demographic characteristics of each patient group also remains stable before and after ZMDP across public and private hospitals.

We document the differences in health care utilization among non-insiders and insiders under ZMDP using a difference-in-differences (DID) model by comparing non-insiders between public and private hospitals and insiders between public and private hospitals before and after the policy. We show that insiders' health care utilization remains similar, whereas non-insiders experience a decrease in drug utilization with increases in utilization of other forms of care. Using a triple-difference model, we show that compared to insiders, non-insiders experience a 1,392 Chinese Yuan (CNY) (25.5%) increase in total medical costs per claim due to ZMDP. However, there is no significant difference in treatment outcomes, as measured by readmission and mortality rates.⁴

³Hospitals, especially public hospitals, are the main healthcare providers in China, covering primary care, specialty care, inpatient care, drug prescription, and drug dispensing. In addition, hospitals are typically big, ranging from hundreds to thousands employees.

⁴There's literature documenting that expert patients may have better access to care, different adherence to medical guidelines, and have 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). We allow for such differences to exist, but as long as these differences remain constant over time, and such differences do not simultaneously

Next, we compare non-insider patients to different-hospital insiders, different-hospital insiders to same-hospital insiders, and same-hospital low-rank insiders to same-hospital high-rank insiders sequentially, to tease out the influence of each channel. We find significant differences between non-insiders and different-hospital insiders in terms of their health care utilization. Similarly, we find significant differences between different-hospital and same-hospital insiders, and the magnitudes are comparable to those between non-insiders and different-hospital insiders. However, compared to same-hospital high-rank patients, same-hospital low-rank patients only experience a significant increase in surgery but not in other forms of care, and their total medical costs are also not statistically different. When looking at the health outcomes, however, none is statistically different between any two groups. Taken altogether, this implies that insider knowledge and social ties play a similarly important role in affecting physician decision making, while organization rank plays a modest role.

If we use same-hospital high-rank patients as the benchmark, ZMDP leads to a insignificant 420 CNY increase for same-hospital low-rank patients, a significant 1,373 CNY (18.3%) increase for different-hospital insiders, and a significant 2,335 CNY (33.8%) increase for non-insiders, without changing any health outcomes. This suggests that less privileged patients receive less efficient care than VIP patients.

Our paper contributes to the following literature. First, we contribute to the literature that examines how patients' characteristics can influence physicians' decision making. [Currie et al. \(2024b\)](#) reviewed existing studies that provide evidence about disparities in treatment because of patients' education, gender, race, 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. 2024a](#)). One strand of this literature is the concordance study, focusing on whether patients who are more similar to doctors in terms of characteristics 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](#)

change with ZDMP, our DID and triple-difference estimates provide causal effects, reflecting how physicians treat insider and non-insider patients differently.

and Dillender 2024). Recent studies look at more nuanced characteristics of patients that are not easily observed in most existing data or settings, such as physicians as patients and high-power patients in the military (Johnson and Rehavi 2016; Chen et al. 2025; Schwab and Singh 2024). Our paper is most close to Chen et al. (2025). However, they look at cancer patients and construct both insiderise and connection measures based on physician patients’ sub-specialty code. In addition, due to lack of quasi-experimental setting, they rely on matching on observed characteristics to examine a physician’s different treatment on physician and non-physician patients, which potentially suffers from omitted variable bias. Our analysis is based on a quasi-experiment to build the causal relationship, and we construct insiderise and connection measures based on patients’ workplace. In addition, due to administrative ranking in public hospitals in China, we are able to further identify insider patients with higher and lower ranks.

Second, we add to the literature examines how physicians respond to changes in financial incentives (Clemens and Gottlieb 2014; Johnson and Rehavi 2016; Brekke et al. 2019; Alexander and Schnell 2024). In particular, we contribute to the literature that studies hospitals’/physicians’ strategic response to regulations (Coudin et al. 2015; Alexander 2020; Gupta 2021; Wilding et al. 2022; Shi 2024). When a policy aims to decrease health care costs in one way, providers can respond strategically by cherry picking patients and/or increasing other non-regulated care, which essentially nullifies the effect or even increases overall health care costs and harms patient welfare (Alexander 2020). In our setting, we show that although ZMDP decreases prescription drug costs, it increases total health care costs via increases in other forms of care. Furthermore, patients without connections are harmed more.

Finally, our paper also adds to studies on the impact of social ties on resource allocation. A substantial literature examines the value of social connections—particularly political ties—in shaping economic outcomes (Fisman, 2001; Khwaja and Mian, 2005; Faccio, 2006). Beyond politics, Li (2017) investigates the determinants of research grant approval and finds that the applicant’s connections with reviewers complement the quality of research projects. Similarly, Fisman et al. (2018) shows that hometown ties to selection committee members increase candidates’ election probability in fellow selection of the Chinese Academies of Sciences and Engineering. Furthermore, social ties can have financial firms and analysts gain

favorable information and arrangement (Hong et al., 2005; Cohen et al., 2008, 2010). Our study extends the research on the impact of social ties to the field of medical decision-making.

The rest of the paper is structured as follows: Section 2 provides background on pharmaceutical markup, the ZMDP policy, and the health care system in China. Section 3 illustrates our stylized framework. Section 4 introduces the data and sample used in the study and outlines the empirical strategy for analysis. Section 5 rules out patient sorting. Section 6 presents the heterogeneous effects of ZMDP on insider 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 the Zero Markup Drug Policy (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 China. 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 in this region are 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; drugs accounted for more than 40% of total hospital expenditures ([National Health Commission of the PRC, 2016](#)).

Drugs Pricing. Beginning in the 1950s, the government allowed hospitals to apply a 15 percent 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-often account for up to 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. These incentives operate differently across care settings. In outpatient care, physicians face strong incentives to prescribe drugs. In inpatient care, physicians have particularly strong incentives to perform surgical procedures, which command higher fees and are typically accompanied by extensive use of drugs, generating substantially higher hospital revenue than non-surgical treatments.

Patient Insurance. China has achieved near-universal health insurance coverage since 2009, with 95% of the population covered by either the Urban Employee Basic Medical Insurance (UEBMI) or the Urban-Rural Resident Basic Medical Insurance (URRBMI). UEBMI covers employees and retirees with urban hukou, while URRBMI covers the remaining population.⁵ 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.⁶ 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. This means that conditional on hospital tier and retirement status, patients’ insurance generosity is homogeneous in our sample.

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 the ZMDP in all public healthcare institutions 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 the ZMDP was a nationwide policy, its implementation varied substantially across regions in timing and scope. We study the ZMDP reform in Changsha, the capital city of

⁵Hukou is China’s household registration system. Based on their registered place of residence, each Chinese citizen holds either a rural or an urban hukou.

⁶Lower-tier hospitals feature higher reimbursement rates and lower deductibles.

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 the ZMDP in 2016, Changsha had a population of 8.56 million and a GDP per capita of \$18,687.

Changsha initiated the ZMDP reform as early as 2012, starting with township hospitals. Figure B1 illustrates the implementation timeline of the ZMDP across hospitals in Changsha. The earliest adoption occurred in October 2012, while nearly 60% of hospitals implemented the policy in January 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). Private hospitals, by contrast, were not subject to this policy.

During our study period, the payment model in Changsha is still fee-for-service, and under ZMDP, to compensate physician compensation loss due to zero drug markups, the government allows hospitals to increase their charges for other services.

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 information, 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 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, 2020) 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. In both settings, the physician’s optimal policy is

⁷In 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.

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 the ZMDP differs by patient traits. Because the ZMDP made surgical treatment relatively more expensive compared to non-surgical treatment, F_i increased due to this policy. As a result, physicians’ optimal cutoff became lower, which implies a higher probability of recommending and performing surgery. We provide graphical illustrations here, with derivations and more model properties in Appendix A.2.

In Figure 1, the blue line shows how the physician’s optimal cutoff responds to an increase in F_i for non-insiders, while the red line shows the response for insiders. Non-insiders exhibit a weakly larger cutoff response and therefore a larger increase in surgery probability following an increase in F_i , holding other factors constant. Panel (a) further 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 reduce the response once α_i^c exceeds a threshold. Panel (b) illustrates the role of patient rank: higher rank (lower σ_i^2) dampens the response, resulting in a smaller increase in surgery probability.

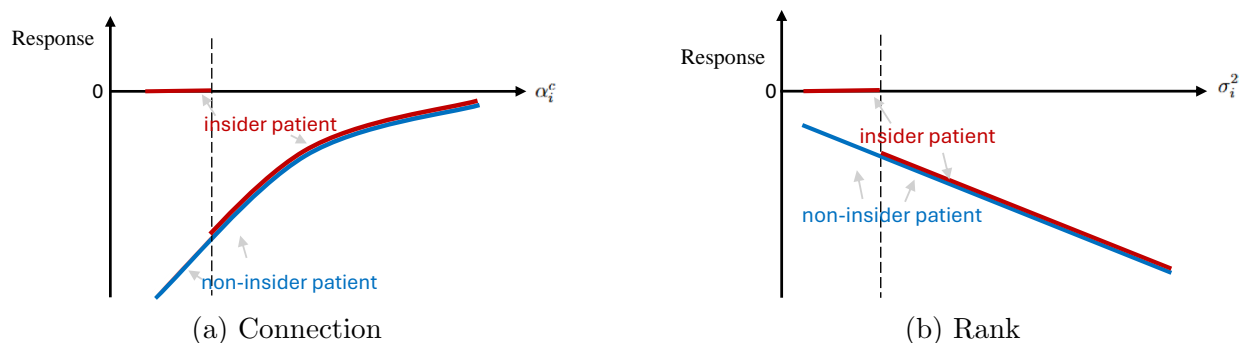


Figure 1: How Response to ZMDP Depends on Connection, Rank, and Insider Information

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 may be larger for non-connected insiders than for connected insiders (conditional on rank), if some insiders strictly prefer the recommended treatment, as do non-insiders.

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 Orthopedic conditions account for approximately one-sixth of all hospital claims in Changsha. We further 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 the 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 traditional Chinese medicine; (2) surgeries and related anesthesia services; (3) diagnostic tests; (4) imaging tests; (5) medical services, such as physician consul-

⁸In the main analysis, we use 100% 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 inpatient claims, which substantially reduces computational burden while yielding statistically indistinguishable estimates in robustness checks.

tations, 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. In addition to these quantity measures, we also consider changes in total costs per claim as an additional primary outcome variable. Finally, we examine patients’ health outcomes, including 7-day and 30-day readmission rates, as well as 30-day and 90-day mortality rates.¹⁰

Measure Insider Information, Connection, and Organizational Rank. We supplement the UEBMI claims data with social security beneficiary summary files, which provide information on individuals’ workplace, administrative rank within the workplace, and demographics (age and gender). We classify an individual as an “insider” if her workplace is a healthcare institution and as a “non-insider” otherwise.¹¹ 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 employees in the public sectors, we observe patients’ 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 differ substantially across patient types. For same-hospital patients, physicians can clearly infer whether a patient outranks them within the same organizational hierarchy, making the patient’s authority directly relevant to the physician’s 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 physician’s career. Focusing on same-hospital patients

⁹Other expenses include blood transfusion, oxygen therapy, and non-specified services, which together account for only a tiny share of total healthcare costs.

¹⁰The 30-day and 90-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.

¹¹We exclude individuals employed by pharmaceutical firms, for whom insider status is difficult to classify.

thus ensures that organizational rank is both well-measured and meaningful. Moreover, comparing same-hospital high-rank patients with same-hospital low-rank patients allows us to hold constant social connections and insider information, thereby isolating the effect of hierarchical authority within the organization.

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 use more care resources per case but deliver slightly worse health outcomes. Public and private hospitals are well balanced in terms of patient age and gender composition. 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, yet achieve better health outcomes. Insiders are younger and have a higher share of female patients. 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. As for demographics, different-hospital insiders are the oldest on average (53), followed by same-hospital high-rank patients (51), while same-hospital low-rank patients are the youngest (47). Same-hospital high-rank insiders have the highest female share (81%), followed by same-hospital low-rank patients (78%), whereas 74% of different-hospital insiders are female. With respect to patients' 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 and hospital choices 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 the 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:

$$y_{iht}^V = \alpha_0 + \sum_{k=-12, k \neq -1}^{k=8} \beta_k^V Pub_h \cdot 1(t_{ih} - t_h^* = k) + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}^V, \quad (4)$$

$$y_{iht}^V = \alpha_0 + \beta^V ZMDP_{ht} + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}^V, \quad (5)$$

where y_{iht}^V represents the outcome of hospital admission i in treating hospital h in quarter t for patient group V , with V being VIPs (insiders) and non-VIPs (non-insiders).¹² The specifications compare patients treated in public versus private hospitals before and after the implementation of the ZMDP, estimated separately for insiders and non-insiders. t_h^* denotes the 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. Event quarters with $k < -12$ are binned into $k = -12$, and those with $k > 8$ are binned into $k = 8$.

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 hospitals. Formally, X_{it} includes individual characteristics that may directly affect y_{iht} , including five-year age bins, 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-healthcare insiders). γ_h and μ_t denote hospital fixed effects and year-quarter fixed effects, respectively.¹³

¹²Figure B2 shows the raw trends in healthcare utilization among insiders and non-insiders in public and private hospitals over time.

¹³We 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 26.57% (= 113,952/195,742) 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

As shown in Figure B1, the majority of public hospitals implemented the ZMDP in October 2016 (83 out of 125 hospitals, accounting for over 95% of observations). Accordingly, in our primary specification we adopt a conventional event-study design that indexes outcomes by event time relative to each hospital’s implementation date. In Section 7, we show that applying recent DiD estimators that explicitly account for staggered policy adoption yields highly similar results.

The identifying assumption here is that, absent the 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 the ZMDP, we expect treated hospitals to decrease 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 $|\beta_k^{nonVIP}| > |\beta_k^{VIP}|$.

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

The analysis above suggests that VIP patients are less responsive to physicians’ financial incentives; however, VIP patients differ along multiple dimensions. To separately identify the roles of insider knowledge, social connections, and organizational rank, we consider three subgroups of insiders: (1) same-hospital high-rank insiders, (2) same-hospital low-rank insiders, and (3) different-hospital insiders.

We first conduct a sequence of two-group comparisons to isolate the role of each VIP traits. Specifically, we first compare non-insiders with different-hospital insiders to assess the role of insider knowledge. Next, we compare different-hospital insiders with same-hospital insiders of all ranks to quantify the additional role of social ties. Finally, we compare same-hospital higher-ranked insiders with same-hospital lower-ranked insiders to further isolate the effect of organizational rank. To implement these comparisons, we estimate a specification analogous to equation (6), restricting the sample to the two groups of interest in each case.

We next compare all four subgroups directly by using same-hospital high-rank patients

individual fixed effects and the results remain robust.

as the benchmark, the premium VIP group who tend to receive most efficient care.¹⁴ The specification (6) is as follows:

$$y_{iht}^g = \alpha_0 + \beta_0 ZMDP_{ht} + \sum_{g=1}^{g=3} \beta^g PatGrp_i * ZMDP_{ht} + \sum_{g=1}^{g=3} \eta^g PatGrp_i + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}^g, \quad (6)$$

where g represents the three subgroups of patients: (1) same-hospital lower-ranked patients, (2) different-hospital insiders, and (3) non-insiders. The baseline group consists of same-hospital higher-rank patients. This analysis aims to identify which mechanism drives the differences in healthcare utilization between insiders and non-insiders. We expect $\beta^g < 0$ when y_{iht}^g represents drug utilization, while $\beta^g > 0$ when y_{iht}^g represents utilization of other services. In terms of the magnitude of β^g , we expect it to be lowest for same-hospital lower-ranked patients, bigger for different-hospital insiders, and largest for non-insiders.

5 Ruling Out Patient Sorting after ZMDP

Our key identification strategy relies on the assumption that the ZMDP changes physicians' financial incentives but does not change patient-physician (hospital) matching. We acknowledge that different patient groups may have different underlying characteristics and different hospital/physician preferences, and thus patient-physician sorting always exists. However, as long as such patient-physician sorting does not change due to ZMDP, our identification strategy still holds. We provide the following evidence to show that the assumption is plausible.

First, we test whether there is any differential patient volume change between public hospitals and private hospitals, and between public hospitals with different pre-ZMDP drug share in their revenues. If a hospital admits more patients in the post-period, the new patient group may have different characteristics from the former patient group and thus may result in different healthcare utilization patterns and health outcomes. We test for sorting between

¹⁴Figure B3 shows that the trend for this subgroup is generally flat across all outcomes.

public and private hospitals using the following equation (7):

$$Y_{ht} = \alpha_0 + \beta Public_h * post_t + \gamma_h + \mu_t + \varepsilon_{ht}, \quad (7)$$

where Y_{ht} represents (i) the number of admissions in hospital h in quarter t and (ii) the share of insider patients.

Similarly, we test for sorting within public hospitals with the same outcome variable Y_{ht} :

$$Y_{ht} = \alpha_0 + \beta preZMDPshareD_h * post_t + \gamma_h + \mu_t + \varepsilon_{ht}, \quad (8)$$

where $preZMDPshareD_h$ represents whether a public hospital h 's share of drugs in its total revenue before ZMDP is above the median of all public hospitals.

Table 1 demonstrates that there is no sorting between public and private hospitals, as there is no significant change in the number of hospitalizations and share of insiders in both columns (1) and (3). Similarly, columns (2) and (4) show that there is no sorting within public hospitals between those who heavily relied on drug sales before the ZMDP.

Next, we rule out differential sorting among the four patient subgroups, which is a key threat to identification for heterogeneous effects among the four patient subgroups. We rely on the following patient-level regression to examine changes in patients' hospital choices and patient composition:

$$Y_{iht} = \alpha_0 + \sum_{g=1}^{g=3} \beta^g Subgroup_i * ZMDP_{ht} + \sum_{g=1}^{g=3} \eta^g Subgroup_i + \delta ZMDP_{ht} + \gamma_h + \mu_t + \varepsilon_{iht}, \quad (9)$$

where Y_{iht} represents that for individual i in quarter t , whether she is hospitalized in (1) a public hospital h , (2) a public hospital h that had a higher share of drug revenue (above median) before ZMDP, (3) a tertiary hospital h , (4) a Tier 2 hospital h , or (5) patient i 's characteristics, e.g., age and gender.¹⁵ As long as β^g is insignificant, it indicates that such patient-physician matching does not change before and after ZMDP, and thus our assumption

¹⁵In China, tertiary hospital are the highest-tier hospitals, providing all types of care and often affiliated with a medical school. Tier 1 hospitals are the lowest-tier hospitals and are generally urban community hospitals or rural township hospitals.

holds.

Table 2 confirms that, despite systematic differences between different patient subgroups, there is no differential sorting driven by ZMDP. Columns (1)–(2) demonstrate that none of the patient groups is more likely to be hospitalized in a public hospital or a public hospital heavily relying on drugs before ZMDP due to the policy. Columns (3)–(4) reveal that there is no difference in sorting among different patient subgroups in terms of the tier of public hospitals. Finally, columns (5)–(6) show that there’s no significant change 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 physicians’ decision-making before and after 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 compared to insider patients prior to the ZMDP.¹⁶ On average, as shown in column (1) of Table 3 panel A, drug utilization for non-insiders in public hospitals decreases by 3.1 unique drugs per claim (32.6%) relative to their counterparts in private hospitals after ZMDP, while panel B column (1) reveals that insiders experience no significant change in drug utilization due to the ZMDP.

For other forms of healthcare utilization, non-insider patients in public hospitals experience larger increases after ZMDP, as a compensation response to the profit loss from prescription drug sales. As shown in Figure 2 panels (b)–(d) and columns (2)–(4) of Table 3 panel B, the ZMDP leads to greater increases in utilization (number of services per claim) for non-insider patients in surgeries, diagnostic tests, and imaging tests, by 0.14 (73.7%),

¹⁶The raw trends in Appendix B2 panel (a) indicate that non-insiders on average had higher prescription drug utilization than insiders before the ZMDP in both public and private hospitals. The trends remain unchanged in private hospitals. However, the gap reversed after the ZMDP in public hospitals, because non-insiders’ utilization of prescription drugs decreased greatly afterwards, whereas drug utilization for insiders slightly increased in public hospitals afterwards.

6.36 (28.7%), and 2.79 (27.5%), respectively.¹⁷ As a result, Figure 2 panel (e) and Table 3 panel B column (5) show that non-insiders end up spending more after ZMDP, with total costs increasing by 1,671 CNY (30.5%) per claim. By contrast, insiders' total costs remain unchanged before and after ZMDP.

Despite of higher medical costs for non-insiders after ZMDP, we do not find an improvement in their health. If anything, Table 3 panel B column (7) indicates that non-insider patients in public hospitals experience a 64 percentage point (20.0%) increase in the likelihood of being readmitted within 30 days from the current admission date. As for 7-day readmission rates and mortality rates, both insiders and non-insiders experience no significant changes.

Moreover, Table 4 analyzes the differences between non-insiders and insiders under ZMDP using a triple-difference framework. Column (1) reveals that compared to insiders, non-insiders' drug utilization per claim decreases by 3.8 unique drugs after ZMDP. However, columns (2)–(4) show that the reduced drug utilization is compensated by increases in other services, where surgeries, diagnostic tests, and imaging tests increase by 0.21, 5.16, and 5.35 times per claim for non-insiders compared to insiders after ZMDP. As a result, column (5) shows that non-insiders' average spending per claim increases by 1,392 CNY after ZMDP compared to insiders. Although non-insiders experience a greater increase in their health care utilization than insiders under ZMDP, columns (6)–(9) demonstrate that there is no difference in health outcomes among these two groups.

In conclusion, non-insider patients' greater utilization of drugs before ZMDP and larger increases in other forms of care utilization after ZMDP, combined with little changes in health outcomes, all suggest that non-insider patients receive less efficient care compared to insider patients, both before (in the form of excessive prescription drugs) and after ZMDP (in the form of unnecessary healthcare services).

¹⁷In Figure B2 panels (b)–(d), we show that prior to ZMDP, non-insiders on average receive similar levels of non-drug treatment as insiders in public hospitals. However, such trends diverge after ZMDP, where insiders still receive the similar amount of other forms of care, but non-insiders receive a greater level of other forms of care, suggesting that physicians only change treatment towards non-insiders.

6.2 Mechanisms: Insider Knowledge, Social Ties, and/or Organizational Rank?

The above section demonstrates that, compared to insiders, non-insider patients experience greater inefficiencies in their healthcare utilization without achieving better health outcomes. 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-ranked patients, same-hospital higher-ranked 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 non-insiders to different-hospital insiders, and it demonstrates that insider knowledge can explain a 859 CNY difference in extra 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 1,132 CNY difference in medical costs. Finally, Panel C compares same-hospital lower-ranked insiders to same-hospital higher-ranked counterparts, where the former group also tends to have lower drug utilization but higher utilization of other forms of care. However, overall, the difference in total medical costs is not statistically significant, suggesting that although organizational rank plays a role, its importance is smaller than that of insider knowledge and social ties.

We then turn to the comparisons among all three less privileged groups relative to the premium VIP group—same-hospital high-rank patients—to show how the remaining patient groups are “worse off” under ZMDP due to physicians' differential treatment of different patients. Figures 4–5 show the event study, and Table 6 shows the DID results. Overall, compared to the premium VIP patients, all other patient groups experience a decrease in

drug utilization after ZMDP and increases in utilization of other forms of care. However, consistent with Table 5, the differences are insignificant between the same-hospital lower-ranked and the same-hospital higher-ranked patients.

Specifically, for drug utilization, as shown in Figure 4(a) and 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 magnitude is largest for non-insiders (4.6 unique drugs per claim), followed by different-hospital insiders (1.2), and the difference (0.8) is not statistically significant between same-hospital low-rank and same-hospital high-rank patients. Similar patterns emerge in the shift towards other forms of care. Figure 4(b) and column (2) of Table 6 reveal that, compared to same-hospital high-rank patients, all the other groups experience an increase in the number of surgeries after ZMDP and follow the same relative magnitude as the reductions in drug utilization. For other types of care, such as diagnostic testing and imaging testing, we similarly find the biggest increases for non-insiders, followed by different-hospital insiders, and the increases among same-hospital low-rank patients are still not statistically different from the premium VIPs, as shown in Figure 4(c)–(d) and columns (3)–(4) of Table 6. As a result, column (5) shows that total medical costs increase by 2,235 CNY for non-insiders and by 1,373 CNY for different-hospital insiders relative to premium VIPs. As for health outcomes, Figure 5 and columns (6)–(9) in Table 6 show that different patient groups do not experience different changes in their readmission rates and mortality rates, despite that they have baseline differences.

7 Additional Results and Robustness Checks

7.1 Log Specification

A potential concern with our level-based estimates is that groups with higher baseline utilization may mechanically experience larger absolute changes even if the percentage response is identical across groups. To address this concern, we re-estimate all specifications using log-transformed outcomes:

$$\log(1 + Y_{it}) = \beta_0 + \beta_1(\text{Group}_i \times \text{Post}_t) + \alpha_i + \gamma_{tm} + \delta_h + \varepsilon_{it} \quad (10)$$

where the coefficient β_1 can be interpreted as an (approximate) percentage change for small values.

Tables B3–B5 present the results. The consistency between these two approaches provides strong evidence that our findings are not driven by mechanical scaling effects. Instead, they reflect genuine differences in how physicians adjust treatment patterns for different patient groups in response to the ZMDP policy shock.

7.2 No Control Variables

While our baseline specification includes a rich set of patient demographics and visit characteristics to improve precision, a parsimonious specification relying solely on fixed effects provides a useful robustness check. In a well-identified DID design with parallel pre-trends, the inclusion of controls should primarily affect standard errors rather than point estimates.

Tables B6–B7 replicates our main and mechanism analyses without any control variables, respectively, relying solely on treating hospital and time fixed effects. The estimated coefficients remain remarkably similar to our baseline specifications.

7.3 Staggered DID

While ZMDP was announced as a uniform policy change, actual implementation occurred gradually across hospitals and quarters throughout 2016. This staggered rollout raises concerns about treatment effect heterogeneity and potential bias in two-way fixed effects (TWFE) estimates 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 estimator proposed by , which computes group-time average treatment effects (ATTs) for each cohort (defined by treatment timing) and then aggregates them appropriately. This approach uses only not-yet-treated or never-treated units as controls, avoiding the "forbidden comparisons" problem inherent in TWFE.

Figure B4–B7 and Table B8 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 3.24 drugs and an increase of 1,581 CNY in total medical costs relative to same-hospital high-rank insiders. The parallel pre-trends across cohorts further validate our identification assumption. These findings confirm that our main results are not driven by treatment effect heterogeneity or improper comparisons across differentially-timed treatment groups.

7.4 Static DID Model

The majority of our sample (around 95%) received treatment in 2016 quarter 1 or quarter 3. 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 B9–B10 presents results from this restricted sample. Despite the reduction in sample size, the estimated treatment effects remain highly consistent with our main findings. For drug utilization, non-insiders experience a differential reduction of 4.47 drugs (compared to -4.62 in the full sample), different-hospital insiders show 1.31 (vs. -1.18), and same-hospital low-rank patients exhibit 1.15 (vs. -0.75). The consistency across the full staggered sample and this restricted uniform-timing sample provides additional confidence that our results are not artifacts of the staggered implementation design.

7.5 Patients with Repeated Hospitalizations

Our main analysis pools all patient-visit observations, including both first-time and repeat visitors. To examine whether our findings hold within individual patients over time, we focus on the subset of patients who have at least one hospitalization both before and after ZMDP implementation. This within-patient design offers the strongest possible control for 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 only about 20% of all patients, raising concerns about generalizability—these are patients with recurring health needs, potentially reflecting more chronic or severe conditions. Second, and more critically, analyzing health outcomes in this sample is problematic: patients cannot die in the pre-period (by construction, 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 them more likely to return). This creates 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 [B11–B12](#) present results for this repeated hospitalization sample. Despite the highly selected nature of this subsample, the patterns remain remarkably consistent with our main findings. In public hospitals, non-insiders experience a 4.20 reduction in drug utilization and a 2,067 CNY increase in total medical costs relative to same-hospital high-rank insiders—effects that are 90.9% and 92.5% of those in the full sample. The within-patient consistency of these differentials provides compelling evidence that our findings reflect genuine changes in physician behavior toward different patient types, rather than compositional changes in the patient pool or unobserved patient heterogeneity.

7.6 Alternative Control Group: Teachers in Secondary and Tertiary Schools

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

To address this concern, we construct an alternative control group consisting of teach-

ers from secondary schools (middle and high schools) and tertiary institutions (colleges and universities). Teachers share several key characteristics with medical professionals: similar education levels (typically requiring at least a bachelor’s degree, with many holding graduate degrees), stable employment in public institutions, and comparable socioeconomic status. Importantly, teachers lack the insider knowledge, social connections, and organizational power within hospitals that medical insiders possess, making them a more appropriate counterfactual for isolating the pure effect of insider privileges.

Tables B13–B14 replicates our main analyses using teachers as the non-insider comparison group. Two findings emerge. First, the baseline differences in pre-ZMDP utilization between teachers and insider groups are substantially smaller than those between the general non-insider population and insiders. For example, teachers’ pre-ZMDP drug utilization is 10.01 compared to 7.81 for same-hospital high-rank insiders, versus 10.86 for general non-insiders in public hospitals. This supports the validity of teachers as a more comparable control group. Second, and more importantly, the differential treatment effects remain large and significant. Teachers still experience a reduction of 5 drugs and an increase of 1,693 CNY in medical costs relative to same-hospital high-rank insiders, representing 50.4% and 23.5% of the effects observed for the general non-insider population. While the magnitudes are somewhat attenuated—consistent with teachers being more sophisticated healthcare consumers—the persistence of substantial differentials even among this highly educated comparison group strongly suggests that insider-specific privileges, rather than general socioeconomic differences, drive our main findings.

7.7 Other Diseases

Our main analysis focuses on orthopedic patients, and one concern is that our findings may only apply to this disease group. To assess the generalizability of our findings, we extend our analysis to other major ICD-10 chapters, including neoplasms (Chapter II: C00-D48), digestive diseases (Chapter XI: K00-K93), genitourinary (Chapter XIV: N00-N99), and injury/poisoning (Chapter XIX: S00-T98). These categories cover a diverse range of conditions with varying degrees of treatment discretion, disease severity, and standard protocols, providing a comprehensive test of whether insider effects persist across different clinical contexts.

Figures B8 and B9 show that similar and consistent findings apply to all these other diseases groups. While the exact magnitudes vary somewhat 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 affect healthcare delivery broadly, rather than being an artifact of specific treatment protocols in respiratory care. The pervasiveness of these differentials across diverse clinical contexts underscores the systemic nature of preferential treatment in this healthcare setting.

8 Discussion and Conclusion

In this paper, we explore how physicians respond heterogeneously to ZMDP, a reform that eliminates drug markup in public hospitals in China, based on patients’ characteristics. We first demonstrate that, compared to insiders, non-insider patients experience a greater reduction in drug costs and a larger increase in other forms of care, suggesting that they receive less efficient care than insiders both before and after ZMDP. By further dividing insider patients into three subgroups, we find that non-same hospital insiders receive moderately more efficient care than non-insiders. By contrast, same-hospital insiders receive much more efficient care and achieve slightly better treatment outcomes. Moreover, same-hospital higher-ranked insiders receive least distorted care. This evidence suggests that insider knowledge and connection plays a critical role in ensuring efficient care in China, and higher organizational rank has additional but limited influence.

Given these findings, the implementation of a medical guideline that ties physicians’ treatment plans to those for same-hospital patients, especially those higher-ranked same-hospital patients, could likely benefit non-same hospital insider patients and non-insider patients while also saving money for the entire healthcare system.

Nevertheless, our study have several limitations. First, our measure of insider knowledge is not perfect. It captures both institutional knowledge and general medical knowledge, but it does not capture disease-specific medical knowledge. Therefore, we cannot identify which dimension of insider knowledge plays the most important role. Second, our findings may

be more applicable to developing countries, where medical guidelines are often lacking and connections between patients and physicians may play a more important role in ensuring efficient care.

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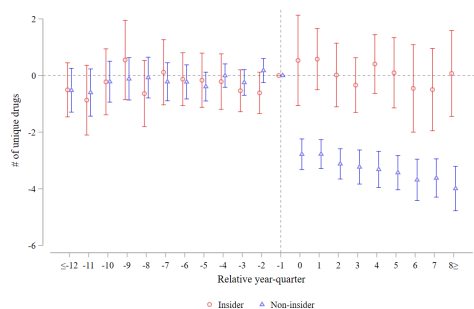
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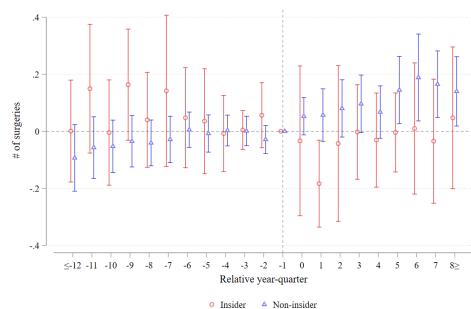
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Figures

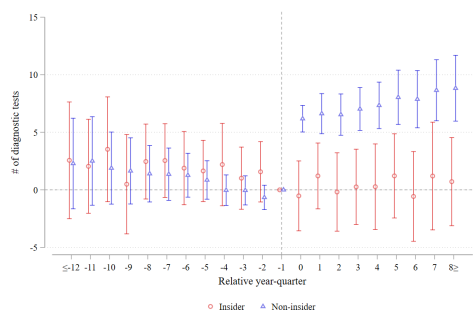
Figure 2: Event Study Results of Health Care Utilization: Insiders vs. Non-insiders Going Through ZMDP



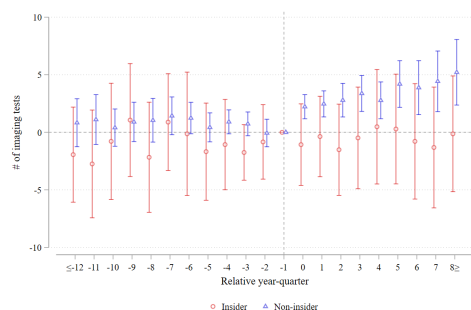
(a) Drug



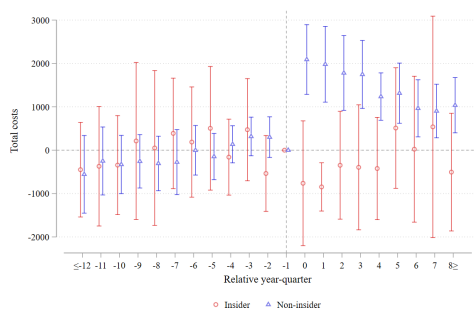
(b) Surgery



(c) Diagnostic test



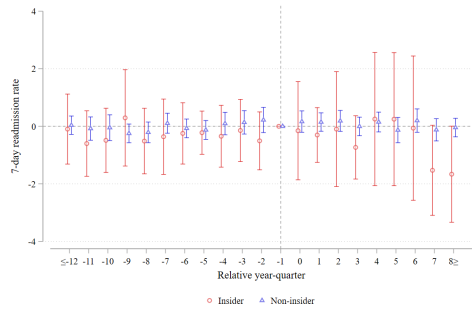
(d) Imaging test



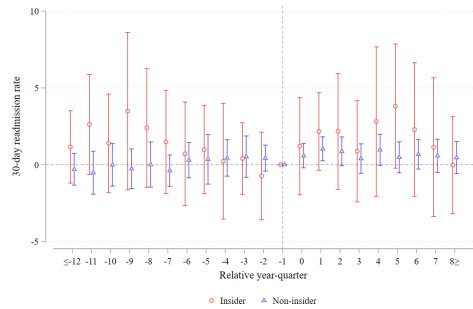
(e) Total costs

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. These figures show event study results of health care utilization of orthopedic patients in public hospitals relative to private hospitals before and after ZMDP, specified in Equation 4. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

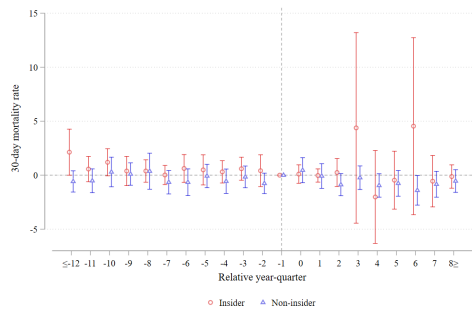
Figure 3: Event Study Results of Health Outcomes: Insiders vs. Non-insiders Going Through ZMDP



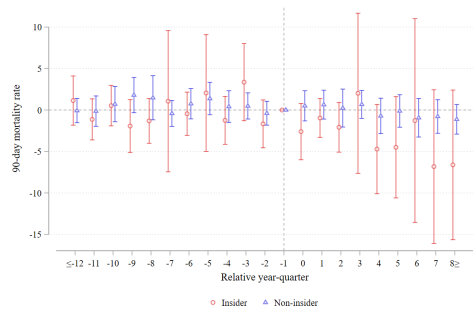
(a) 7-day readmission rate



(b) 30-day readmission rate



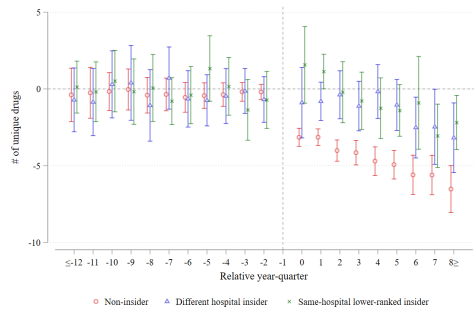
(c) 30-day mortality rate



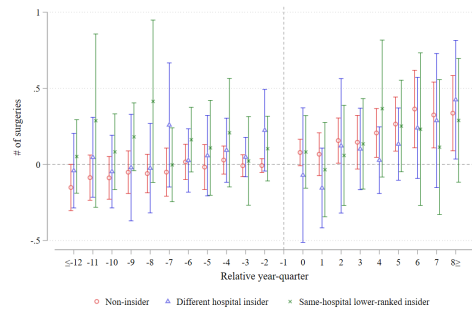
(d) 90-day mortality rate

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. These figures show event study results of health outcomes of orthopedic patients in public hospitals relative to private hospitals before and after ZMDP, specified in Equation 4. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

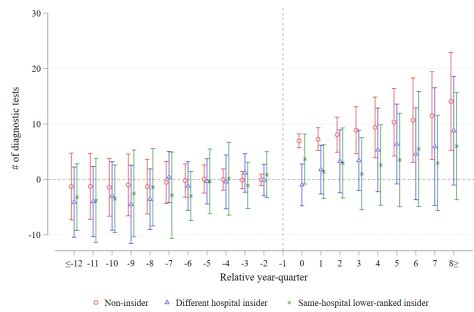
Figure 4: Event Study Results of Health Care Utilization: Public Hospitals Only, Relative to Same-hospital Higher-rank Patients



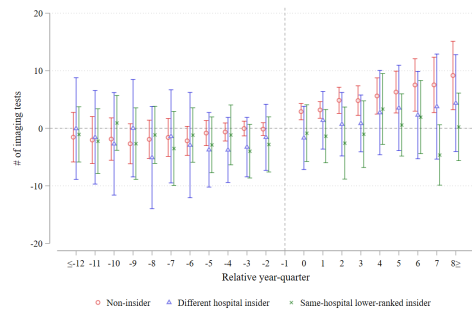
(a) Drug



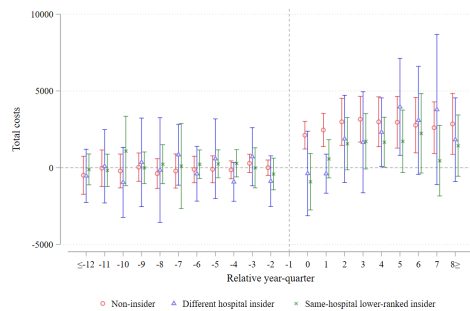
(b) Surgery



(c) Diagnostic test



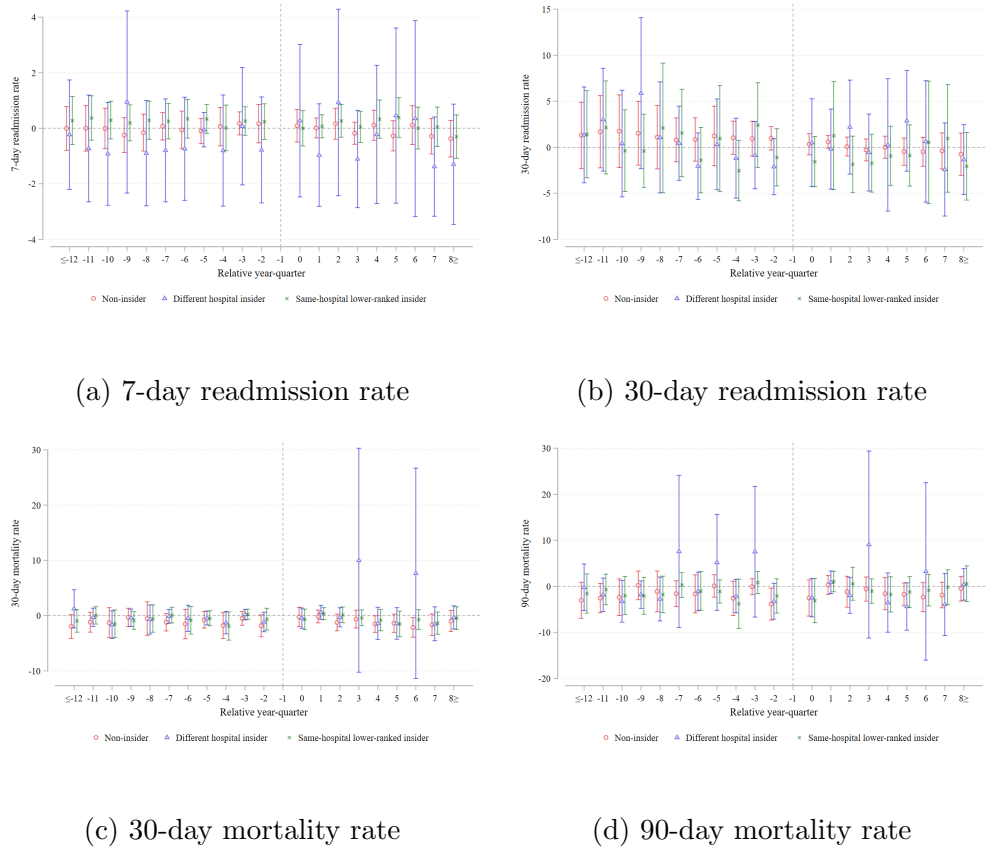
(d) Imaging test



(e) Total costs

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. These figures show event study results of health care utilization of orthopedic patients relative to same-hospital higher-ranked patients in public hospitals before and after ZMDP, specified in Equation ?? . Dots represent point estimates. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Figure 5: Event Study Results of Health Outcomes: Public Hospitals Only, Relative to Same-hospital Higher-rank Patients



Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. These figures show event study results of health outcomes of orthopedic patients relative to same-hospital higher-ranked patients in public hospitals before and after ZMDP, specified in Equation ???. Dots represent point estimates. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 Level

| | (1) | (2) | (3) | (4) |
|-------------------------|-----------------|------------------|----------------|----------------|
| | # of hosp. | # of hosp. | Insider share | Insider share |
| Public*post | -6.70 (9.45) | | 0.01 (0.01) | |
| High shareD*post | | -1.04 (13.54) | | 0.02 (0.01) |
| Hospital FE | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes |
| Observations | 5,071 | 2,585 | 5,071 | 2,585 |
| Mean of Y (Pre-ZMDP) | 83.72 | 92.57 | 0.03 | 0.04 |

Notes: Hospital-level data from November 2010 to December 2018 are used for analysis with a DiD model. Public*post equals 1 if a hospital is a public hospital after ZMDP, as specified in Equation 7; High shareD*post equals 1 if a public hospital has a higher pre-ZMDP share of drugs in its total revenue (above the median) after ZMDP, as specified in Equation 8. Standard errors clustered at hospital level. *** p<0.01, ** p<0.05, * p<0.1.

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

| | (1) Public | (2) High shareD | (3) Tier 2 | (4) Tier 3 | (5) Age | (6) Female |
|-----------------------------|--------------------|--------------------|--------------------|--------------------|-------------------|-------------------|
| Subgroup*post | | | | | | |
| Same hospital-low rank*post | -0.02 (0.08) | -0.00 (0.07) | -0.06 (0.11) | -0.07 (0.07) | -0.37 (1.24) | -0.02 (0.05) |
| Diff hospital*post | 0.04 (0.05) | -0.03 (0.05) | 0.02 (0.07) | -0.06 (0.08) | -0.27 (1.30) | -0.00 (0.03) |
| Non-insider*post | 0.01 (0.04) | -0.06 (0.04) | -0.02 (0.07) | -0.05 (0.09) | 0.03 (0.71) | -0.03 (0.03) |
| Subgroup | | | | | | |
| Same hospital-low rank | -0.21** (0.09) | 0.01 (0.07) | 0.15* (0.08) | -0.15*** (0.04) | -2.30 (1.93) | -0.06** (0.02) |
| Diff hospital | -0.45*** (0.08) | 0.11 (0.08) | 0.08 (0.07) | -0.09 (0.06) | 2.91** (1.34) | 0.01 (0.03) |
| Non-insider | -0.50*** (0.08) | 0.16 (0.10) | 0.20** (0.08) | -0.20** (0.09) | 5.83*** (2.12) | 0.10** (0.05) |
| Post | 0.46*** (0.07) | -0.05 (0.12) | -0.37*** (0.12) | 0.47*** (0.14) | 0.44 (0.71) | 0.03 (0.03) |
| Hospital FE | No | No | No | No | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| 3-digit ICD FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Workplace Tier FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 418,288 | 224,492 | 224,492 | 224,492 | 224,490 | 224,490 |
| Mean of Y (Pre-ZMDP) | 0.53 | 0.30 | 0.31 | 0.55 | 57.06 | 0.66 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model, as specified in Equation 9. Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the hospitalization time is after ZMDP. Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP. Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP. Standard errors clustered at hospital level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: DiD Results: Insiders vs. Non-insiders Going Through ZMDP

| Panel A. Insider patients | | | | | | | | | |
|---------------------------|-----------------|------------------|------------------|----------------|---------------------|-----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | 0.46 (0.36) | -0.07* (0.04) | -1.35 (1.24) | 0.54 (1.08) | -270.14 (271.61) | -0.25 (0.23) | 0.83 (0.67) | -0.28 (0.40) | -3.16 (1.91) |
| Observations | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 |
| Mean of Y (Pre-ZMDP) | 8.18 | 0.22 | 20.37 | 10.56 | 5,105 | 0.26 | 1.82 | 0.26 | 0.92 |

| Panel B. Non-insider patients | | | | | | | | | |
|-------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------------|----------------|------------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | -3.07*** (0.35) | 0.14*** (0.05) | 6.36*** (1.32) | 2.79*** (0.94) | 1,670.52*** (349.77) | 0.05 (0.07) | 0.64** (0.32) | -0.10 (0.16) | -0.40 (0.32) |
| Observations | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 |
| Mean of Y (Pre-ZMDP) | 9.42 | 0.19 | 22.19 | 10.15 | 5,471 | 0.47 | 3.20 | 0.56 | 1.85 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation 5. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: Outcomes of ZMDP: Triple Difference Method

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|-------------------------|--------------------|-------------------|--------------------|--------------------|-------------------------|-----------------|-----------------|------------------|------------------|
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*Non-insider*post | -3.84*** (0.41) | 0.21*** (0.05) | 5.16*** (0.97) | 5.35*** (1.05) | 1,392.31*** (324.69) | 0.05 (0.17) | -0.12 (0.44) | -0.35 (0.85) | 0.74 (1.07) |
| Non-insider | -0.02 (0.30) | 0.04 (0.04) | 0.31 (0.55) | -3.76*** (1.06) | -462.88* (260.84) | -0.11 (0.19) | 0.09 (0.38) | 0.02 (0.58) | 0.84 (0.76) |
| Public*post | 0.76* (0.42) | -0.07 (0.05) | 1.15 (1.26) | -2.48** (1.13) | 271.44 (312.00) | -0.01 (0.19) | 0.76 (0.55) | 0.24 (0.82) | -1.18 (0.96) |
| Public*Non-insider | 0.62** (0.25) | 0.03 (0.06) | -1.74*** (0.55) | 2.60*** (0.72) | 407.74** (176.25) | 0.18* (0.11) | 0.27 (0.38) | 0.08 (0.39) | 0.73 (0.90) |
| Observations | 427,424 | 427,424 | 427,424 | 427,424 | 427,424 | 427,424 | 427,424 | 427,424 | 427,424 |
| Mean of Y (Pre-ZMDP) | 9.39 | 0.19 | 22.15 | 10.16 | 5,463 | 0.47 | 3.17 | 0.55 | 1.83 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a triple difference model. As specified in Equation ??, Public*Non-insider*post takes 1 if a patient is an insider, a hospital is a public hospital, and the time is after ZMDP; Public*post 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 an insider; Non-insider takes 1 if the patient is an insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: DiD Results: Public Hospitals Only, Two-Sample Comparisons

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|--|--------------------|------------------------------|--------------------|-------------------|-------------------------|-------------------|-----------------|-------------------------------------|------------------|
| | Unique drugs | No. of services Surgeries | Diagnostic tests | Imaging tests | Costs Total costs | 7-day readm. | 30-day readm. | Health outcomes 30-day mortality | 90-day mortality |
| Panel A. Non-insider vs. Different hospital insider | | | | | | | | | |
| Non-insider*post | -3.45*** (0.37) | 0.16** (0.07) | 3.83*** (0.92) | 3.89*** (1.32) | 859.47** (402.13) | 0.03 (0.31) | -0.61 (0.80) | -0.69 (1.50) | 1.45 (1.78) |
| Non-insider | 0.27 (0.32) | 0.10 (0.06) | -1.34*** (0.36) | -1.92 (1.38) | -49.42 (268.05) | 0.15 (0.25) | 0.50 (0.53) | 0.21 (1.35) | 1.50 (1.37) |
| Observations | 222,656 | 222,656 | 222,656 | 222,656 | 222,656 | 222,656 | 222,656 | 222,656 | 222,656 |
| Mean of Y (Pre-ZMDP) | 10.85 | 0.37 | 22.66 | 15.67 | 7,525.42 | 0.70 | 3.36 | 0.97 | 2.91 |
| Panel B. Different hospital insider vs. Same hospital insider | | | | | | | | | |
| Diff hospital*post | -1.20* (0.65) | 0.12** (0.06) | 3.15** (1.36) | 4.19** (1.80) | 1,131.53** (450.48) | -0.09 (0.41) | 1.13 (0.99) | -0.09 (0.82) | -1.67 (1.28) |
| Diff hospital | 1.02*** (0.36) | 0.14** (0.06) | 0.89 (0.60) | 4.61*** (0.77) | 1,080.53*** (326.71) | 0.55*** (0.15) | 0.92 (0.59) | -0.76 (0.66) | 0.87 (1.53) |
| Observations | 5,812 | 5,812 | 5,812 | 5,812 | 5,812 | 5,812 | 5,812 | 5,812 | 5,812 |
| Mean of Y (Pre-ZMDP) | 8.95 | 0.33 | 20.56 | 14.35 | 6,241.36 | 0.31 | 1.96 | 0.51 | 1.27 |
| Panel C. Same hospital lower-ranked insider vs. Same hospital higher-ranked insider | | | | | | | | | |
| Same hospital-low rank*post | -0.91 (0.64) | 0.09*** (0.03) | 1.07 (1.88) | -0.38 (1.57) | -365.52 (464.79) | -0.02 (0.30) | 0.02 (0.60) | | |
| Same hospital-low rank | 1.62*** (0.23) | 0.01 (0.02) | 0.70 (0.72) | 0.38 (0.52) | 1,017.70*** (192.89) | -0.12 (0.09) | 0.26 (0.42) | | |
| Observations | 2,616 | 2,616 | 2,616 | 2,616 | 2,616 | 2,616 | 2,616 | | |
| Mean of Y (Pre-ZMDP) | 7.67 | 0.19 | 19.26 | 11.17 | 4,960.94 | 0.11 | 1.45 | | |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. As specified in Equation ??, Non-insider*post takes 1 if a patient is a non-insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: DiD Results: Public Hospitals Only, Relative to Same-hospital High-rank Patients

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|-----------------------------|--------------------|--------------------|-------------------|--------------------|-------------------------|-----------------|-----------------|------------------|------------------|
| | Unique drugs | No. of services | Diagnostic tests | Imaging tests | Costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Subgroup*post | | | | | | | | | |
| Same hospital-low rank*post | -0.75 (0.67) | 0.10 (0.08) | 2.56 (1.68) | 1.96 (1.21) | 420.06 (414.25) | -0.02 (0.25) | 0.23 (0.47) | 0.29 (0.38) | 0.32 (0.93) |
| Diff hospital*post | -1.18* (0.62) | 0.18* (0.10) | 4.33** (1.82) | 4.56** (1.90) | 1,373.12** (529.70) | 0.01 (0.44) | 1.18 (1.03) | 1.05 (1.53) | -1.15 (1.83) |
| Non-insider*post | -4.62*** (0.69) | 0.33*** (0.08) | 8.17*** (1.88) | 8.47*** (1.52) | 2,234.69*** (435.86) | 0.04 (0.24) | 0.58 (0.40) | 0.34 (0.26) | 0.30 (0.75) |
| Subgroup | | | | | | | | | |
| Same hospital-low rank | 1.83*** (0.28) | 0.02 (0.04) | 0.15 (0.86) | 0.66 (0.63) | 990.83*** (290.99) | -0.11 (0.15) | 0.40 (0.41) | 0.74* (0.38) | 1.63 (1.09) |
| Diff hospital | 2.17*** (0.35) | 0.22** (0.10) | 0.24 (1.03) | 3.59*** (1.33) | 1,354.26*** (423.24) | 0.13 (0.17) | 0.46 (0.46) | 1.16* (0.61) | 2.79** (1.16) |
| Non-insider | 2.43*** (0.31) | 0.31*** (0.11) | -1.09 (1.07) | 1.68 (1.89) | 1,304.20*** (437.53) | 0.28 (0.29) | 0.95 (0.59) | 1.39 (1.41) | 4.31** (1.67) |
| Post | 1.63** (0.73) | -0.28*** (0.09) | -1.27 (2.05) | -5.41*** (1.46) | 120.37 (500.83) | -0.05 (0.27) | -0.71 (0.47) | 0.12 (0.36) | 0.13 (1.14) |
| Observations | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 |
| Mean of Y (Pre-ZMDP) | 10.81 | 0.37 | 22.62 | 15.62 | 7,494.36 | 0.69 | 3.33 | 0.96 | 2.88 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is an non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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

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

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

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

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

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

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

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

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

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 $s \geq (\kappa_i - \frac{F_i}{\alpha_i^c})(1 + \sigma_i^2)$, 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} :

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

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

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 (2020) 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:

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

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 $\mathbb{E}[\xi_i | s] = \frac{s}{1+\sigma_i^2}$ increases with s , the optimal cutoff $c_i^{*I(\text{interior})}$ is the signal at which the integrand equals zero:

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

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,

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

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

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

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

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

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

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

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

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

where $h^{-1}(x)$ is the inverse function of the inverse mills ratio $h(x) \equiv \frac{\phi(x)}{1-\Phi(x)}$. Particularly, when $F_i = 0$, $c_i^{*I} = \kappa_i(1 + \sigma_i^2)$. To see this, by the property of inverse mills ratio, we know $h(x) > x$. Therefore, $h(\kappa_i \sqrt{1 + \sigma_i^2}) > \kappa_i \sqrt{1 + \sigma_i^2}$. This implies $\kappa_i(1 + \sigma_i^2) > \sqrt{1 + \sigma_i^2} h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})$.

$c_i^{*I} = \left(\kappa_i - \frac{F_i}{\alpha_i^c} \right) (1 + \sigma_i^2)$ is the interior solution where the constraint does not bind, and it coincides with the non-insider patient's cutoff. $c_i^{*I} = \sqrt{1 + \sigma_i^2} h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})$ 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.

A.2 Model Properties

In this section, we study how physicians' distortions and policy responses change with patient traits.

We first of all 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

$$Distortion^{NI} = \kappa_i(1 + \sigma_i^2) - \left(\kappa_i - \frac{F_i}{\alpha_i^c}\right)(1 + \sigma_i^2) = \frac{F_i}{\alpha_i^c}(1 + \sigma_i^2) \quad (\text{A.10})$$

$$\frac{Distortion^{NI}}{\alpha_i^c} = -\frac{F_i(1 + \sigma_i^2)}{\alpha_i^{c2}} < 0 \quad (\text{A.11})$$

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

The distortion for an insider is

$$Distortion^I = \mathbf{1}\{\text{constraint non-binding}\} \underbrace{\frac{F_i}{\alpha_i^c}(1 + \sigma_i^2)}_{Distortion^{(interior)}} + \mathbf{1}\{\text{constraint binding}\} \underbrace{\left(\kappa_i(1 + \sigma_i^2) - \sqrt{1 + \sigma_i^2} h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})\right)}_{Distortion^{corner}} \quad (\text{A.12})$$

$$\frac{Distortion^I}{\alpha_i^c} = \mathbf{1}\{\text{constraint binding}\} \cdot 0 + \mathbf{1}\{\text{constraint non-binding}\} \left(-\frac{F_i(1 + \sigma_i^2)}{\alpha_i^{c^2}} \right) \quad (\text{A.13})$$

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 A1.

For insider patients, when the obedience constraint binds and $c_i^{*I(\text{interior})} < c_i^{*I(\text{corner})}$, 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 smaller than for non-insider patients. Graphically, the red line (insiders) lies weakly below the blue line (non-insiders), indicating lower distortion for insider patients.

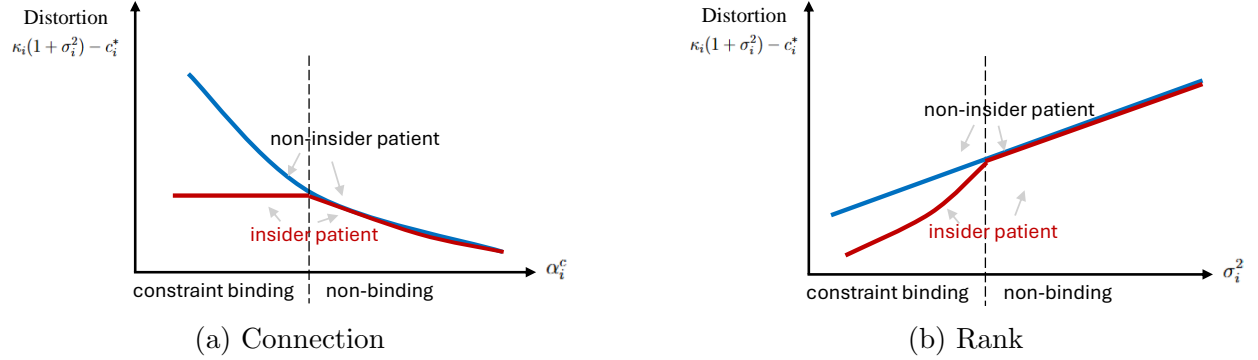


Figure A1: How Distortion Depends on Connection, Rank, and Insider Information

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:

$$\frac{\partial Distortion^{NI}}{\partial \sigma_i^2} = \frac{Distortion^{(\text{interior})}}{\partial \sigma_i^2} = \frac{F_i}{\alpha_i^c} > 0 \quad (\text{A.14})$$

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:

$$\begin{aligned}
\frac{\partial Distortion^{(corner)}}{\partial \sigma_i^2} &= \kappa_i - \frac{h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})}{2\sqrt{1 + \sigma_i^2}} - \sqrt{1 + \sigma_i^2} \frac{1}{h' \left[h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2}) \right]} \frac{\kappa_i}{2\sqrt{1 + \sigma_i^2}} \\
&= \kappa_i - \frac{h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})}{2\sqrt{1 + \sigma_i^2}} - \frac{1}{2\sqrt{1 + \sigma_i^2} \left[\kappa_i \sqrt{1 + \sigma_i^2} - h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2}) \right]} \quad (\text{use } h'(x) = h(x)[h(x) - x]) \\
&> \kappa_i - \frac{h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})}{2\sqrt{1 + \sigma_i^2}} - \frac{h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})}{2\sqrt{1 + \sigma_i^2}} \quad (\text{let } x = h^{-1}(\cdot) > 0, \text{ use } h(x) > x + \frac{1}{x}) \\
&> \kappa_i - \frac{\kappa_i}{2} - \frac{\kappa_i}{2} \quad (\text{use } h^{-1}(x) < x) \\
&= 0. \tag{A.15}
\end{aligned}$$

Next, we show that under a stronger assumption than $\kappa_i \sqrt{1 + \sigma_i^2} > h(0)$, 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).

$$\begin{aligned}
\frac{\partial(c_i^{*I(\text{interior})} - c_i^{*I(\text{corner})})}{\partial \sigma_i^2} &= \frac{\partial(Distortion^{(corner)} - Distortion^{(interior)})}{\partial \sigma_i^2} \\
&> \kappa_i - \frac{h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})}{\sqrt{1 + \sigma_i^2}} - \frac{F_i}{\alpha_i^c} \\
&\geq 0 \quad \text{if } \frac{F_i}{\alpha_i^c} \leq \kappa_i - \frac{h^{-1}(\kappa_i \sqrt{1 + \sigma_i^2})}{\sqrt{1 + \sigma_i^2}} \tag{A.16}
\end{aligned}$$

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. When the constraint is binding, we know

$$c_i^{*I(\text{interior})} - c_i^{*I(\text{corner})} = Distortion^{(corner)} - Distortion^{(interior)} < 0 \tag{A.17}$$

Therefore, for a given σ_i^2 , the distortion for insider patients with a binding constraint is strictly smaller than that for non-insider patients. The role of rank in determining distortion is illustrated in panel (b) of Figure A1.

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

$$\frac{\partial c_i^{*NI}}{\partial F_i} = -\frac{1}{\alpha_i^c}(1 + \sigma_i^2) \quad (\text{A.18})$$

For insider patients, the cutoff response is:

$$\frac{\partial c_i^{*I}}{\partial F_i} = \mathbf{1}\{\text{constraint non-binding}\} \left(-\frac{1}{\alpha_i^c}(1 + \sigma_i^2) \right) + \mathbf{1}\{\text{constraint binding}\} 0 \quad (\text{A.19})$$

Response to Financial Incentives F_i w.r.t Connection

$$\frac{\partial(\frac{c_i^{*NI}}{F_i})}{\partial \alpha_i^c} = \frac{1 + \sigma_i^2}{\alpha_i^{c2}} > 0 \quad (\text{A.20})$$

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.

$$\frac{\partial(\frac{c_i^{*I}}{F_i})}{\partial \alpha_i^c} = \mathbf{1}\{\text{constraint binding}\} \cdot 0 + \mathbf{1}\{\text{constraint non-binding}\} \frac{1 + \sigma_i^2}{\alpha_i^{c2}} \quad (\text{A.21})$$

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. Panel (a) of Figure A2 illustrates the role of patient connections in

shaping physicians' responses to financial incentives.

Response to Financial Incentives F_i w.r.t Rank

$$\frac{\partial(\frac{c_i^{*NI}}{F_i})}{\partial\sigma_i^2} = -\frac{1}{\alpha_i^c} < 0 \quad (\text{A.22})$$

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.

$$\frac{\partial(\frac{c_i^{*I}}{F_i})}{\partial\sigma_i^2} = \mathbf{1}\{\text{constraint binding}\} \cdot 0 + \mathbf{1}\{\text{constraint non-binding}\} \left(-\frac{1}{\alpha_i^c}\right) \quad (\text{A.23})$$

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 A2 illustrates the role of patient rank in shaping physicians' responses to financial incentives.

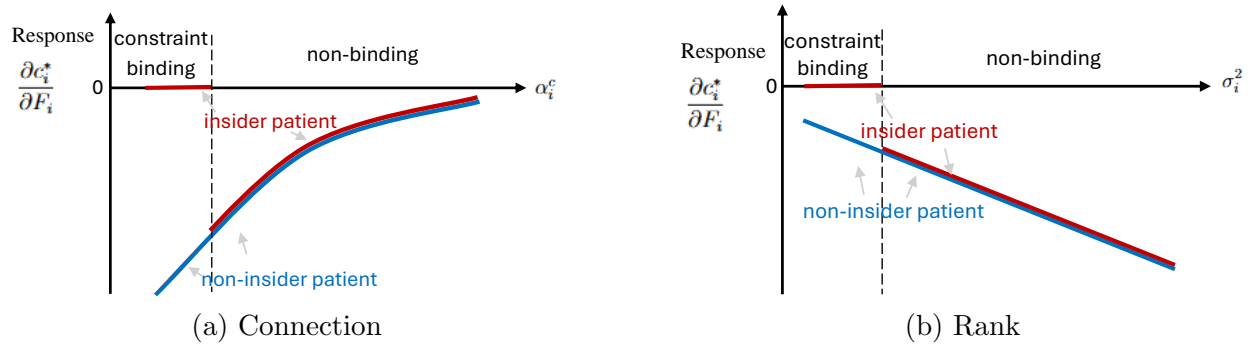
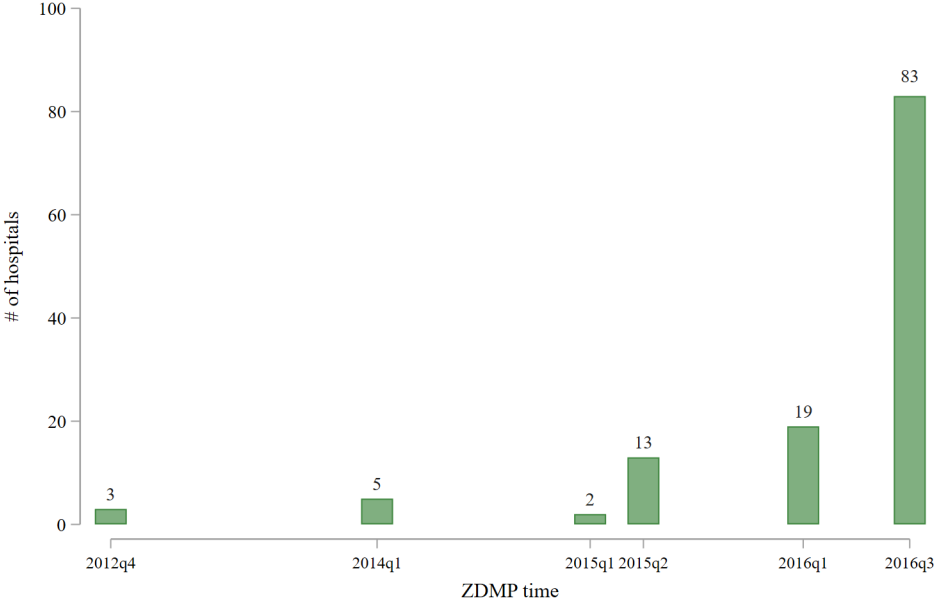


Figure A2: How Response to ZMDP Depends on Connection, Rank, and Insider Information

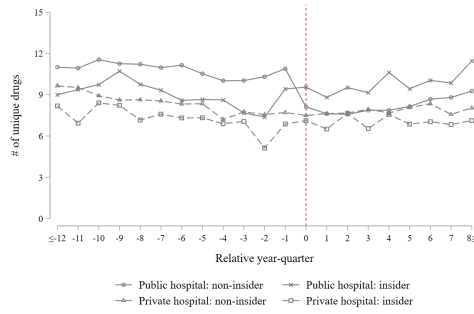
Appendix B: Additional Figures and Tables

Figure B1: ZMDP Implementation Time in Changsha

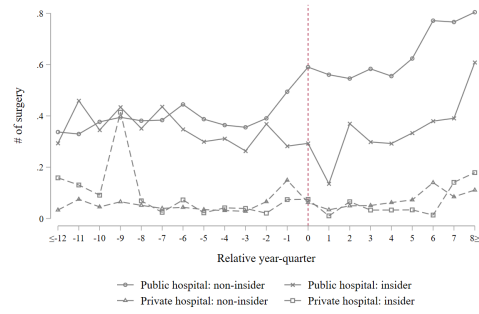


Notes: This figure shows the implementation timing of ZMDP across hospitals in Changsha, the capital city of Hunan Province. The number of hospitals implemented at different time is shown on top of each bar.

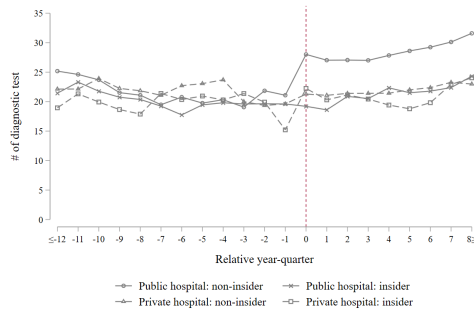
Figure B2: Raw Trends of Insiders and Non-insiders in Public and Private Hospitals: Health Care Utilization



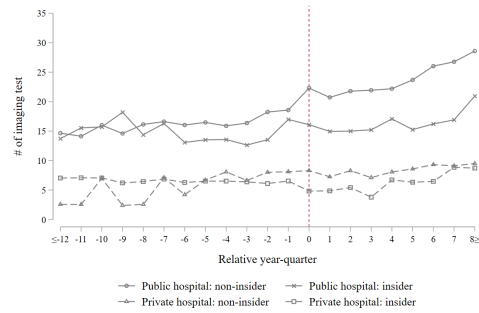
(a) Drug



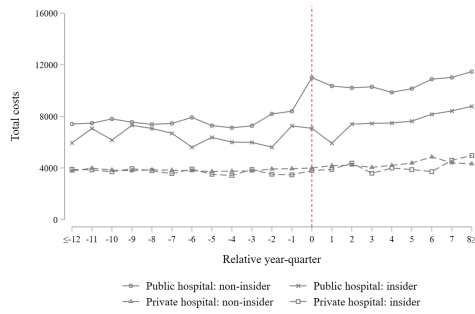
(b) Surgery



(c) Diagnostic test

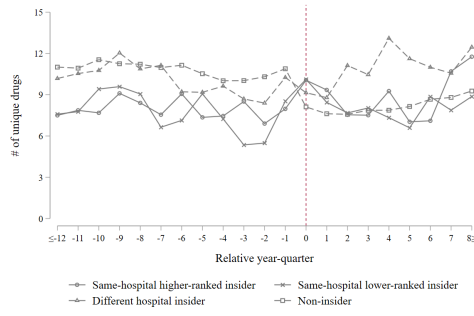


(d) Imaging test

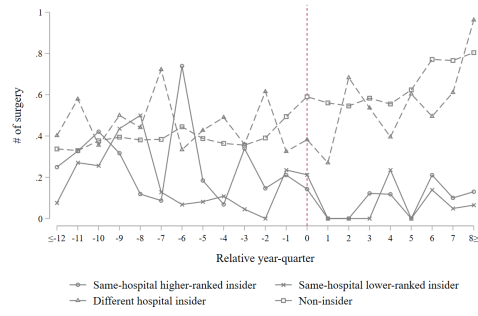


(e) Total costs

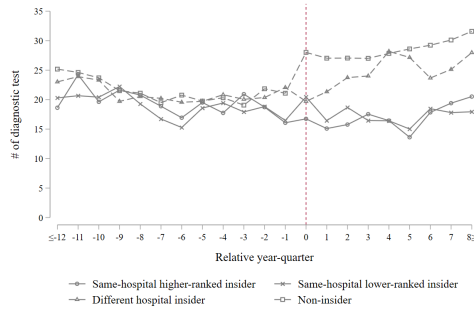
Figure B3: Raw Trends of Sub-type of Insiders and Non-insiders in Public Hospitals: Health Care Utilization



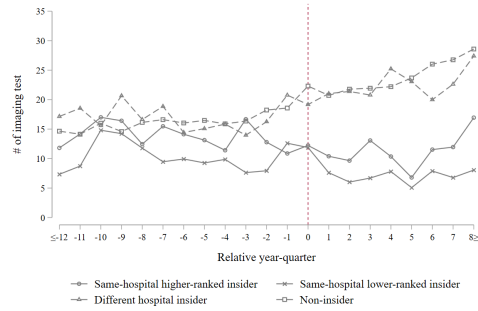
(a) Drug



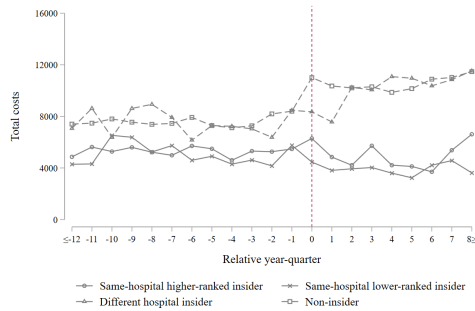
(b) Surgery



(c) Diagnostic test

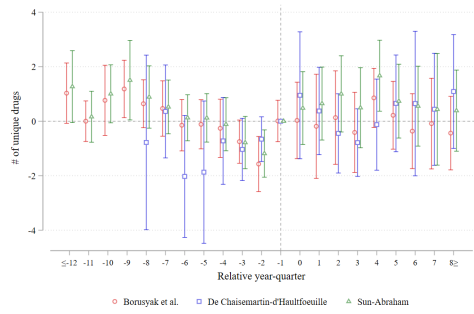


(d) Imaging test

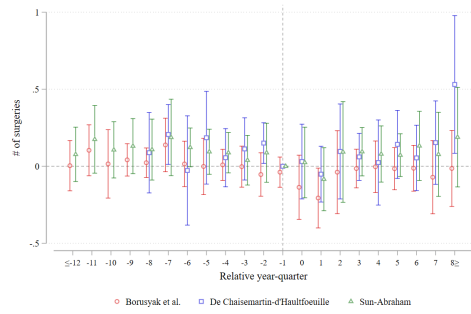


(e) Total costs

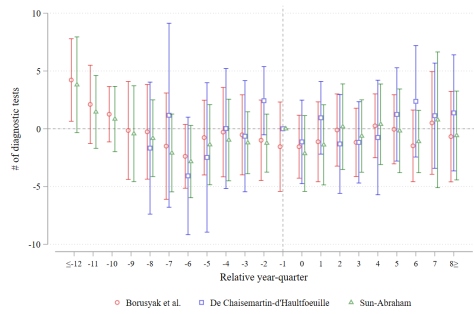
Figure B4: Alternative Event Study Models: Health Care Utilization of Insiders



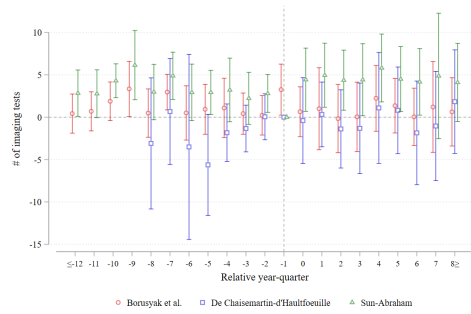
(a) Drug



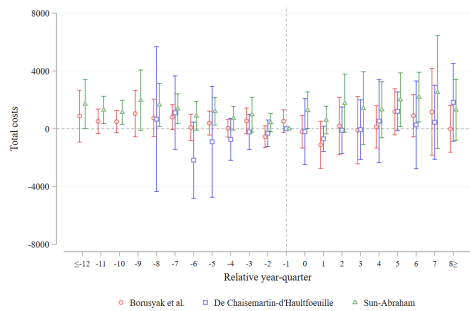
(b) Surgery



(c) Diagnostic test



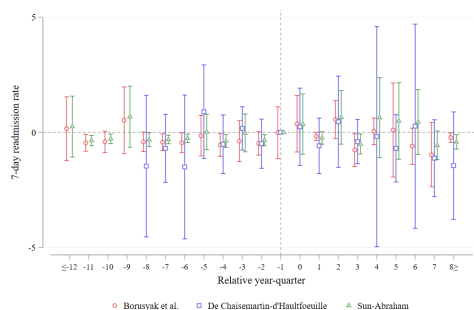
(d) Imaging test



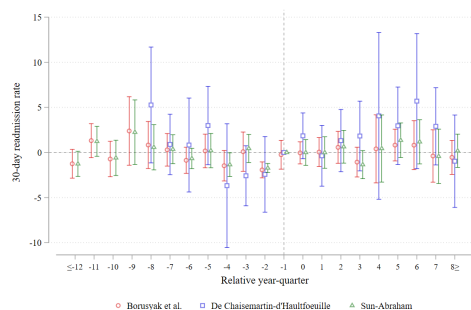
(e) Total costs

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

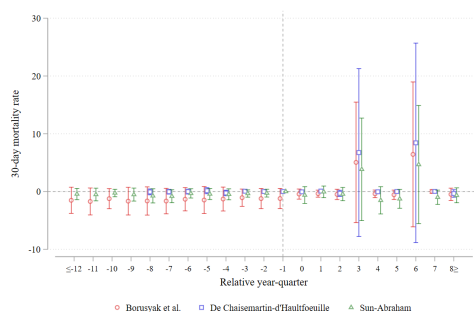
Figure B5: Alternative Event Study Models: Health Outcomes of Insiders



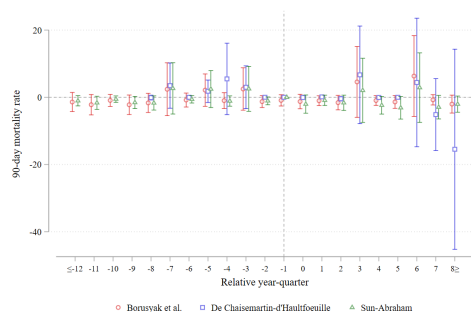
(a) 7-day readmission rate



(b) 30-day readmission rate



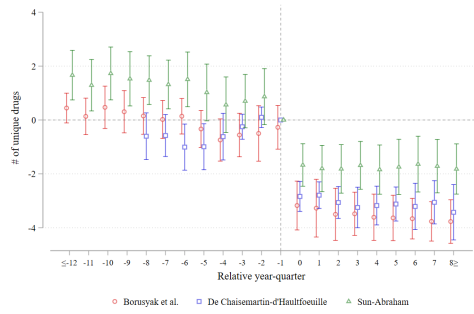
(c) 30-day mortality rate



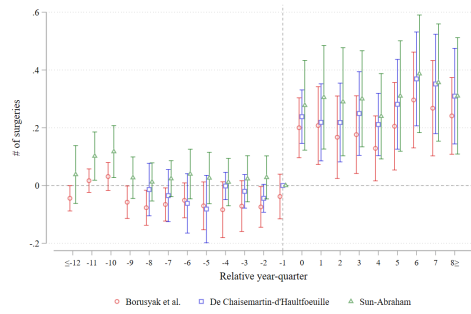
(d) 90-day mortality rate

Notes: These figures show health outcomes of insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. Event study results with alternative estimation using [Borusyak et al. \(2024\)](#), [De Chaisemartin and d'Haultfoeuille \(2020\)](#), and [Sun and Abraham \(2021\)](#) are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

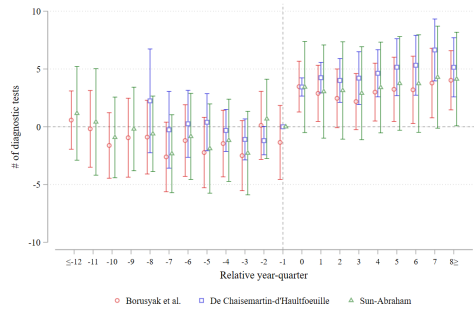
Figure B6: Alternative Event Study Models: Health Care Utilization of Non-insiders



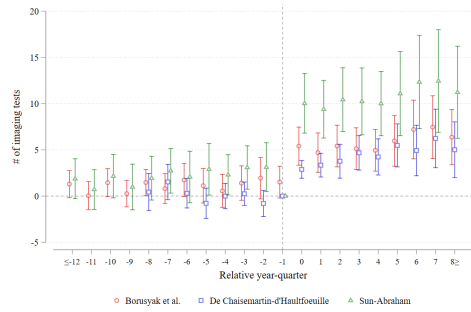
(a) Drug



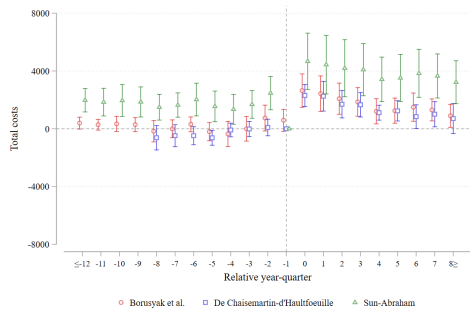
(b) Surgery



(c) Diagnostic test



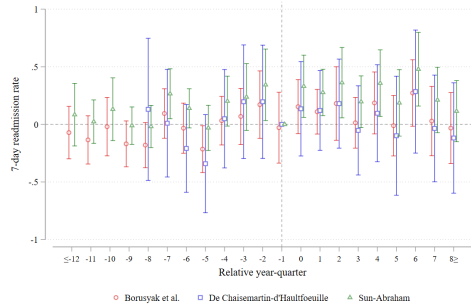
(d) Imaging test



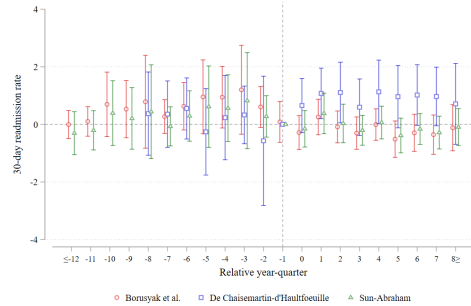
(e) Total costs

Notes: These figures show health care utilization of non-insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. Event study results with alternative estimation using [Borusyak et al. \(2024\)](#), [De Chaisemartin and d’Haultfoeuille \(2020\)](#), and [Sun and Abraham \(2021\)](#) are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, hospital fixed effects, and year-quarter fixed effects. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

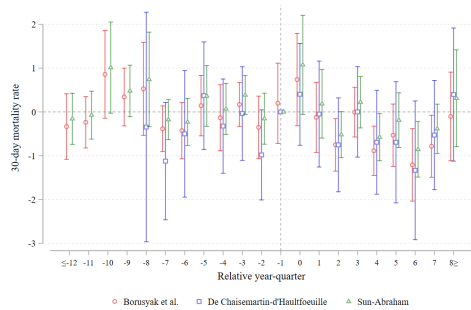
Figure B7: Alternative Event Study Models: Health Outcomes of Non-insiders



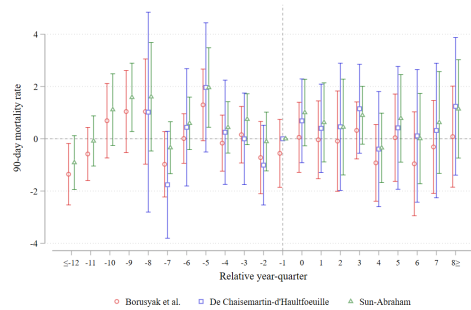
(a) 7-day readmission rate



(b) 30-day readmission rate



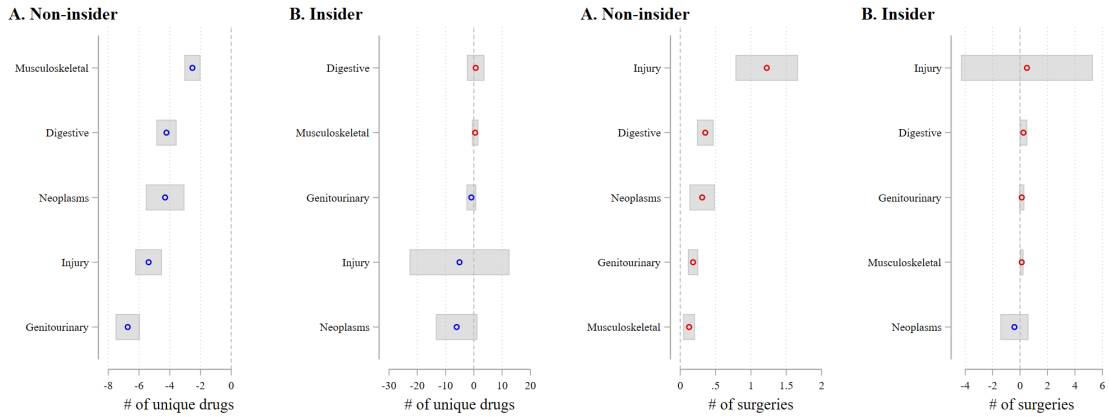
(c) 30-day mortality rate



(d) 90-day mortality rate

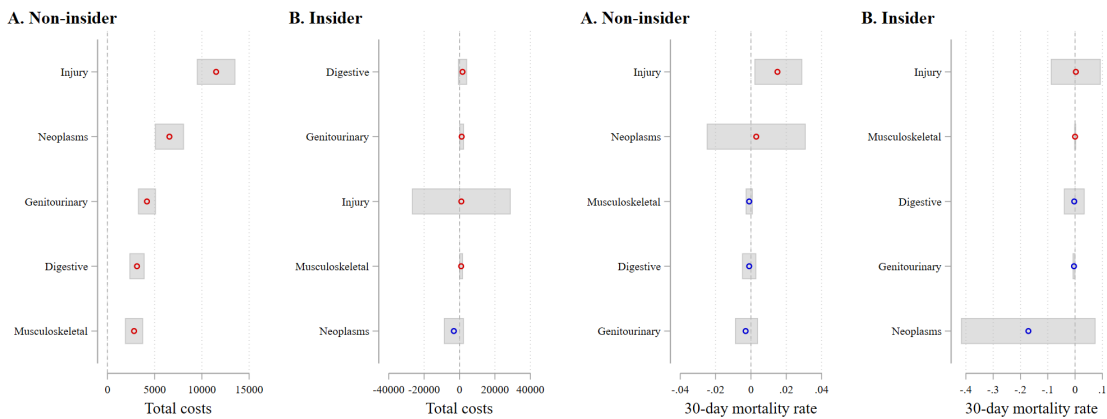
Notes: These figures show health outcomes of non-insider orthopedic patients in public hospitals relative to private hospitals before and after ZMDP. Event study results with alternative estimation using [Borusyak et al. \(2024\)](#), [De Chaisemartin and d'Haultfoeuille \(2020\)](#), and [Sun and Abraham \(2021\)](#) are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: Public (=1) vs. Private (=0) Hospitals by Disease: Health Care Utilization and Health Outcomes



(a) Drug quantity

(b) Surgery quantity

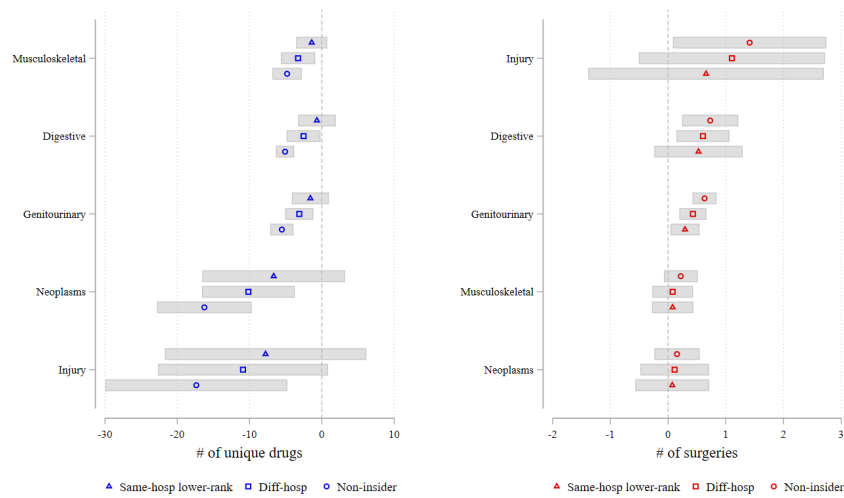


(c) Total costs

(d) 30-day mortality rate

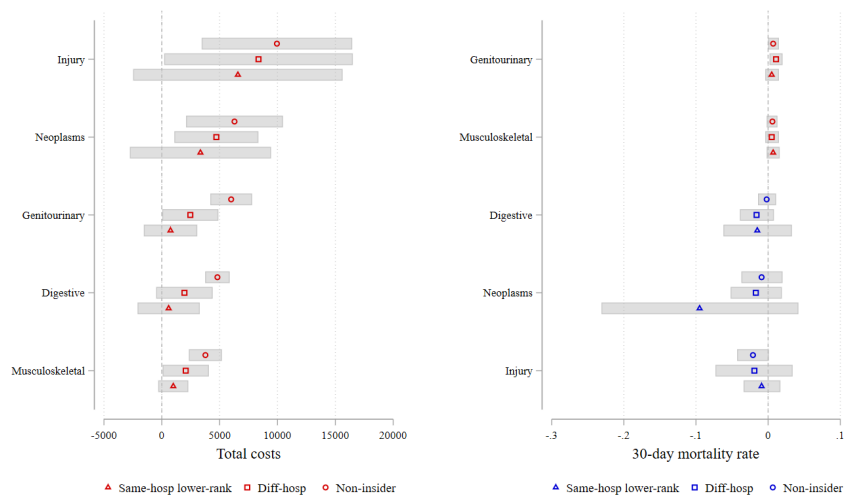
Notes: These figures compare the effects of ZMDP on health care utilization and health outcomes between public and private hospitals by diseases. For each outcome, Panel A shows the results for non-insiders, while Panel B shows the results for insiders. Categories of disease include: Neoplasms (ICD-10: C00–D46), Diseases of the Digestive System (ICD-10: K00–K93), Diseases of the Musculoskeletal System and Connective Tissue (ICD-10: M00–M99), Diseases of the Genitourinary System (ICD-10: N00–N99), and Injury and External Causes (ICD-10: S00–T98). Dots represent point estimates (**with blue color for negative estimates and red color for positive estimates**). Shadow bars indicate 90% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: Subgroup of Patients in Public Hospitals by Disease: Health Care Utilization and Health Outcomes



(a) Drug quantity

(b) Surgery quantity



(c) Total costs

(d) 30-day mortality rate

Notes: These figures compare the effects of ZMDP on health care utilization outcomes between same-hospital higher-ranked insider patients (=0) and other patient groups in public hospitals by diseases. Categories of disease include: Neoplasms (ICD-10: C00–D46), Diseases of the Digestive System (ICD-10: K00–K93), Diseases of the Musculoskeletal System and Connective Tissue (ICD-10: M00–M99), Diseases of the Genitourinary System (ICD-10: N00–N99), and Injury and External Causes (ICD-10: S00–T98). Dots represent point estimates (**with blue color for negative estimates and red color for positive estimates**). Shadow bars indicate 90% confidence intervals. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 Hospital vs Private Hospital, Insider vs Non-insider

| | All | | Non-insider | | Insider | |
|---|-------------------------|------------------------|-------------------------|------------------------|------------------------|------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Public | Private | Public | Private | Public | Private |
| Panel A. Outcome variables | | | | | | |
| Health care utilization | | | | | | |
| # of unique drugs | 10.04 (8.37) | 8.34 (4.68) | 10.06 (8.38) | 8.36 (4.69) | 9.35 (7.95) | 7.36 (4.30) |
| # of surgeries | 0.47 (1.47) | 0.06 (0.58) | 0.47 (1.48) | 0.06 (0.57) | 0.34 (1.28) | 0.10 (1.01) |
| # of diagnostic tests | 24.74 (18.74) | 21.80 (14.51) | 24.84 (18.80) | 21.83 (14.53) | 20.97 (16.09) | 20.16 (13.29) |
| # of imaging tests | 18.61 (25.76) | 6.12 (7.17) | 18.70 (25.84) | 6.11 (7.18) | 15.27 (22.29) | 6.55 (6.89) |
| Total costs | 8,510.75 (12,554.12) | 3,966.17 (2,711.59) | 8,557.73 (12,622.35) | 3,960.65 (2,692.86) | 6,742.87 (9,475.05) | 3,905.01 (2,616.25) |
| Health outcomes | | | | | | |
| 7-day readmission rate (%) | 0.81 (8.97) | 0.30 (5.46) | 0.82 (9.02) | 0.30 (5.47) | 0.38 (6.12) | 0.21 (4.63) |
| 30-day readmission rate (%) | 3.39 (18.11) | 3.05 (17.21) | 3.43 (18.20) | 3.08 (17.28) | 2.05 (14.17) | 1.66 (12.80) |
| 30-day mortality rate (‰) | 1.03 (32.14) | 0.25 (17.21) | 1.04 (32.28) | 0.25 (15.87) | 0.68 (26.14) | 0 (0) |
| 90-day mortality rate (‰) | 3.18 (56.28) | 1.05 (32.44) | 3.23 (56.70) | 1.06 (32.59) | 1.37 (36.95) | 0.54 (23.17) |
| Length of stay (day) | 10.49 (5.05) | 6.46 (3.28) | 10.45 (5.01) | 6.46 (3.29) | 11.69 (6.11) | 6.44 (3.04) |
| Panel B. Individual and hospital characteristics | | | | | | |
| Demographic characteristics | | | | | | |
| Age (in years) | 58.50 (10.45) | 57.27 (12.37) | 57.73 (10.20) | 57.43 (12.23) | 45.76 (14.99) | 51.03 (15.61) |
| Gender (1 = female) | 0.70 (0.46) | 0.65 (0.48) | 0.70 (0.46) | 0.65 (0.48) | 0.74 (0.44) | 0.76 (0.43) |
| Insider (1 = health related employment) | 0.03 (0.16) | 0.02 (0.13) | - (-) | - (-) | - (-) | - (-) |
| Rank (1 = Cadre) | 0.15 (0.36) | 0.07 (0.26) | 0.15 (0.35) | 0.07 (0.25) | 0.43 (0.50) | 0.21 (0.40) |
| Treating Hospital tier | | | | | | |
| Share of Tier 1 | 0.15 (0.35) | 0.67 (0.47) | 0.15 (0.35) | 0.67 (0.47) | 0.18 (0.38) | 0.58 (0.49) |
| Share of Tier 2 | 0.27 (0.44) | 0.32 (0.47) | 0.27 (0.44) | 0.32 (0.46) | 0.26 (0.44) | 0.40 (0.49) |
| Share of Tier 3 | 0.59 (0.49) | 0.02 (0.13) | 0.59 (0.49) | 0.02 (0.13) | 0.57 (0.50) | 0.03 (0.16) |
| Observation | 226,470 | 202,351 | 220,607 | 198,625 | 5,863 | 3,726 |

Notes: Orthopedics patients' claim-level data from November 2010 to December 2018 are used for analysis. Means of variables are reported with standard deviations in parentheses. Number of unique drugs is the count of the type of distinct medications prescribed during the admission. Number of surgeries is the total number of surgical procedures performed. Number of diagnostic tests and number of imaging tests are the counts of diagnostic and imaging procedures, respectively. Total costs are total inpatient medical expenditures per admission, measured in RMB. 7-day readmission rate and 30-day readmission rate indicate whether the patient is readmitted within 7 or 30 days after discharge, respectively. 30-day mortality rate and 90-day mortality rate indicate whether the patient dies within 30 or 90 days since admission, respectively, and are reported in per thousand (‰).

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

| | (1) | (2) | (3) |
|---|---------------------------------|--------------------------------|----------------------------|
| | Same-hospital high-rank insider | Same-hospital low-rank insider | Different-hospital insider |
| Panel A. Outcome variables | | | |
| Health care utilization | | | |
| # of unique drugs | 8.22 (6.62) | 7.79 (6.11) | 10.46 (8.90) |
| # of surgeries | 0.21 (0.94) | 0.11 (0.69) | 0.50 (1.55) |
| # of diagnostic tests | 18.79 (14.44) | 18.53 (12.20) | 22.88 (17.85) |
| # of imaging tests | 13.00 (18.14) | 8.47 (12.96) | 19.11 (25.86) |
| Total costs | 5,163.64 (4,581.23) | 4,496.56 (4,275.88) | 8,335.44 (11,916.95) |
| Health outcomes | | | |
| 7-day readmission rate (%) | 0.24 (4.89) | 0 (0) | 0.59 (7.68) |
| 30-day readmission rate (%) | 1.04 (10.14) | 1.36 (11.60) | 2.75 (16.34) |
| 30-day mortality rate (‰) | 0 (0) | 0 (0) | 1.25 (35.31) |
| 90-day mortality rate (‰) | 0 (0) | 0 (0) | 2.50 (45.91) |
| Length of stay (day) | 13.16 (6.73) | 11.31 (5.74) | 11.28 (5.92) |
| Panel B. Individual and hospital characteristics | | | |
| Demographic characteristics | | | |
| Age (in years) | 50.83 (13.55) | 46.51 (14.92) | 53.06 (16.23) |
| Gender (1 = female) | 0.81 (0.40) | 0.78 (0.42) | 0.74 (0.44) |
| Rank (1 = Cadre) | - - | - - | 0.40 (0.49) |
| Hospital tier | | | |
| Share of Tier 1 | 0.10 (0.30) | 0.29 (0.45) | 0.16 (0.37) |
| Share of Tier 2 | 0.15 (0.36) | 0.39 (0.49) | 0.24 (0.43) |
| Share of Tier 3 | 0.75 (0.43) | 0.33 (0.47) | 0.60 (0.49) |
| Observation | 1,253 | 1,397 | 3,213 |

Notes: Insider orthopedics patients' claim-level data from November 2010 to December 2018. Means of variables are reported with standard deviations in parentheses. Number of unique drugs is the count of the type of distinct medications prescribed during the admission. Number of surgeries is the total number of surgical procedures performed. Number of diagnostic tests and number of imaging tests are the counts of diagnostic and imaging procedures, respectively. Total costs are total inpatient medical expenditures per admission, measured in RMB. 7-day readmission rate and 30-day readmission rate indicate whether the patient is readmitted within 7 or 30 days after discharge, respectively. 30-day mortality rate and 90-day mortality rate indicate whether the patient dies within 30 or 90 days since admission, respectively, and are reported in per thousand (‰).

Table B3: DiD Results: Insiders vs. Non-insiders Going Through ZMDP, $\log(1 + Y)$

| Panel A. Insider patients | | | | | |
|----------------------------------|-----------------|-----------|------------------|---------------|-------------|
| | (1) | (2) | (3) | (4) | (5) |
| | No. of services | | | | Costs |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs |
| Public*post | 0.04 | -0.04*** | -0.12* | -0.10 | -0.12*** |
| | (0.04) | (0.02) | (0.06) | (0.08) | (0.03) |
| Observations | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 |
| Mean of Y (Pre-ZMDP) | 2.04 | 0.08 | 2.81 | 1.93 | 8.33 |

| Panel B. Non-insider patients | | | | | |
|--------------------------------------|-----------------|-----------|------------------|---------------|-------------|
| | (1) | (2) | (3) | (4) | (5) |
| | No. of services | | | | Costs |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs |
| Public*post | -0.31*** | 0.03** | 0.21*** | -0.24*** | 0.08*** |
| | (0.04) | (0.01) | (0.05) | (0.05) | (0.02) |
| Observations | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation 5. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B4: Outcomes of ZMDP: Triple Difference Method, $\log(1 + Y)$

| | (1) | (2) | (3) | (4) | (5) |
|-------------------------|-----------------|-----------|------------------|---------------|-------------|
| | No. of services | | | | Costs |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs |
| Public*Non-insider*post | -0.36*** | 0.08*** | 0.22*** | 0.39*** | 0.14*** |
| | (0.03) | (0.02) | (0.04) | (0.05) | (0.02) |
| Non-insider | 0.01 | 0.02 | -0.00 | -0.34*** | -0.04 |
| | (0.03) | (0.01) | (0.03) | (0.07) | (0.03) |
| Public*post | 0.06 | -0.05** | -0.01 | -0.61*** | -0.06* |
| | (0.05) | (0.02) | (0.06) | (0.07) | (0.03) |
| Public*Non-insider | 0.04* | 0.01 | -0.06* | 0.19*** | 0.02 |
| | (0.03) | (0.02) | (0.03) | (0.06) | (0.02) |
| Observations | 427,424 | 427,424 | 427,424 | 427,424 | 427,424 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a triple difference model. as As specified in Equation ??, Public*Non-insider*post takes 1 if a patient is an insider, a hospital is a public hospital, and the time is after ZMDP; Public*post 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 an insider; Non-insider takes 1 if the patient is an insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: DiD Results: Public Hospitals Only, Relative to Same-hospital High-rank Patients, $\log(1 + Y)$

| | (1) | (2) | (3) | (4) | (5) |
|-----------------------------|--------------------|------------------------------|-------------------|--------------------|----------------------|
| | Unique drugs | No. of services Surgeries | Diagnostic tests | Imaging tests | Costs Total costs |
| Subgroup*post | | | | | |
| Same hospital-low rank*post | -0.08 (0.06) | 0.05 (0.04) | 0.21* (0.12) | -0.11 (0.16) | -0.01 (0.04) |
| Diff hospital*post | -0.11** (0.05) | 0.07 (0.05) | 0.28** (0.11) | 0.34** (0.14) | 0.18*** (0.05) |
| Non-insider*post | -0.49*** (0.04) | 0.15*** (0.04) | 0.44*** (0.11) | 0.63*** (0.13) | 0.24*** (0.04) |
| Subgroup | | | | | |
| Same hospital-low rank | 0.22*** (0.03) | 0.01 (0.01) | -0.01 (0.05) | -0.01 (0.11) | 0.15*** (0.02) |
| Diff hospital | 0.22*** (0.04) | 0.10** (0.04) | -0.00 (0.06) | 0.30*** (0.11) | 0.19*** (0.04) |
| Non-insider | 0.25*** (0.04) | 0.14*** (0.05) | -0.07 (0.07) | 0.07 (0.13) | 0.17*** (0.03) |
| Post | 0.16** (0.06) | -0.15*** (0.04) | -0.12 (0.12) | -0.61*** (0.14) | -0.13*** (0.05) |
| Observations | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is an non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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: DiD Results: Insiders vs. Non-insiders Going Through ZMDP, Without Demographic and Socioeconomic Covariates

| Panel A. Insider patients | | | | | | | | | |
|---------------------------|-----------------|-----------------|------------------|----------------|---------------------|-----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | 0.54 (0.36) | -0.07 (0.04) | -1.17 (1.27) | 0.60 (1.11) | -204.28 (269.53) | -0.26 (0.23) | 0.83 (0.67) | -0.12 (0.37) | -3.10 (1.98) |
| Observations | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 |
| Mean of Y (Pre-ZMDP) | 8.18 | 0.22 | 20.37 | 10.56 | 5,105.43 | 0.26 | 1.82 | 0.26 | 0.92 |

| Panel B. Non-insider patients | | | | | | | | | |
|-------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------------|----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | -3.10*** (0.35) | 0.14*** (0.05) | 6.32*** (1.32) | 2.75*** (0.94) | 1,657.38*** (347.43) | 0.05 (0.07) | 0.63* (0.32) | -0.11 (0.16) | -0.43 (0.32) |
| Observations | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 |
| Mean of Y (Pre-ZMDP) | 9.42 | 0.19 | 22.19 | 10.15 | 5,470.76 | 0.47 | 3.20 | 0.56 | 1.85 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation 5. All specifications include 3-digit ICD code fixed effects, 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: DiD Results: Public Hospitals Only, Relative to Same-hospital High-rank Patients, Without Demographic and Socioeconomic Covariates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|-----------------------------|--------------------|--------------------|-------------------|--------------------|-------------------------|-------------------|-------------------|------------------|-------------------|
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Subgroup*post | | | | | | | | | |
| Same hospital-low rank*post | -0.96 (0.71) | 0.10 (0.08) | 2.26 (1.79) | 1.60 (1.39) | 337.11 (395.59) | -0.04 (0.25) | -0.10 (0.43) | 0.29 (0.34) | 0.17 (0.97) |
| Diff hospital*post | -1.41** (0.71) | 0.19* (0.11) | 3.84* (1.96) | 4.01** (1.98) | 1,216.53** (555.45) | 0.01 (0.45) | 1.13 (1.00) | 0.97 (1.49) | -1.54 (1.84) |
| Non-insider*post | -4.81*** (0.75) | 0.35*** (0.08) | 7.70*** (1.96) | 7.86*** (1.63) | 2,091.35*** (461.90) | 0.04 (0.25) | 0.57 (0.40) | 0.29 (0.27) | 0.07 (0.81) |
| Subgroup | | | | | | | | | |
| Same hospital-low rank | 2.37*** (0.26) | 0.11*** (0.04) | 1.00 (0.93) | 2.88*** (0.83) | 1,510.82*** (270.78) | 0.03 (0.14) | 0.63 (0.41) | 0.22 (0.21) | 0.81 (0.51) |
| Diff hospital | 2.92*** (0.60) | 0.20*** (0.07) | 1.60 (1.19) | 6.37*** (1.52) | 1,874.21*** (468.55) | 0.27 (0.18) | 0.76 (0.46) | 1.00 (0.62) | 2.59** (1.00) |
| Non-insider | 3.47*** (0.50) | 0.18** (0.07) | 1.00 (1.11) | 6.28*** (1.07) | 1,878.34*** (393.24) | 0.45*** (0.14) | 1.75*** (0.31) | 0.77** (0.30) | 2.27*** (0.62) |
| Post | 1.86** (0.79) | -0.30*** (0.08) | -0.74 (2.09) | -4.71*** (1.58) | 280.78 (528.47) | -0.04 (0.28) | -0.68 (0.46) | 0.22 (0.37) | 0.46 (1.18) |
| Observations | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 |
| Mean of Y (Pre-ZMDP) | 10.81 | 0.37 | 22.62 | 15.62 | 7,494.36 | 0.69 | 3.33 | 0.96 | 2.88 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is an non-insider. All specifications include 3-digit ICD code fixed effects, 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: Outcomes of ZMDP Using [Borusyak et al. \(2024\)](#) Public vs. Private Hospitals, by Insider and Non-insider Orthopedics Patients

| Panel A. Insider patients | | | | | | | | | |
|---------------------------|-----------------|-----------------|------------------|----------------|-------------------|-----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | 0.45 (0.40) | -0.06 (0.05) | -0.93 (1.30) | 0.72 (1.16) | 20.96 (308.70) | -0.42 (0.37) | 1.05 (0.79) | 0.83 (0.83) | -2.63 (2.36) |
| Observations | 9,478 | 9,478 | 9,478 | 9,478 | 9,478 | 9,478 | 9,478 | 9,478 | 9,478 |
| Mean of Y (Pre-ZMDP) | 8.19 | 0.22 | 20.39 | 10.56 | 5,116.95 | 0.26 | 1.81 | 0.26 | 1.04 |

| Panel B. Non-insider patients | | | | | | | | | |
|-------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------------|----------------|------------------|------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | -3.24*** (0.34) | 0.16*** (0.05) | 6.87*** (1.29) | 3.22*** (1.04) | 1,580.75*** (298.30) | 0.00 (0.08) | 0.66** (0.33) | -0.25 (0.18) | -0.84** (0.39) |
| Observations | 417,013 | 417,013 | 417,013 | 417,013 | 417,013 | 417,013 | 417,013 | 417,013 | 417,013 |
| Mean of Y (Pre-ZMDP) | 9.42 | 0.19 | 22.19 | 10.15 | 5,470.96 | 0.47 | 3.20 | 0.56 | 1.85 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Models are estimated based on [Borusyak et al. \(2024\)](#). Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, 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 B9: Static DD: Public vs. Private Hospitals, by Insider and Non-insider Orthopedics Patients

| Panel A. Insider patients | | | | | | | | | |
|---------------------------|-----------------|-----------------|------------------|----------------|---------------------|-----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | 0.40 (0.36) | -0.06 (0.04) | -1.65 (1.46) | 0.59 (1.26) | -164.90 (282.62) | -0.25 (0.24) | 0.62 (0.74) | -0.17 (0.46) | -3.22 (2.08) |
| Observations | 9,403 | 9,403 | 9,403 | 9,403 | 9,403 | 9,403 | 9,403 | 9,403 | 9,403 |
| Mean of Y (Pre-ZMDP) | 8.58 | 0.26 | 20.42 | 11.77 | 5,432.50 | 0.22 | 2.01 | 0.34 | 0.84 |

| Panel B. Non-insider patients | | | | | | | | | |
|-------------------------------|--------------------|-------------------|-------------------|------------------|-------------------------|----------------|------------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | -2.75*** (0.39) | 0.14*** (0.05) | 5.42*** (1.53) | 2.50** (1.04) | 1,574.31*** (359.10) | 0.10 (0.08) | 0.85** (0.36) | -0.18 (0.15) | -0.52 (0.33) |
| Observations | 407,575 | 407,575 | 407,575 | 407,575 | 407,575 | 407,575 | 407,575 | 407,575 | 407,575 |
| Mean of Y (Pre-ZMDP) | 10.00 | 0.23 | 22.67 | 10.84 | 5,971.26 | 0.51 | 3.52 | 0.66 | 2.13 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Public hospitals with ZMDP time only after 2016 are included in analysis. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation (5). All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B10: Static DD: Public Hospitals Only, Relative to Same-hospital High-rank Patients

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|-----------------------------|--------------|------------------------------|------------------|---------------|----------------------|--------------|---------------|-------------------------------------|------------------|
| | Unique drugs | No. of services Surgeries | Diagnostic tests | Imaging tests | Costs Total costs | 7-day readm. | 30-day readm. | Health outcomes 30-day mortality | 90-day mortality |
| Subgroup*post | | | | | | | | | |
| Same hospital-low rank*post | -1.15* | 0.09 | 2.05 | 1.42 | 120.69 | -0.04 | -0.01 | 0.19 | 0.13 |
| | (0.69) | (0.07) | (1.66) | (1.12) | (406.25) | (0.24) | (0.46) | (0.36) | (0.89) |
| Diff hospital*post | -1.31** | 0.16 | 3.81** | 3.29 | 1,087.17** | -0.10 | 1.01 | 0.79 | -1.76 |
| | (0.66) | (0.10) | (1.84) | (2.16) | (545.69) | (0.44) | (1.07) | (1.49) | (1.78) |
| Non-insider*post | -4.47*** | 0.33*** | 7.06*** | 7.36*** | 1,936.64*** | 0.05 | 0.60 | 0.10 | -0.51 |
| | (0.76) | (0.08) | (1.88) | (1.58) | (455.44) | (0.25) | (0.41) | (0.27) | (0.76) |
| Subgroup | | | | | | | | | |
| Same hospital-low rank | 1.85*** | 0.03 | 0.09 | 0.48 | 1,051.71*** | -0.11 | 0.49 | 0.54 | 1.15 |
| | (0.28) | (0.04) | (0.89) | (0.60) | (295.78) | (0.15) | (0.41) | (0.35) | (1.07) |
| Diff hospital | 2.20*** | 0.22** | 0.20 | 3.53** | 1,333.43*** | 0.11 | 0.43 | 1.11* | 2.63** |
| | (0.36) | (0.10) | (1.06) | (1.40) | (444.43) | (0.17) | (0.49) | (0.61) | (1.18) |
| Non-insider | 2.47*** | 0.32*** | -0.83 | 1.56 | 1,335.24*** | 0.19 | 0.82 | 1.26 | 4.07** |
| | (0.32) | (0.12) | (1.09) | (1.92) | (447.14) | (0.29) | (0.61) | (1.42) | (1.70) |
| Observations | 214,899 | 214,899 | 214,899 | 214,899 | 214,899 | 214,899 | 214,899 | 214,899 | 214,899 |
| Mean of Y (Pre-ZMDP) | 10.92 | 0.39 | 23.07 | 16.11 | 7,742.48 | 0.69 | 3.34 | 0.97 | 2.92 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Public hospitals with ZMDP time only after 2016 are included in analysis. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is an non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B11: DiD Results: Insiders vs. Non-insiders Going Through ZMDP, Add Individual Fixed Effects

| Panel A. Insider patients | | | | | |
|--------------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------------|
| | (1) | (2) | (3) | (4) | (5) |
| | | No. of services | | | Costs |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs |
| Public*post | 0.39 (0.85) | -0.11 (0.22) | 0.72 (1.60) | 1.18 (3.03) | -1,448.31 (907.10) |
| Observations | 2,088 | 2,088 | 2,088 | 2,088 | 2,088 |
| Mean of Y (Pre-ZMDP) | 7.81 | 0.21 | 19.78 | 10.67 | 5,121.55 |
| Panel B. Non-insider patients | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| | | No. of services | | | Costs |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs |
| Public*post | -2.58*** (0.28) | 0.11*** (0.04) | 6.33*** (1.17) | 2.78*** (0.76) | 1,818.50*** (363.86) |
| Observations | 101,740 | 101,740 | 101,740 | 101,740 | 101,740 |
| Mean of Y (Pre-ZMDP) | 9.27 | 0.13 | 21.25 | 9.75 | 5,441.70 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. For individuals in public hospitals, only those with at least one observation before and after ZMDP are included in analysis. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation 5. All specifications include individual fixed effects, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B12: DiD Results: Public Hospitals Only, Relative to Same-hospital High-rank Patients, Adding Individual Fixed Effects

| | (1) | (2) | (3) | (4) | (5) |
|-----------------------------|--------------------|------------------------------|-------------------|--------------------|-------------------------|
| | Unique drugs | No. of services Surgeries | Diagnostic tests | Imaging tests | Costs Total costs |
| Subgroup*post | | | | | |
| Same hospital-low rank*post | -1.72 (1.44) | 0.02 (0.11) | 0.95 (1.99) | 0.33 (1.82) | -603.75 (989.49) |
| Diff hospital*post | -2.33*** (0.86) | 0.18 (0.18) | 5.42** (2.40) | 5.74* (3.38) | 1,552.30** (628.40) |
| Non-insider*post | -4.20*** (0.91) | 0.29* (0.16) | 8.35*** (2.33) | 7.37*** (1.47) | 2,066.95*** (497.96) |
| Subgroup | | | | | |
| Same hospital-low rank | 2.26 (1.99) | 0.75 (0.49) | -0.41 (4.99) | 2.37 (5.32) | -2,231.28 (2,762.48) |
| Diff hospital | 1.07 (1.28) | 0.15 (0.17) | -3.29 (3.48) | 4.08 (3.01) | -1,708.65 (1,588.53) |
| Post | 1.13 (0.96) | -0.28 (0.17) | -1.32 (2.43) | -5.22*** (1.68) | -378.30 (541.07) |
| Observations | 63,036 | 63,036 | 63,036 | 63,036 | 63,036 |
| Mean of Y (Pre-ZMDP) | 9.97 | 0.22 | 20.98 | 12.96 | 6,679.18 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DiD model. Only individuals with at least one observation before and after ZMDP are included in analysis. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is an non-insider. All specifications include individual fixed effects, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B13: DiD Results: Insiders vs. Non-insiders in Middle, Professional, and Higher Education Institutions Going Through ZMDP

| Panel A. Insider patients | | | | | | | | | |
|----------------------------------|-----------------|------------------|------------------|----------------|---------------------|-----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | 0.46 (0.36) | -0.07* (0.04) | -1.35 (1.24) | 0.54 (1.08) | -270.14 (271.61) | -0.25 (0.23) | 0.83 (0.67) | -0.28 (0.40) | -3.16 (1.91) |
| Observations | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 |
| Mean of Y (Pre-ZMDP) | 8.18 | 0.22 | 20.37 | 10.56 | 5,105 | 0.26 | 1.82 | 0.26 | 0.92 |

| Panel B. Non-insider patients | | | | | | | | | |
|--------------------------------------|--------------------|----------------|-------------------|-----------------|-------------------------|----------------|-----------------|------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No. of services | | | Costs | | | Health outcomes | | |
| | Unique drugs | Surgeries | Diagnostic tests | Imaging tests | Total costs | 7-day readm. | 30-day readm. | 30-day mortality | 90-day mortality |
| Public*post | -3.40*** (0.48) | 0.08 (0.07) | 5.62*** (1.15) | 1.95* (1.02) | 1,219.33*** (360.91) | 0.25 (0.30) | -0.62 (0.60) | 0.13 (0.14) | -0.31 (1.53) |
| Observations | 10,588 | 10,588 | 10,588 | 10,588 | 10,588 | 10,588 | 10,588 | 10,588 | 10,588 |
| Mean of Y (Pre-ZMDP) | 9.89 | 0.24 | 21.02 | 11.95 | 6,585.21 | 0.58 | 3.47 | 0.13 | 1.06 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation (5). Non-insiders refer to those working in middle, professional, and higher education institutions. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B14: DiD Results: Public Hospitals Only, Non-insiders in Middle, Professional, and Higher Education Institutions, Relative to Same-hospital High-rank Patients

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|-----------------------------|--------------------|------------------------------|-------------------|-------------------|-------------------------|-----------------|----------------------------------|------------------|------------------|
| | Unique drugs | No. of services Surgeries | Diagnostic tests | Imaging tests | Costs Total costs | 7-day readm. | Health outcomes 30-day readm. | 30-day mortality | 90-day mortality |
| Subgroup*post | | | | | | | | | |
| Same hospital-low rank*post | -0.99 (0.69) | 0.12** (0.06) | 1.00 (1.61) | 0.69 (1.16) | -127.10 (426.04) | -0.04 (0.36) | -0.24 (0.72) | -0.17 (0.22) | -1.25 (0.78) |
| Diff hospital*post | -1.44** (0.71) | 0.18** (0.08) | 3.92** (1.79) | 4.37** (1.87) | 1,195.68* (606.26) | -0.02 (0.55) | 0.62 (0.95) | 0.47 (1.28) | -0.90 (1.73) |
| Non-insider*post | -5.00*** (0.81) | 0.32*** (0.07) | 6.57*** (1.85) | 6.91*** (1.61) | 1,693.04*** (528.11) | 0.22 (0.33) | -0.15 (0.72) | 0.00 (0.21) | 1.24 (1.63) |
| Subgroup | | | | | | | | | |
| Same hospital-low rank | 1.76*** (0.29) | 0.01 (0.04) | 0.25 (0.76) | 0.13 (0.44) | 1,066.06*** (269.84) | -0.18 (0.13) | 0.50 (0.41) | 0.25 (0.22) | 0.52 (0.72) |
| Diff hospital | 1.92*** (0.36) | 0.18** (0.09) | 0.29 (0.87) | 4.09*** (1.11) | 1,501.21*** (377.27) | 0.14 (0.18) | 0.99** (0.48) | 0.63 (0.50) | 2.16* (1.14) |
| Non-insider | 1.54*** (0.36) | 0.18* (0.10) | -2.22** (0.95) | 0.86 (1.51) | 1,096.39** (499.97) | 0.28 (0.34) | 1.91** (0.77) | -0.25 (1.37) | 3.13* (1.88) |
| Post | 2.48*** (0.74) | -0.32*** (0.08) | -0.89 (1.80) | -2.72 (1.69) | -143.36 (589.83) | -0.14 (0.52) | -1.09 (0.99) | -0.47 (0.45) | -1.77 (1.20) |
| Observations | 13,489 | 13,489 | 13,489 | 13,489 | 13,489 | 13,489 | 13,489 | 13,489 | 13,489 |
| Mean of Y (Pre-ZMDP) | 9.93 | 0.34 | 20.93 | 14.91 | 7,208.71 | 0.55 | 2.96 | 0.23 | 1.17 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is a non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is a non-insider. Non-insiders refer to those working in middle, professional, and higher education institutions. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B15: Cost Outcomes of ZMDP: Public vs. Private Hospitals, by Insider and Non-insider Orthopedics Patients

| Panel A. Insider patients | | | | | | | |
|--------------------------------------|------------------------|----------------------|----------------------|----------------------|-----------------------|-----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Drugs | Surgeries | Diagnostic tests | Imaging tests | Medical services | Materials | Nursing and beds |
| Public*post | -339.71*** (87.24) | 91.36* (47.55) | -21.05 (30.31) | 136.73** (52.84) | -90.70 (159.75) | -38.43 (181.43) | -7.78 (18.36) |
| Observations | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 | 9,528 |
| Mean of Y (Pre-ZMDP) | 1,574.38 | 106.83 | 415.64 | 520.50 | 1,585.76 | 571.28 | 295.48 |
| Panel B. Non-insider patients | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Drugs | Surgeries | Diagnostic tests | Imaging tests | Medical services | Materials | Nursing and beds |
| Public*post | -632.17*** (110.52) | 314.54*** (83.72) | 136.80*** (22.51) | 394.17*** (49.50) | 601.07*** (154.47) | 714.15*** (234.35) | 124.00*** (22.90) |
| Observations | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 | 417,851 |
| Mean of Y (Pre-ZMDP) | 2,024.89 | 117.51 | 382.39 | 459.27 | 1,485.95 | 695.17 | 273.81 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. Public*post takes 1 if a hospital is a public hospital and the time is after ZMDP, as specified in Equation 5. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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 B16: Cost Outcomes for Mechanism

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|-----------------------------|------------------------|----------------------|-----------------------|----------------------|-----------------------|-----------------------|-----------------------|
| | Drugs | Surgeries | Diagnostic tests | Imaging tests | Medical services | Materials | Nursing and beds |
| 30-day mortality | | | | | | | |
| Subgroup*post | | | | | | | |
| Same hospital-low rank*post | -149.88 (146.07) | 34.42 (90.45) | 101.68* (55.79) | 93.21 (68.06) | 78.73 (138.61) | 237.84 (220.69) | 22.07 (20.59) |
| Diff hospital*post | -267.07* (157.13) | 174.36* (107.78) | 222.24*** (59.22) | 350.55*** (84.75) | 545.15*** (115.89) | 329.22 (304.99) | 56.10* (30.60) |
| Non-insider*post | -458.17*** (146.77) | 221.75* (113.80) | 279.42*** (61.93) | 436.73*** (77.31) | 906.06*** (85.26) | 697.23*** (234.00) | 139.42*** (30.61) |
| Subgroup | | | | | | | |
| Same hospital-low rank | 463.56*** (78.04) | -26.72 (25.68) | 37.11 (36.60) | -59.81 (38.08) | 381.73*** (99.62) | 192.11 (168.83) | -5.44 (27.10) |
| Diff hospital | 681.26*** (129.84) | 50.13 (39.49) | -78.31** (38.93) | -36.36 (56.91) | 330.27*** (82.23) | 459.15* (261.47) | -49.38 (39.50) |
| Non-insider | 898.87*** (180.02) | 84.71* (49.61) | -131.66*** (44.01) | -135.18 (86.38) | 345.01*** (96.73) | 371.11 (289.59) | -103.24*** (33.38) |
| Post | -458.19*** (137.89) | 252.33** (124.80) | -171.42*** (63.30) | -88.34 (70.54) | -170.44 (130.55) | 772.58*** (289.87) | -14.17 (31.93) |
| Observations | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 | 225,304 |
| Mean of Y (Pre-ZMDP) | 2,509.63 | 217.30 | 482.75 | 696.78 | 1,708.01 | 1,457.85 | 375.09 |

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. As specified in Equation 6, Same hospital-low rank*post takes 1 if a patient is a same hospital lower-ranked insider and the time is after ZMDP; Diff hospital*post takes 1 if a patient is a different hospital insider and the time is after ZMDP; Non-insider*post takes 1 if a patient is an non-insider and the time is after ZMDP; Same hospital-low rank takes 1 if a patient is a same hospital lower-ranked insider; Diff hospital takes 1 if a patient is a different hospital insider; Non-insider takes 1 if a patient is an non-insider. All specifications include gender, age-cohort fixed effects, 3-digit ICD code fixed effects, workplace tier fixed effects, 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.