interested in both the full-length and shorter presentations

Heterogeneous Responses to Changes in Physicians' Financial Incentives: The Role of Expertise, Connection, and Rank of Patients*

Jiaowei Gong† Chuanchuan Zhang‡ Xuan Zhang§

March 20, 2025

Abstract

It is well known that physicians respond to financial incentives, which can distort patients' health care utilization. However, it is less known that how patient characteristics affect physicians' decision-making. We make use of a natural experiment arising from a drug markup reduction policy to investigate how physicians respond to financial incentives differentially with expert and non-expert patients. With 100% inpatient claim data from a Chinese city, we first document that the policy reduces drug utilization while increases utilization of other forms of care. However, such distortion in care is almost solely borne by non-expert patients. Furthermore, higher-ranked expert patients who work in the same hospital as physicians experience the least distortion in care, followed by same-hospital lower-ranked patients. Non-same hospital experts, who, despite also receiving less distorted care, exhibit healthcare utilization patterns more similar to those of non-experts. These suggest that connection plays a key role in ensuring efficient care in China, administrative rank additionally intensifies such a favorable effect, while medical expertise plays a relatively moderate role.

Keywords: expertise, connection, rank, physician behavior, financial incentives

JEL Codes: I11, I18, J44, J70

*We thank Liran Einav, Johannes Kunz, Yunan Ji, Imran Rasul, and participants at the SMU Applied Micro Workshop for their helpful comments.

†T.H. Chan School of Public Health, Harvard University.

‡School of Economics, Zhejiang University.

§School of Economics, Singapore Management University. Email: xuanzhang@smu.edu.sg.

1 Introduction

Health care costs have increased tremendously in many countries, prompting the implementation of numerous policies aimed at containing these escalating expenses. Many of these policies are tied to changes in financial incentives of physicians. However, altering physician's financial incentives can lead to strategic responses by physicians, which may not only undermine the intended goal of the policy, but also lead to unintended consequences that harm patients (Alexander 2020). Moreover, such strategic behavior may vary depending on patient characteristics. Yet, we still know relatively little about which types of patients are more (or less) affected by physicians' strategic responses to changes in financial incentives, the associated welfare implications, and the underlying mechanisms driving these effects (Currie et al. 2024*b*).

To address these questions, this paper examines how physicians' responses to financial incentives, introduced by a drug pricing policy reform in China, vary by expert and non-expert patients. Moreover, we examine what mechanisms can explain the differences. Specifically, we make use of the Zero Markup Drug Policy (ZDMP) implemented in public hospitals in 2010s, which eliminated the previous 15% markup on drug prices. This reform substantially altered financial incentives for physicians in public hospitals, as drug sales account for approximately 40% of hospital revenue prior to the policy's implementation (National Health Commission of the PRC, 2016) and physicians' bonus is tied to drug revenue.

We start by documenting the overall effect of ZDMP on healthcare provision, comparing changes before and after the reform between public and private hospitals, as only public hospitals were subject to the ZDMP. This serves as a baseline for the degree of distortion being incurred due to ZDMP. We then move on to the main analysis – investigate how physicians' responses vary by whether a patient is an expert or not, with expert patients defined as those work in health care institutions. Given information asymmetry is a serious issue in the patient-physician relationship, we expect that experts can receive less distorted care than non-experts given their informational advantage. However, expert patients may not only have more informational advantage, i.e., medical expertise, but also have stronger connections to physicians. Therefore, to disentangle the two confounding mechanisms – expertise

versus connection – we compare physicians' treatment between the same-hospital and non-same hospital expert patients, as the former group should have much stronger connection than the latter even though they have similar levels of medical knowledge. Furthermore, we examine the role of hierarchy within the same hospital to determine whether administrative ranking would further intensify the expert effect, as physicians may treat more powerful colleagues better than less powerful colleagues.

To estimate these effects and mechanisms, we use an event study model by exploiting the exogenous timing of ZDMP implementation across different regions and tiers of public hospitals in our sample city. Our main data source is 100% insurance claim data for hospital stays 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 conservative (e.g., medications) and intensive 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), as we have unique information on their (current and pre-retirement) workplaces and administrative ranking. This allows us to classify patients into experts and non-experts based on whether they work in a health care institution. In addition, by categorizing expert patients into three subgroups – same-hospital higher ranked experts, same-hospital lower ranked experts, and non-same-hospital expert patients – we can further investigate how different patient factors, such as expertise, connection, and internal rank, influence physicians' decision making.

We first show that the ZDMP decreases the utilization of prescription drugs by 497 CNY per claim (23.1%) in public hospitals due to the elimination of profits from prescribing drugs. However, it increases other forms of health care utilization, consistent with previous findings (Luan et al. 2020; Fang et al. 2021; Shi et al. 2023).[1] Moreover, we observe an increase in the length of hospitalization by 0.97 days (10.5%) and a rise in total health care costs by 1364 CNY per claim (23.5%). These shifts in care also negatively impact patients' health outcomes, as evidenced by a 1.28 percentage point (33.1%) increase in 30-day hospital

[1] 1 CNY is about 0.16 USD in 2015.

readmission rates.

Next, when comparing non-experts to expert patients within public hospitals, we find that non-experts experiences a larger decrease in prescription drug utilization (364 CNY per claim, -14.5%) and a greater increase in costs for medical examination, surgeries, and nursing care. As a result, the average total costs of non-experts increase by 1175 per claim (15.6%) compared to expert patients following the implementation of the ZDMP. However, there is no significant difference in treatment outcomes, as measured by readmission and mortality rates. This evidence indicates that non-expert patients experience greater distortion in healthcare utilization both before (over-prescription of drugs) and after ZDMP (over-prescription of other forms of care). Compared to the overall distortion, non-expert patients bear 86% (1175/1364 CNY) of it.

To investigate the mechanisms, we compare same-hospital higher ranked experts, same-hospital lower ranked experts, and non-same-hospital experts with non-expert patients one by one. We find that although there are moderate differences in health care utilization between non-same-hospital experts and non-experts, the effects only appear in the first several quarters after the ZDMP, suggesting that informational advantage (medical expertise) plays a significant but moderate role in affecting physicians' decision-making.[2] By contrast, the differences between the same-hospital experts and non-experts are much bigger, with the biggest difference between higher-ranked same-hospital experts and non-experts. Given that non-same hospital experts are most likely to only have informational advantage, same-hospital experts have not only informational advantage but also connection, same-hospital higher-ranked experts additionally have power on top of the former two advantages, these findings imply that connection plays an important role in China to ensure efficient care, administrative rank has an additional value on top of expertise and connections, and informational advantage plays a smaller role than connection.

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. (2024*b*) reviewed existing studies that provide evidence about disparities in treatment

[2]We acknowledge that our measure for medical knowledge/expertise is only an approximate for general medical knowledge/expertise but not specialty-specific knowledge/expertise.

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. 2024*a*). 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 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. 2023; Schwab and Singh 2024). Our paper is most close to Chen et al. (2023). However, they look at cancer patients and construct both expertise 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 expertise and connection measures based on patients' workplace. In addition, due to administrative ranking in public hospitals in China, we are able to further identify expert 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 ZDMP 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 (personal connection)

on resource allocation. A substantial body of literature examines the impact of social connections, particularly with politicians. Studies such as Fisman (2001), Khwaja and Mian (2005), Blanes i Vidal et al. (2012), and Jia et al. (2015), Fisman et al. (2020), Shi et al. (2021), Nian and Wang (2023) estimate the value of political connections in various contexts. 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. 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 ZDMP policy, and the health care system in China. Section 3 introduces the data and sample used in the study and outlines the empirical strategy for analysis. Section 4 presents the overall effects of ZDMP, the heterogeneous effects on expert and non-experts, and the mechanism on expertise, connection, and rank. Finally, section 6 concludes.

2 Institutional Background

This section outlines the institutional background of China's healthcare system, the urban employee basic medical insurance (UEBMI), the drug pricing system, and the ZDMP reform, with a particularl focus on the ZDMP reform in Changsha. As the capital city of Hunan Province, Changsha's healthcare system, public health insurance, and drug pricing system are representative of China as a whole. When the ZDMP reform was launched on a large scale in 2016, Changsha had a population of 8.56 million–comparable to the populations of Israel[3], and a GDP per capita of $18,687.

[3]The city spans 12,000 square kilometers, approximately half the size of Israel.

2.1 Healthcare System and Health Insurance

Healthcare services are predominantly provided by public hospitals in China. In 2015, 88.0% of outpatient services and 85.3% of inpatient services were provided by public hospitals (National Health Commission of the PRC, 2016), with the remainder provided by private hospitals. Public hospitals have strong incentives to generate revenue. Before the economic reforms initiated in early 1980s, public hospitals received substantial government financial support, but this declined sharply in subsequent decades. In the early 1980s, state financing represented approximately 60% of hospital revenues, but by 2003, this figure had dropped to just 8.2% (Sun et al. 2008). As a result, hospitals have increasingly relied on revenue-generating activities, such as drug sales and high-tech diagnostic tests, to sustain their financial viability (Sun et al., 2008; Milcent, 2018).[4]

Physicians in public hospitals are salaried employees whose income consists of both a base salary and a bonus. While the base salary is low, the bonus–which is tied to patient treatment– typically accounts for up to three-quarters of physicians' total income (Milcent, 2018). These bonuses are tied to hospital revenue, as all revenue is first accumulated at the hospital level and then distributed to physicians. As a result, we assume throughout our analysis that hospitals and physicians share the same financial incentives to increase hospital revenue.

China has achieved universal health insurance coverage since 2009, with 95% of the population now covered by either the UEBMI or Urban-Rural Resident Basic Medical Insurance (URRBMI). The URRBMI integrates the former Urban Resident Basic Medical Insurance and New Cooperative Medical Scheme. UEBMI covers employees and retirees with urban hukou, while URRBMI covers the remaining population.[5] Although UEBMI insures only about one-fourth of the population, it accounts 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 higher reimbursement rate for patients compared to URRBMI. This study focuses on workers and retirees covered by UEBMI, as we have unique information

[4] 77% of prescription drugs are prescribed and dispensed by hospitals. Clinics and retail pharmacies only account for a small market share (IMS Health, 2016).

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

on their current and pre-retirement workplace as well as their administrative ranking.

2.2 Pharmaceutical Policy and the ZDMP

Pharmaceuticals account for a significant proportion of health spending in China. For instance, in 2015, they accounted for over 40% of total health expenditures, representing 36.9% of spending per inpatient episode and 48.3% of spending per outpatient visit (National Health Commission of the PRC, 2016). Thus, pharmaceutical policy plays a critical role in government efforts to control health spending and ensure affordability of healthcare.

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). Since the share of government subsidies out of hospitals' total revenue has declined significantly to less than 10% in the early 2000s, hospitals have relied on drug sales as a major sources of revenue. From the mid-1950s to early 2010s, the Chinese government officially permitted a 15% mark-up for drugs sold by hospitals. In 2006, the National Development and Reform Commission (NDRC), who is in charge of pharmaceutical price regulation, reaffirmed that retail prices should be set at the provider's procurement price plus a 15% profit margin. This policy further entrenched the role of drug sales in hospital revenue streams.

To address the issue of overprescribing medications and also improve people's access to low-cost and high-quality essential medicines, the Chinese government introduced the ZDMP in all public healthcare institutions across the country (State Council of the People's Republic of China, 2016). The policy was initially rolled out through pilot programs in 2009, targeting primary healthcare institutions such as community health centers and township hospitals (Fang 2017). By the end of 2015, the ZDMP had been implemented in all rural county-level public hospitals, as well as several urban pilot public hospitals. By 2017, the ZDMP had expanded nationwide to all public hospitals. To mitigate the loss of revenue from drug sales, the government introduced compensation mechanisms for healthcare institutions. These measures included adjustment to the prices of medical services and procedures, along with increased government subsidies, ensuring that healthcare institutions remained financially viable without relying on drug markups (State Council of the People's Republic of China,

2016).

Changsha initiated the ZDMP reform as early as 2012, starting with township hospitals. The reform was gradually expanded to urban hospitals in subsequent years, with the majority of public hospitals adopting the ZDMP in 2016. Figure 1 shows the implementation timeline of the ZDMP across different districts/rural counties in Changsha. The earliest adoption occurred in October 2012, while the majority of districts (nearly 60%) implemented the policy in January 2016. By the end of 2016, all public hospitals in Changsha had adopted ZDMP. Although detailed documentation on changes to hospital service fees is limited, the goal of Hunan Province–where Changsha is the capital– was to compensate for approximately 80% of revenue losses from prescription drugs by increasing the prices of medical services (Xinhua News Agency, 2017).

3 Data, Sample, and Empirical Strategy

3.1 Data and Sample

We use the 100% UEBMI claim data for hospital stays from November 2010 to December 2018 in Changsha.[6] For our main analysis, we focus on orthopedic diseases because their treatment options often involve a discretionary choice between conservative treatment (e.g., medications) and intensive treatment (e.g., surgery) (Ding and Liu 2021). Orthopedic diseases account for approximately 1/6 of all hospital claims in the dataset. The hospital claim data include detailed expense information, allowing us to identify the specific drugs and services provided during each hospital stay. This enables us to calculate the quantity and costs of different types of healthcare utilization.[7] We categorize healthcare utilization into eight types: (1) prescription drugs, including both western and traditional Chinese medicine; (2) surgeries, which also includes anesthesia utilization; (3) diagnostic tests; (4) imaging tests; (5) medical services, such as consultations; (6) materials; (7) nursing and bed fees, and (8)

[6]Hospital claims include both inpatient care and observational care.

[7]Since quantities of across items within certain types of care are not easy to calculate, we choose to use costs as our main outcome and show results of calculable quantities in the Appendix.

other expenses.[8] In addition to analyzing specific cost categories, we also examine changes in total costs and length of hospital stays. Finally, we examine patients' health outcomes, including 7-day and 30-day readmission rates, as well as 30-day and 90-day mortality rates.[9]

We supplement the UEBMI claim data with social security beneficiary summary files, which provide information on individuals' workplace, administrative rank in their workplace, demographic characteristics, cessation of their social security record, and the reason for stopping receiving social security benefits (including the date of death, where applicable). We classify an individual as an "expert" if her workplace is a healthcare institution, and as a "non-expert" otherwise.[10] Among experts, we further categorize them as "same-hospital experts" if they have visited their own workplace for medical care, and as "non-same hospitals expert" otherwise. For public employees, we also have information on their administrative rank. Based on this, we define a "higher-ranked patient" as someone with a cadre-level administrative rank, and a "lower-ranked patient" as someone with the rank of a normal worker or who works in the private sector.

We exclude individuals aged 80 and above, as they are eligible for more generous insurance coverage (Human Resources and Social Security Administration 2011). In addition, we drop hospitalizations exceeding 30 days, as long-term hospitalizations are rare ($< 1\%$) and may differ fundamentally from short-term hospitalizations.

Table A1 compares claim-level characteristics for patients visiting public vs. private hospitals before and after ZDMP. Generally, patients spend more for hospital stays in public hospitals, which is partially due to that public hospitals account for a larger share in Tier 3 hospitals (general hospitals) while private hospitals account for a larger share in Tier 1 hospitals (community hospitals). By comparing columns (1)–(2) and columns (3)–(4), we find that drug costs decrease by 433 CNY per claim for public hospitals and by 243 CNY per claim for private hospitals after ZDMP. Furthermore, public hospitals increase utilization of other forms of care greatly, while private hospitals only slightly increase other forms of care.

[8] Others include blood transfusion, oxygen therapy and non-specified services. In total, they only account for a tiny share in total healthcare spending.

[9] 30-day and 90-day mortality rates are derived from the social security beneficiary summary files, which records when a person drops out from the benefit pool and the reason for it.

[10] However, we drop the sample who work in a pharmaceutical firm, because their expert/non-expert status is hard to determine.

As a result, total costs increase by 2931 CNY per claim for public hospitals and only by 429 CNY per claim for private hospitals after ZDMP. When comparing patient characteristics, we find that patients visiting public hospitals are younger, less likely to be female, have a slightly higher share of rural Hukou, have a higher share of experts, and have a higher rank.

Table A2 shows summary statistics of expert and non-expert patients within public hospitals, i.e., our main analysis sample, before and after ZDMP. Comparing columns (1) and (3) in the pre-ZDMP period, non-expert patients have significantly higher drug expenditures than expert patients, with mean drug costs of 2,541 CNY per claim for non-expert patients compared to 1,639 CNY per claim for expert patients. However, non-expert patients' other healthcare costs, including surgical costs, nursing and bed costs, and testing costs, are comparable to those of expert patients, with differences averaging around 50 CNY per claim, except for material costs, where non-experts spend 440 CNY more than expert patients per claim. As a result, non-expert patients on average spend 1,250 CNY more than expert patients per claim in the pre-ZDMP period. Then, in the post-period, drug costs for non-experts decrease by 440 CNY per claim, while they decrease by around 200 CNY for experts. As for other forms of care, although both groups experience increases, the increases are bigger among non-experts, especially for medical services and materials. As a result, total costs increase by about 3,000 CNY for non-experts, while they only increase by 1,400 CNY for experts. In addition, experts tend to have better health outcomes, as they have lower readmission rates and mortality rates. As for patient characteristics, non-experts are older, less likely to be a female, and have a lower rank.

Finally, Table A3 considers different expert subgroups and compare their characteristics before and after ZDMP. In general, same-hospital experts (columns [3]–[6]) have lower health care utilization in all aspects, with same-hospital lower-ranked experts spend least in care, except for medical services. By contrast, non-same hospital experts receive similar levels of care as non-experts. After ZDMP, unlike non-experts or non-same hospital experts, same-hospital experts, regardless of rank, experience only slightly change in their healthcare utilization. By contrast, non-same hospital experts experience greater increases in other forms of care, and thus their total costs increase by almost 3,000 CNY per claim after ZDMP, similar to the increase of non-experts.

3.2 Test for Patient Sorting

Since we focus on how physicians treat different types of patients differently, a potential threat to identification is the possibility of patient sorting–where patients of different types may select into different hospitals before and after the implementation of the ZDMP.

First, we test whether there is any sorting into a public (or private) hospital between expert and non-expert patients after ZDMP. For example, if more sophisticated expert patients were to sort into public hospitals after ZDMP and tend to use more drugs and fewer other medical services, the observed differences between expert and non-expert patients could partially reflect such patient sorting behavior. Table 1 columns (1)–(2) addresse this concern by showing no significant difference between expert and non-expert patients in terms of the probability of staying in a public hospital before and after ZDMP. This suggests that patient sorting between public and private hospitals is not a significant issue.

Second, another type of sorting could happen within public hospitals. For example, if certain type of patients knew which public hospitals relied heavily on prescription drug revenue prior to ZDMP and sorted into these hospitals due to lower drug prices after ZDMP., this could bias our results. Alternatively, if sophisticated patients anticipated that hospitals with high pre-ZDMP drug share might over-utilize other forms of care to compensate for revenue losses , they might avoid such hospitals.[11] If such sorting were to occur, the observed differences between expert and non-expert patients within public hospitals could reflect both physicians' (heterogeneous) response and patient sorting. To test for this type of sorting, we construct a measure of each public hospital's pre-ZDMP drug revenue share and examine whether expert and non-expert patients differently sort into or avoid hospitals with higher (above median) pre-ZDMP drug shares. Table 1 columns (3)–(4) show no evidence of such sorting behavior, further alleviating concerns about patient sorting within public hospitals.

Finally, we test if there is any change in patients' demographic composition over time within public hospitals. Table 1 columns (5)–(7) show that there's no significant change in patient characteristics. Nevertheless, we still control for patients' demographic characteristics as a robustness check.

[11] In principle, we think either way of sorting is very unlikely, because patients, even expert patients, hardly have knowledge on such detailed and private health care utilization patterns of each hospital.

3.3 Empirical Strategy

3.3.1 Average effects

To examine the overall effects of the ZDMP, we estimate the following equation:

$$y_{ihct} = \alpha_0 + \sum_{k=-12, k\neq -1}^{k=11} \beta_k Public_h \cdot 1(t_{ihc} - t_h^* = k) + X_{it} + \gamma_h + \mu_t + \varepsilon_{ihct}, \quad (1)$$

where y_{iht} represents the outcome of patient i in hospital h for claim c in quarter t. Here we compare patients treated in public hospitals vs. private hospital before and after the implementation of ZDMP. t_h^* represents the time when ZDMP was implemented in hospital h, and k indicates the relative quarter with respect to the timing of the implementation of ZDMP. We consider 12 relative quarters before and 12 relative quarters after ZDMP. $k < -12$ are binned into $k = -12$, and $k > 11$ are binned into $k = 11$. X_{it} represents individual characteristics, including age, squared age, and a dummy for male. The terms γ_h and μ_t represents hospital fixed effects and time effects, respectively.[12]

The identification assumption here is that, conditional on hospital fixed effects, public and private hospitals would have followed parallel trends in healthcare utilization and patient health outcomes in the absence of ZDMP. However, after the implementation of ZDMP, we expect public hospitals to decrease prescription drug utilization while increasing other forms of care to compensate for their profit losses. Specifically, we anticipate $\beta_k < 0$ when $k > 0$ for drug utilization, and $\beta_k > 0$ when $k > 0$ for other forms of healthcare utilization.

3.3.2 Experts vs. non-experts

We next restrict the analysis to public hospitals only and compare non-expert patients to expert patients using the following equation (2):[13]

$$y_{ihct} = \alpha_0 + \sum_{k=-12, k\neq -1}^{k=11} \beta_k Nonexpert_{ihc} \cdot 1(t_{ihc} - t_h^* = k) + Nonexpert_i + X_{it} + \gamma_h + \mu_t + \varepsilon_{iht}, \quad (2)$$

[12] We do not include individual fixed effects because our analysis focus on inpatient care and the majority of patients have only one hospital stay for an orthopedic condition during the study period.

[13] Alternatively, we can compare experts and non-expert patients between public and private hospitals, similar to a triple-differences design. We use it as a robustness check, shown in Section 5.1.

where $Nonexpert_i$ is a dummy variable indicating whether a patient is a non-expert. Our hypothesis is that, compared to experts, non-expert patients are more likely to experience greater distortion in their healthcare utilization both before and after the implementation of ZDMP. Specifically, we expect non-experts to exhibit over-prescription of drugs before ZDMP and over-prescription of lucrative procedures after ZDMP. Therefore, after the ZDMP, we anticipate that non-experts patients will experience a larger decrease in prescription drug utilization and a larger increase in other forms of healthcare. This implies that $\beta_k < 0$ for $k > 0$ in the case of drug utilization, and $\beta_k > 0$ for $k > 0$ in the case of other forms of healthcare utilization.

3.3.3 Mechanisms: expertise, connection, and/or rank?

To explore why experts may receive less distorted care, we categorize experts into three subgroups: (1) same-hospital higher-ranked patients, (2) same-hospital lower-ranked patients, and (3) non-same-hospital expert patients. We then estimate the following equation (3):

$$y^g_{ihct} = \alpha_0 + \sum_{k=-12, k\neq -1}^{k=11} \beta^g_k Expert^g_{ih} \cdot 1(t_{ihc} - t^*_h = k) + Expert^g_i + X_{it} + \gamma_h + \mu_t + \varepsilon^g_{iht}, \quad (3)$$

where g represents the three subgroups of expert patients, and the comparison group is the non-expert group. This analysis aims to identify which subgroup drives the differences in healthcare utilization between experts and non-experts. Since the treatment and control groups are switched in this specification, the expected signs of the coefficients will be opposite to those in equation (2). Specifically, we expect $\beta^g_k > 0$ for $k > 0$ in the case of drug utilization and $\beta^g_k < 0$ for $k > 0$ in the case of other forms of healthcare utilization. This implies that, compared to non-experts, expert patients are likely to receive relatively more prescription drugs and less of other forms of care after the implementation of ZDMP.

4 Results

4.1 Overall Effects of ZDMP on Health Care Utilization and Health Outcomes

We first show the overall effect of the ZDMP by comparing public hospitals and private hospitals, as ZDMP applies exclusively to public hospitals. As shown by Figure 2 and Table 2 Panel A, ZDMP significantly reduces patients' drug expenditures in public hospitals but increases costs for other forms of healthcare utilization.[14] Specifically, compared to private hospitals, patients' drug expenditure in public hospitals decreases by 497 CNY (23.1%) per claim after ZDMP. However, this reduction is offset by significant increases in expenditures for surgeries, diagnostic tests, imaging tests, medical services, material, and nursing and beds, which rise by 260 CNY (191.6%), 153 CNY (38.2%), 195 CNY (38.6%), 536 CNY (36.9%), 567 CNY (68.7%), and 127 CNY (44%), respectively. Consequently, while ZDMP successfully reduces drug costs, the increases in other forms of care outweigh the savings from reduced drug expenditures. As shown in Figure 2 (h) and column (8) of Table 2 Panel A, total costs per hospital claim increase by 1364 (23.5%) after ZDMP. To disentangle whether these costs are driven by quantity or price effects, we present evidence in Table A4 Panel A showing that patients in public hospitals indeed reduce the number of drugs prescribed while increase the number of surgeries, testing, and medical services after ZDMP. Given these utilization patterns, we attribute the observed effects primarily to physicians behavior. This is because, if patients were driving these changes, they would likely respond to lower drug prices by using more prescription drugs and to higher prices for medical services by reducing their use of other forms of care – patterns that are the opposite of what we observe.

Moreover, the increase in healthcare costs – driven by higher treatment intensity and longer hospital stays (0.97 days)– is associated with a decline in patients' health outcomes. As shown in Figure 3 (c) and column (11) of Table 2 , 30-day readmission rates in public hospitals increase by 1.28 percentage points (29.3%) following the implementation of ZDMP.

[14] We show the raw trends in Appendix Figure A1. The estimated effects are driven by the changes of public hospitals after ZDMP.

15

4.2 Physicians' Treatment on Non-expert vs. Expert Patients

We then examine whether a patient is an expert or not affects physicians' decision-making before and after the implementation of ZDMP. Figure 4 (a) reveals that the decrease in drug costs is more pronounced among non-experts, suggesting that drug over-prescription was a more serious problem for non-experts compared to expert patients prior to ZDMP.[16] On average, as shown in column (1) of Table 3 , drug costs for non-experts decrease by 364 CNY (14.47%) more than those for experts after ZDMP.

For other forms of healthcare utilization, non-expert patients in public hospitals experience larger increases after ZDMP, likely as a compensation response to the revenue loss from reduced prescription drug sales. As shown in columns (2)–(7) of Table 3, compared to expert patients, ZMDP leads to greater increases in costs for non-expert patients in surgeries, diagnostic tests, imaging tests, medical services, materials, and nursing and bed by 115 CNY (52.01%), 136 CNY (28.04%), 163 CNY (23.28%), 599 CNY (35.09%), 388 CNY (26.29%), and 105 CNY (27.96%) respectively.[17] As a result, non-experts end up spending even more than experts after ZDMP, with total costs increasing by 1175 CNY (15.61%) per claim relative to experts. Appendix Table A4 further shows that compared to experts, non-expert patients experience a decrease in drug utilization (measured by the unique number of drugs) but increases in the number of surgeries, diagnostic and imaging tests, and medical services.

Additionally, Figure 5 (a) and column (9) of Table 3 show that non-expert patients in public hospitals experience longer hospital stays by 1.9 days (17.11%).[18] Furthermore, Figure

[15]However, the change in LOS is driven by private hospitals which reduce LOS over time, whereas public hospitals remain the same LOS, as shown in Appendix Figure A2.

[16]We show the raw trends in Appendix Figure A3. As shown by panel (a), non-experts on average have higher prescription drug costs than experts before ZDMP, and the gap reduces greatly after ZDMP because non-experts' spending on prescription drugs decreases afterwards.

[17]In Appendix Figure A3 panels (c)–(f), we show that prior to ZDMP, non-experts on average receive less non-drug treatment than experts. However, such trends revert after ZDMP, where experts still receive the similar amount of other forms of care, whereas non-experts receive a greater level of other forms of care, suggesting that physicians only change treatment towards non-experts.

[18]However, Appendix Figure A4 shows that differences are driven by the decrease in LOS by expert patients over time, which is consistent with the government goal of reducing LOS in health reforms during

5 (b)–(e) and columns (10)–(13) of Table 3 show that the additional treatment and costs on non-experts do not lead to any improvement in health outcomes, as there are no significant changes in readmission or mortality rates.

In conclusion, the greater utilization of drugs by non-experts before ZDMP and the larger increase in costs of other forms of care after ZDMP suggest that non-expert patients receive more distorted care compared to expert patients,, both before (in the form of prescription drugs) and after ZDMP (in the form of other healthcare services).

4.3 Mechanisms: Expertise, Connection, and/or Rank?

The above results demonstrate that, compared to experts, non-expert patients experience greater distortion in their healthcare utilization without achieving better health outcomes. This raise the question of what drives such differences in treatment decisions and outcomes. Compared to non-experts, expert patients possess better medical knowledge and are more likely to have closer relationship with treating physicians. To disentangle the roles of expertise and connection, we divide expert patients into two categories: same-hospital expert patients and non-same-hospital expert patients. While both groups have superior medical knowledge compared to non-experts, the former group is more likely to have stronger connection with treating physicians than the latter.

Moreover, since we have access to the administrative rankings of employees in public hospitals, we further categorize same-hospital expert patients into two subgroups: same-hospital lower-ranked experts and same-hospital higher-ranked experts, based on whether they hold cadre status.[19] Compared to same-hospital lower-ranked experts, higher-ranked experts have greater authority and privilege in their workplace, and which may result in more favorable treatment.

Figures 6–7 and Table 4 show the event study and DID results for healthcare utilization across the three subgroups of expert patients, compared to non-expert patients.Overall, all expert subgroups receive more efficient care than non-expert patients. However, the extent

the 2010s.

[19]In China's administrative ranking system, lower-ranked experts are ordinary staff members (e.g., doctors and nurses), and higher-ranked experts hold managerial positions (e.g., Dean, Vice Dean, and Department Head).

of this efficiency varies: it is greatest for same-hospital higher-ranked patients, followed by same-hospital lower-ranked patients, and least for non-same hospital expert patients. For drug expenditure, as shown in Figure 6(a) and column (1) of Table 4, same-hospital higher-ranked experts, same-hospital lower-ranked experts, and non-same hospital experts experience reductions in drug costs that are 507, 383, and 225 CNY smaller, respectively, compared to non-experts after ZDMP. Similar patterns emerge in the shift towards other forms of care. Figure 6(b) and column (2) of Table 4 indicate that same-hospital patients experiece smaller increase in surgeries compared to non-experts, while non-same hospital experts only initially see smaller increases in surgeries after ZDMP. For other types of care, such as diagnostic testing, imaging testing, medical services, all three expert groups exhibit smaller increase in utilization compared to non-experts. However, the increases are smallest for same-hospital higher-ranked patients, followed by same-hospital lower-ranked patients, with non-same hospital experts showing the mildest effects, as shown in Figure 6(c)–(e) and columns (3)–(5) of Table 4. In addition, Panels C–E of Appendix Table A4 show the changes in quantity, and again we find that changes in costs are largely driven by changes in quantity of drugs and different services.

Overall, column (8) of Table 4 reveals that, compared to non-experts, same-hospital higher-ranked experts, same-hospital lower-ranked experts, and non-same hospital experts experience decreases in total costs of 2230 (30%), 1622 (21.5%), and 851 CNY (11%), respectively, after ZDMP. However, Figures 6–7 show that the effects for non-same hospital experts are only evident in the first 2–4 quarters, except for drugs (7 quarters) and medical services, which exhibit lasting effects.

Regarding the length of hospitalization, Figure 8 (a) and column (1) of Table 5 demonstrate that LOS follows a similar pattern: same-hospital higher-ranked patients have the shortest LOS (2.7 days), followed by same-hospital lower-ranked patients (2.2 days), while non-same hospital experts also have moderately shorter LOS (1.4 days) than non-experts. Finally, Figure 8 (b)–(c), Figure 9, and columns (2)–(5) of Table 5 show that, despite differences in treatment intensity across the subgroups, there are no significant differences in health outcomes between the expert subgroups and non-experts.

The above evidence suggests that general medical expertise plays a moderate role in en-

suring efficient care, accounting for approximately 10% lower total healthcare costs compared to non-experts. On the other hand, connection appear to play a relatively more important role: even the lower-ranked same-hospital patients receive around 20% less intensive care than non-experts, while higher-ranked same-hospital patients receive even more efficient care, with 30% lower total costs.

5 Additional Results and Robustness Checks

5.1 Triple-differences model

In the analysis above, we restrict the sample to public hospitals only and compare non-expert patients to expert patients, under the implicit assumption that experts should receive more efficient care. However, since we have variation both between public and private hospitals and between expert and non-expert patients, an alternative approach is to employ a triple-differences (DDD) design, as specified in the following equation:

$$y_{ihct} = \alpha_0 + \sum_{k=-12,k\neq-1}^{k=11} \delta_k public_h \cdot 1(t_{ihc} - t_h^* = k) + \sum_{k=-12,k\neq-1}^{k=11} \eta_k Nonexpert_i \cdot 1(t_{ihc} - t_h^* = k)$$
$$+ \sum_{k=-12,k\neq-1}^{k=11} \beta_k Nonexpert_i \cdot public_h \cdot 1(t_{ihc} - t_h^* = k) + Nonexpert_i + X_{it} + \gamma_h + \mu_t + \varepsilon_{ihct}, \tag{4}$$

where the variables maintain the same definition as in equations (1) and (2). The results are shown in Appendix Figures A5–A6 and Appendix Table A5.

5.2 Advanced staggered DID methods

Although the majority of public hospitals implemented the ZDMP in Oct 2016, we still have variation in implementation timing. Therefore, we adopt the advanced staggered DID methods to test for the robustness of our findings. The results are robust as shown in Appendix Figures A7–A10.

5.3 All diseases

Our main analysis focuses on orthopedic patients, and one concern is that our findings may only apply to this disease group. However, Appendix Figures A11 and A12 show that similar and consistent findings apply to almost all (>80%) diseases groups.

6 Discussion and Conclusion

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

Given these findings, the implementation of a connection-free 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 expert patients and non-expert patients while also saving money for the entire healthcare system.

Nevertheless, our study have several limitations. First, our measure of expertise is not perfect. It does not capture disease-specific medical knowledge, which may explain why general medical knowledge plays a relatively limited 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 "appropriate" care.

References

Alexander, Diane. 2020. "How Do Doctors Respond to Incentives? Unintended Consequences of Paying Doctors to Reduce Costs." *Journal of Political Economy*, 128(11): 4046–4096.

Alexander, Diane, and Molly Schnell. 2024. "The Impacts of Physician Payments on Patient Access, Use, and Health." *American Economic Journal: Applied Economics*, 16(3): 142–177.

Alsan, Marcella, Owen Garrick, and Grant Graziani. 2019. "Does Diversity Matter for Health? Experimental Evidence from Oakland." *American Economic Review*, 109(12): 4071–4111.

Angerer, Silvia, Christian Waibel, and Harald Stummer. 2019. "Discrimination in Health Care: A Field Experiment on the Impact of Patients' Socioeconomic Status on Access to Care." *American Journal of Health Economics*, 5(4): 407–427. Publisher: The University of Chicago Press.

Blanes i Vidal, Jordi, Mirko Draca, and Christian Fons-Rosen. 2012. "Revolving Door Lobbyists." *American Economic Review*, 102(7): 3731–48.

Brekke, Kurt R., Tor Helge Holmås, Karin Monstad, and Odd Rune Straume. 2018. "Socioeconomic status and physicians' treatment decisions." *Health Economics*, 27(3): e77–e89. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3621.

Brekke, Kurt R., Tor Helge Holmås, Karin Monstad, and Odd Rune Straume. 2019. "Competition and physician behaviour: Does the competitive environment affect the propensity to issue sickness certificates?" *Journal of Health Economics*, 66: 117–135.

Cabral, Marika, and Marcus Dillender. 2024. "Gender Differences in Medical Evaluations: Evidence from Randomly Assigned Doctors." *American Economic Review*, 114(2): 462–499.

Chandra, Amitabh, and Douglas Staiger. 2010. "Identifying Provider Prejudice in Healthcare." National Bureau of Economic Research w16382, Cambridge, MA.

Chen, Alice, and Darius N. Lakdawalla. 2019. "Healing the poor: The influence of patient socioeconomic status on physician supply responses." *Journal of Health Economics*, 64: 43–54.

Chen, Stacey H., Jennjou Chen, Hongwei Chuang, and Tzu-Hsin Lin. 2023. "Physicians Treating Physicians: Relational and Informational Advantages in Treatment and Survival." *Journal of Labor Economics*. Publisher: The University of Chicago Press.

Clemens, Jeffrey, and Joshua D. Gottlieb. 2014. "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?" *American Economic Review*, 104(4): 1320–49.

Coudin, Elise, Anne Pla, and Anne-Laure Samson. 2015. "GP responses to price regulation: evidence from a French nationwide reform." *Health Economics*, 24(9): 1118–1130. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3216.

Currie, Janet, Paul Kurdyak, and Jonathan Zhang. 2024*a*. "Socioeconomic status and access to mental health care: The case of psychiatric medications for children in Ontario Canada." *Journal of Health Economics*, 93: 102841.

Currie, Janet, W. Bentley MacLeod, and Kate Musen. 2024*b*. "First Do No Harm? Doctor Decision Making and Patient Outcomes."

Ding, Yu, and Chenyuan Liu. 2021. "Alternative payment models and physician treatment decisions: Evidence from lower back pain." *Journal of Health Economics*, 80: 102548.

Eli, Shari, Trevon D. Logan, and Boriana Miloucheva. 2019. "Physician Bias and Racial Disparities in Health: Evidence from Veterans' Pensions."

Fang, Hanming, Xiaoyan Lei, Julie Shi, and Xuejie Yi. 2021. "Physician-Induced Demand: Evidence from China's Drug Price Zero-Markup Policy."

Fang, Yu. 2017. "Pharmaceutical Policy in China." *Pharmaceutical Policy in Countries with Developing Healthcare Systems*, , ed. Zaheer-Ud-Din Babar, 169–191. Cham:Springer International Publishing.

Fisman, Raymond. 2001. "Estimating the Value of Political Connections." *American Economic Review*, 91(4): 1095–1102.

Fisman, Raymond, Jing Shi, Yongxiang Wang, and Rong Xu. 2018. "Social ties and favoritism in Chinese science." *Journal of Political Economy*, 126(3): 1134–1171.

Fisman, Raymond, Jing Shi, Yongxiang Wang, and Weixing Wu. 2020. "Social ties and the selection of China's political elite." *American Economic Review*, 110(6): 1752–1781.

Frakes, Michael D., and Jonathan Gruber. 2022. "Racial Concordance and the Quality of Medical Care: Evidence from the Military."

Fumarco, Luca, Benjamin Harrell, Patrick Button, David Schwegman, and E. Dils. 2020. "Gender Identity, Race, and Ethnicity-based Discrimination in Access to Mental Health Care: Evidence from an Audit Correspondence Field Experiment."

Greenwood, Brad N., Rachel R. Hardeman, Laura Huang, and Aaron Sojourner. 2020. "Physician-patient racial concordance and disparities in birthing mortality for newborns." *Proceedings of the National Academy of Sciences of the United States of America*, 117(35): 21194–21200.

Greenwood, Brad N., Seth Carnahan, and Laura Huang. 2018. "Patient–physician gender concordance and increased mortality among female heart attack patients." *Proceedings of the National Academy of Sciences*, 115(34): 8569–8574. Publisher: Proceedings of the National Academy of Sciences.

Gupta, Atul. 2021. "Impacts of Performance Pay for Hospitals: The Readmissions Reduction Program." *American Economic Review*, 111(4): 1241–1283.

Hill, Andrew J., Daniel B. Jones, and Lindsey Woodworth. 2023. "Physician-patient race-match reduces patient mortality." *Journal of Health Economics*, 92: 102821.

Hoffman, Kelly M., Sophie Trawalter, Jordan R. Axt, and M. Norman Oliver. 2016. "Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites." *Proceedings of the National Academy of Sciences*, 113(16): 4296–4301. Publisher: Proceedings of the National Academy of Sciences.

Human Resources and Social Security Administration. 2011. "Medical Insurance Preferential Treatment Scheme for Insured Persons over 80 Years Old in Changsha." Human Resources and Social Security Administration.

IMS Health. 2016. "Panorama of China's pharmaceutical market in 2016."

Jia, Ruixue, Masayuki Kudamatsu, and David Seim. 2015. "Political selection in China: The complementary roles of connections and performance." *Journal of the European Economic Association*, 13(4): 631–668.

Johnson, Erin M., and M. Marit Rehavi. 2016. "Physicians Treating Physicians: Information and Incentives in Childbirth." *American Economic Journal: Economic Policy*, 8(1): 115–141.

Khwaja, Asim Ijaz, and Atif Mian. 2005. "Do lenders favor politically connected firms?

Rent provision in an emerging financial market." *The Quarterly Journal of Economics*, 120(4): 1371–1411.

Li, Danielle. 2017. "Expertise versus Bias in Evaluation: Evidence from the NIH." *American Economic Journal: Applied Economics*, 9(2): 60–92.

Luan, Mengna, Xiang Shao, and Fengman Dou. 2020. "Financial conditions, health care provision, and patient outcomes: Evidence from Chinese public hospitals." *Economics Letters*, 186: 108876.

McDevitt, Ryan C., and James W. Roberts. 2014. "Market structure and gender disparity in health care: preferences, competition, and quality of care." *The RAND Journal of Economics*, 45(1): 116–139. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12044.

Milcent, Carine. 2018. *Healthcare Reform in China: From Violence To Digital Healthcare | SpringerLink.* . 1 ed., Palgrave Pivot Cham.

National Health Commission of the PRC. 2016. "Statistical Bulletin on the Development of Health and Family Planning in 2015."

Nian, Yongwei, and Chunyang Wang. 2023. "Go with the Politician." *American Economic Journal: Economic Policy*, 15(2): 467–496.

Schwab, Stephen D., and Manasvini Singh. 2024. "How power shapes behavior: Evidence from physicians." *Science*, 384(6697): 802–808. Publisher: American Association for the Advancement of Science.

Shi, Julie, Lirong Liang, and Manqi Hou. 2023. "The impacts of China's drug price zero-markup policy on medical expenditures and health outcomes." *China Economic Review*, 79: 101949.

Shi, Maggie. 2024. "Monitoring for Waste: Evidence from Medicare Audits." *The Quarterly Journal of Economics*, 139(2): 993–1049.

Shi, Xiangyu, Tianyang Xi, Xiaobo Zhang, and Yifan Zhang. 2021. ""Moving umbrella": Bureaucratic transfers and the comovement of interregional investments in China." *Journal of Development Economics*, 153: 102717.

Singh, Manasvini, and Atheendar Venkataramani. 2022. "Rationing by Race."

State Council of the People's Republic of China. 2016. "Several opinions for Deepening the

Reform of the Medical and Health System."

Sun, Qiang, Michael A. Santoro, Qingyue Meng, Caitlin Liu, and Karen Eggleston. 2008. "Pharmaceutical Policy In China." *Health Affairs*, 27(4): 1042–1050. PMID: 18607039.

Wallis, Christopher J. D., Angela Jerath, Natalie Coburn, Zachary Klaassen, Amy N. Luckenbaugh, Diana E. Magee, Amanda E. Hird, Kathleen Armstrong, Bheeshma Ravi, Nestor F. Esnaola, Jonathan C. A. Guzman, Barbara Bass, Allan S. Detsky, and Raj Satkunasivam. 2022. "Association of Surgeon-Patient Sex Concordance With Postoperative Outcomes." *JAMA Surgery*, 157(2): 146–156.

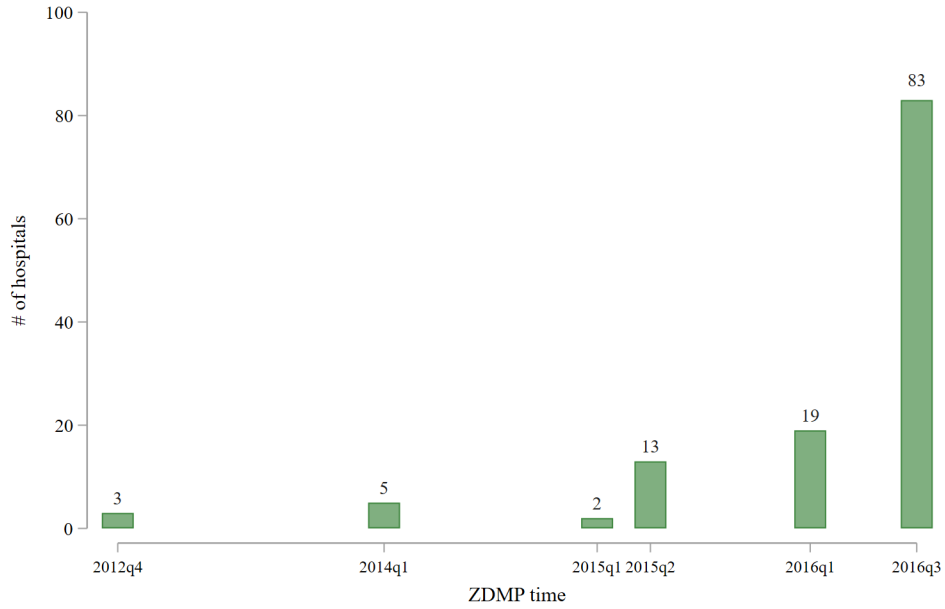
Wilding, Anna, Luke Munford, Bruce Guthrie, Evangelos Kontopantelis, and Matt Sutton. 2022. "Family doctor responses to changes in target stringency under financial incentives." *Journal of Health Economics*, 85: 102651.

Xinhua News Agency. 2017. "Suggestions for improving hospital operting conditions after Zero Drug Markup policy from Members of Chinese People's Political Consultative Conference."

Ye, Han, and Junjian Yi. 2023. "Patient-Physician Race Concordance, Physician Decisions, and Patient Outcomes." *The Review of Economics and Statistics*, 105(4): 766–779. Publisher: MIT Press.

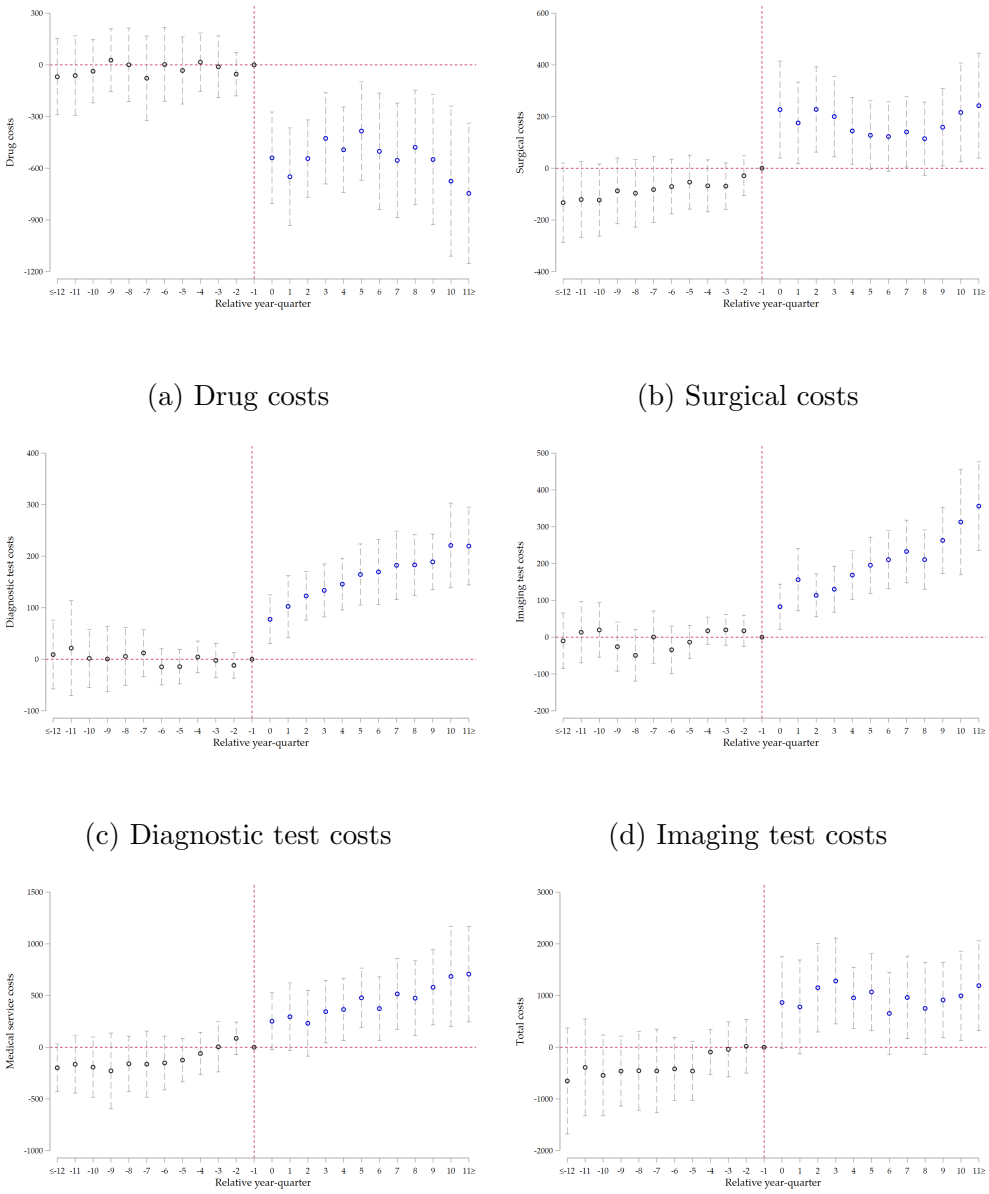
Figures

Figure 1: ZDMP Implementation Time in Changsha



Notes: This figure shows the implementation timing of ZDMP 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 2: Public vs. Private Hospitals: Health Care Utilization (Costs)



(a) Drug costs

(b) Surgical costs

(c) Diagnostic test costs

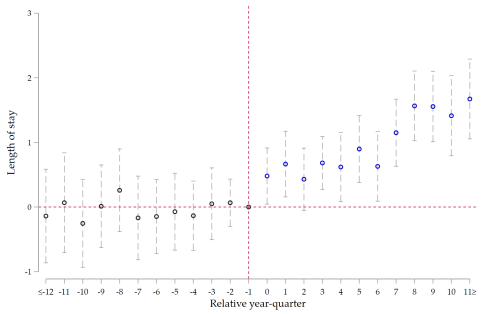
(d) Imaging test costs

(e) Medical services costs

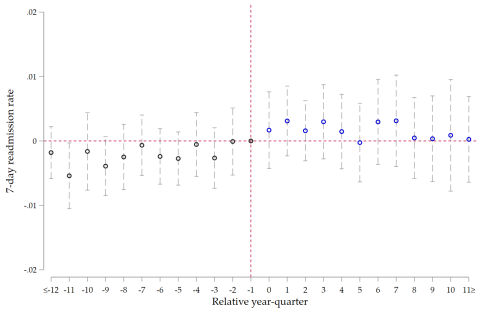
(f) Total costs

Notes: These figures show health care utilization of orthopedic patients in public hospitals relative to private hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

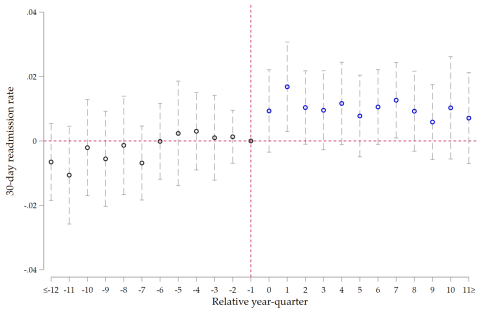
Figure 3: Public vs. Private Hospitals: Length of Stay and Health Outcomes



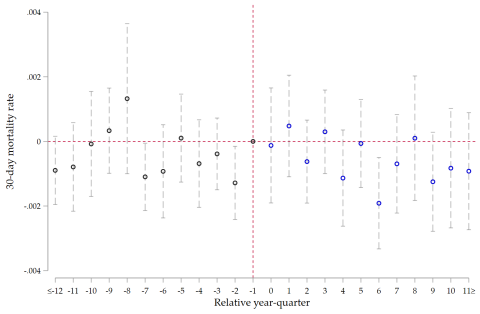
(a) Length of stay



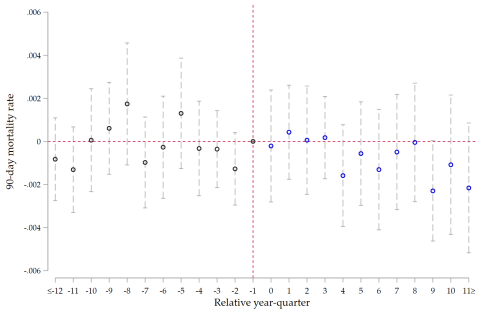
(b) Readmission within 7 days



(c) Readmission within 30 days



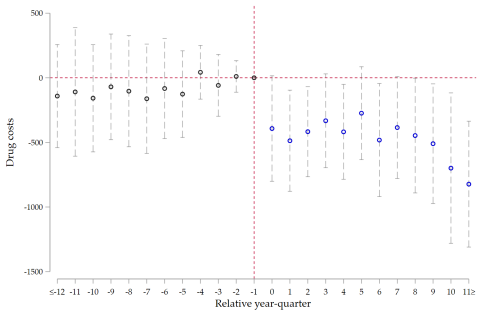
(d) 30-day mortality rate



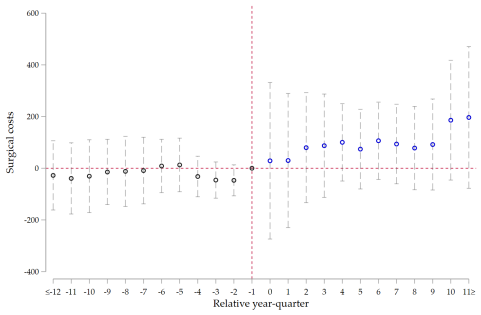
(e) 90-day mortality rate

Notes: These figures show health outcomes of orthopedic patients in public hospitals relative to private hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

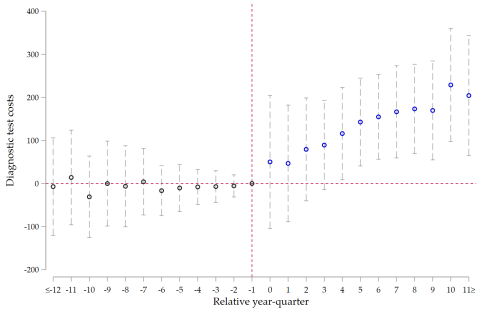
Figure 4: Non-expert vs. Expert Patients: Health Care Utilization (Costs)



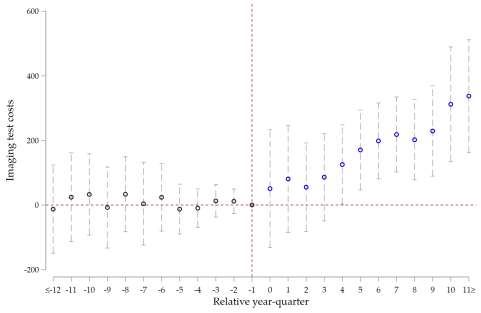
(a) Drug costs



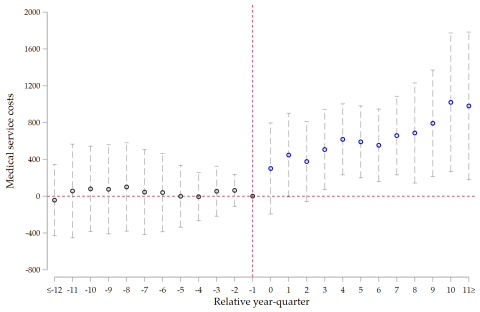
(b) Surgical costs



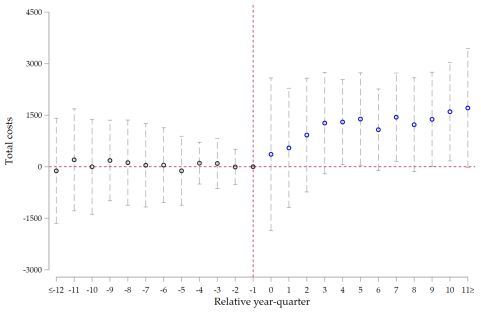
(c) Diagnostic test costs



(d) Imaging test costs



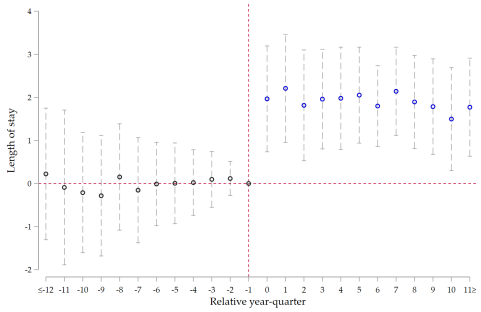
(e) Medical services costs



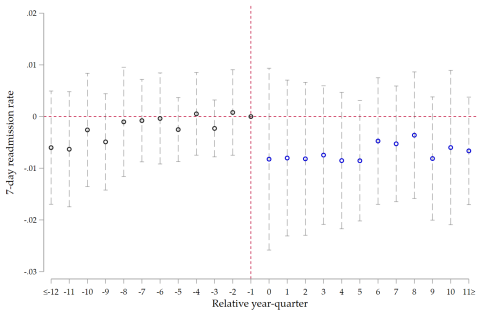
(f) Total costs

Notes: These figures show health care utilization of expert orthopedic patients, relative to non-expert orthopedic patients in public hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

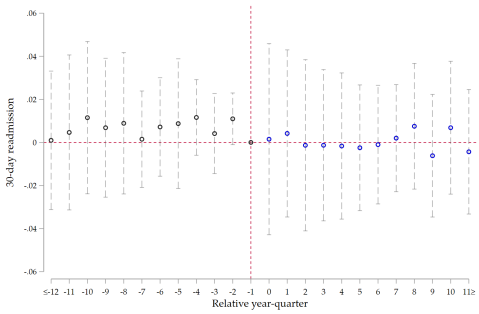
Figure 5: Non-expert vs. Expert Patients: Length of Stay and Health Outcomes



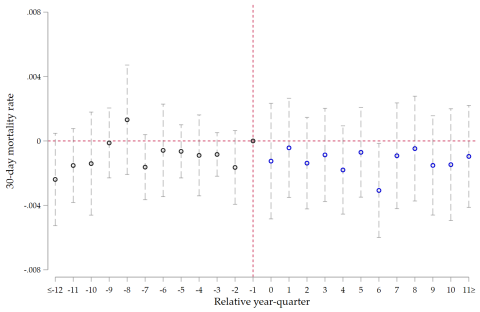
(a) Length of stay



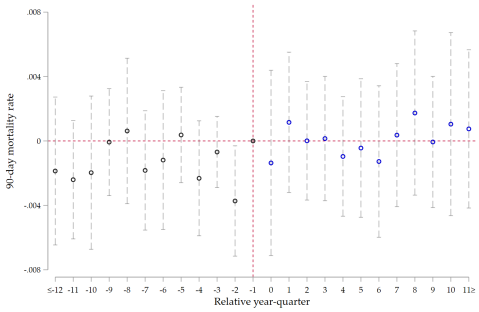
(b) Readmission within 7 days



(c) Readmission within 30 days



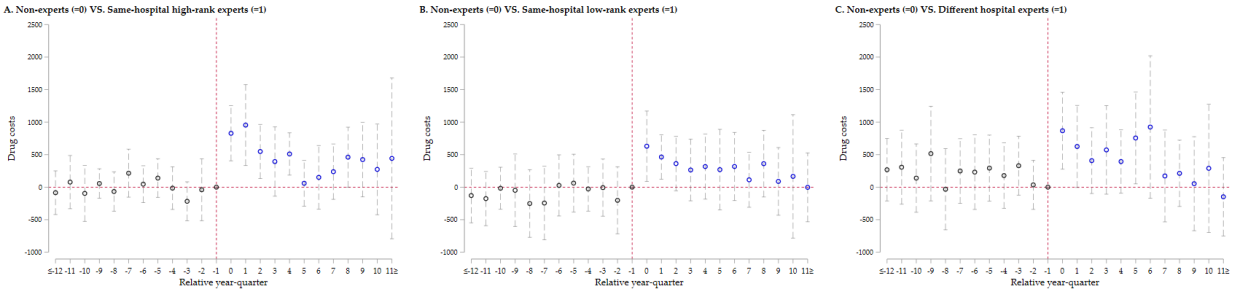
(d) 30-day mortality rate



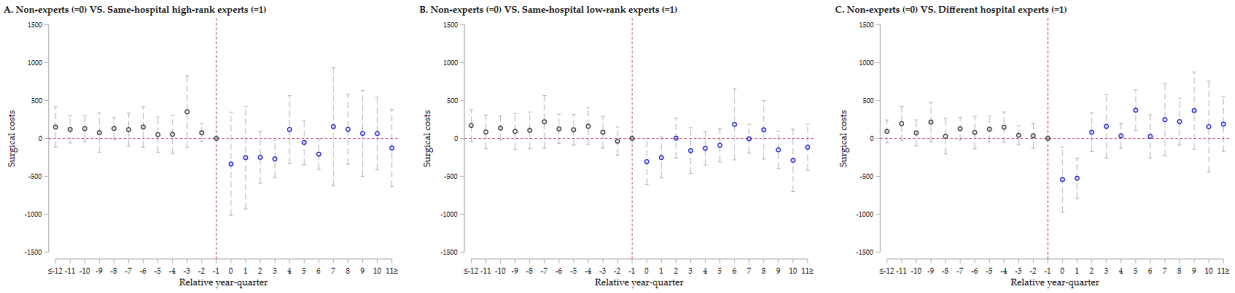
(e) 90-day mortality rate

Notes: These figures show health outcomes of expert orthopedic patients, relative to non-expert orthopedic patients in public hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

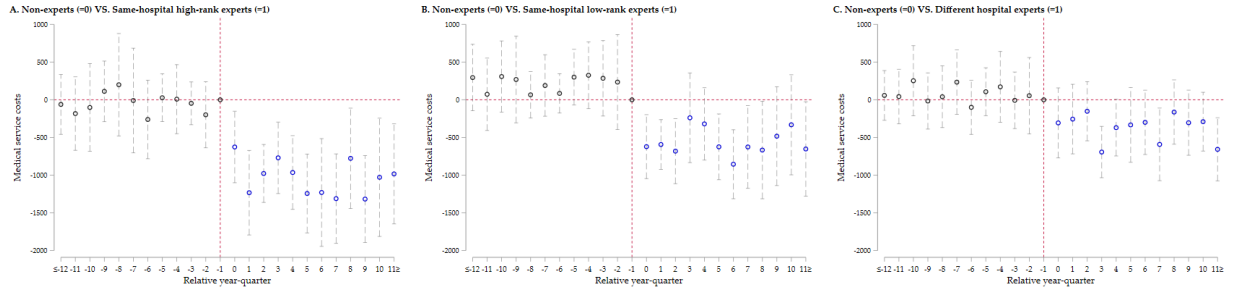
Figure 6: Expertise, Connection, and Rank: Health Care Utilization (Costs)



(a) Drug costs



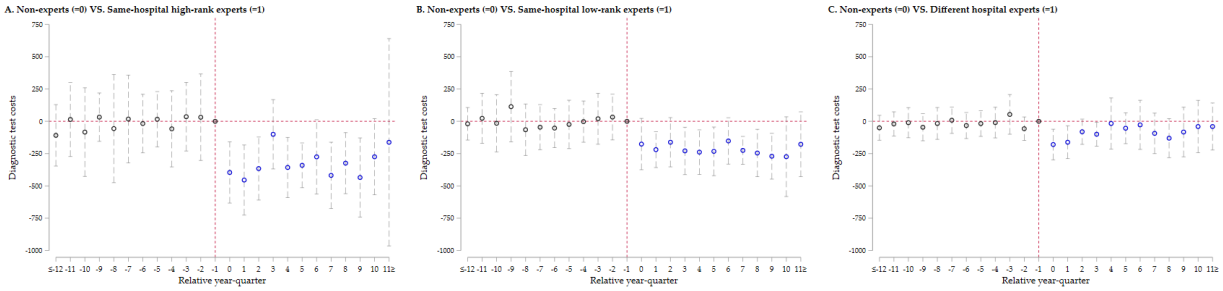
(b) Surgical costs



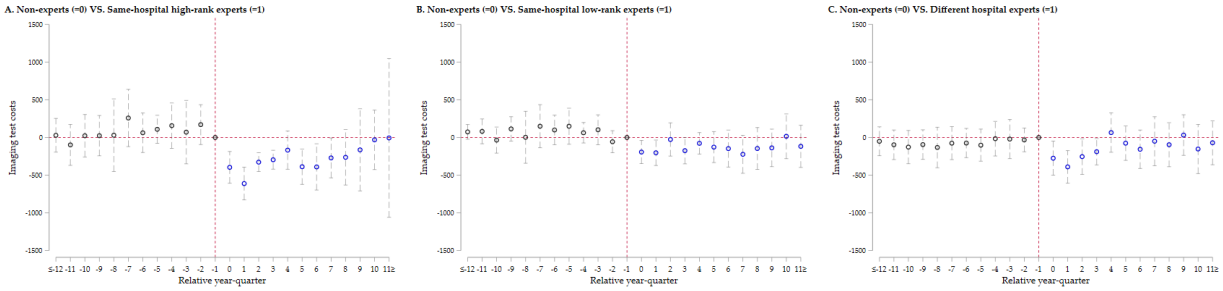
(c) Medical services costs

Notes: These figures compare health care utilization in three subgroups of experts to non-experts before and after ZDMP in public hospitals. The three expert subgroups are: (1) same-hospital higher-ranked expert patients; (2) same-hospital lower-ranked expert patients; (3) non-same hospital expert patients. Higher rank is defined as having a cadre status in the administrative ranking of public employees in China. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

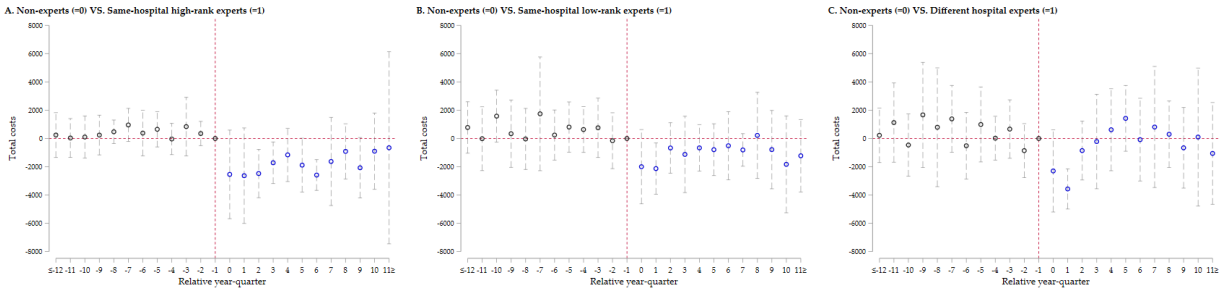
Figure 7: Expertise, Connection, and Rank: Health Care Utilization (Costs) (Continued)



(a) Diagnostic test costs



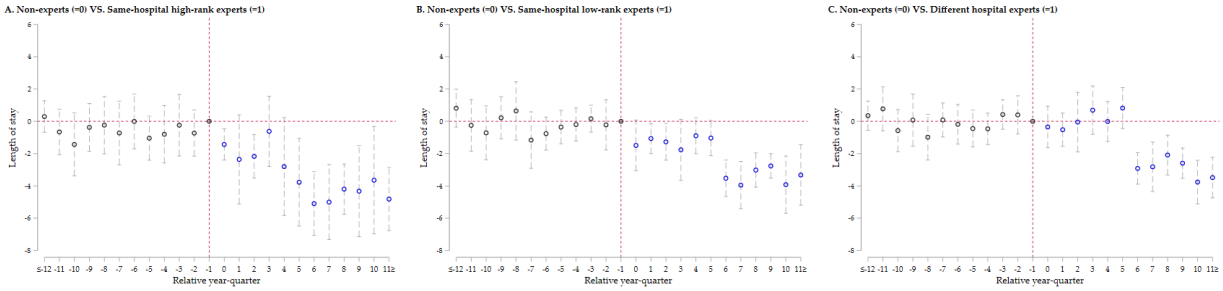
(b) Imaging test costs



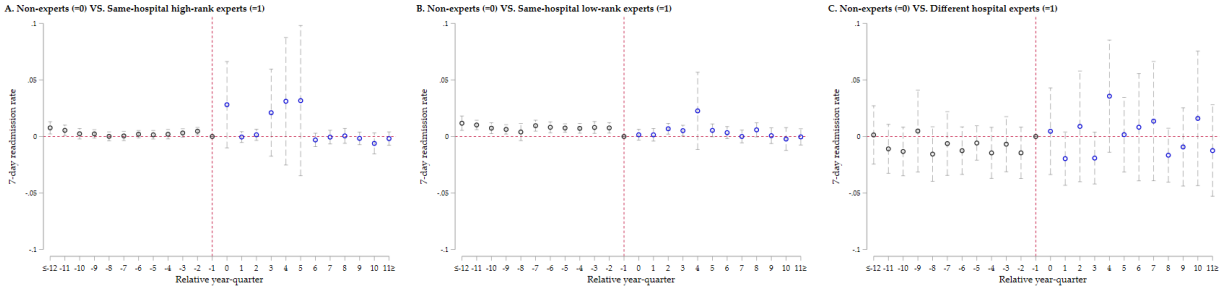
(c) Total costs

Notes: These figures compare health care utilization in three subgroups of experts to non-experts before and after ZDMP in public hospitals. The three expert subgroups are: (1) same-hospital higher-ranked expert patients; (2) same-hospital lower-ranked expert patients; (3) non-same hospital expert patients. Higher rank is defined as having a cadre status in the administrative ranking of public employees in China. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

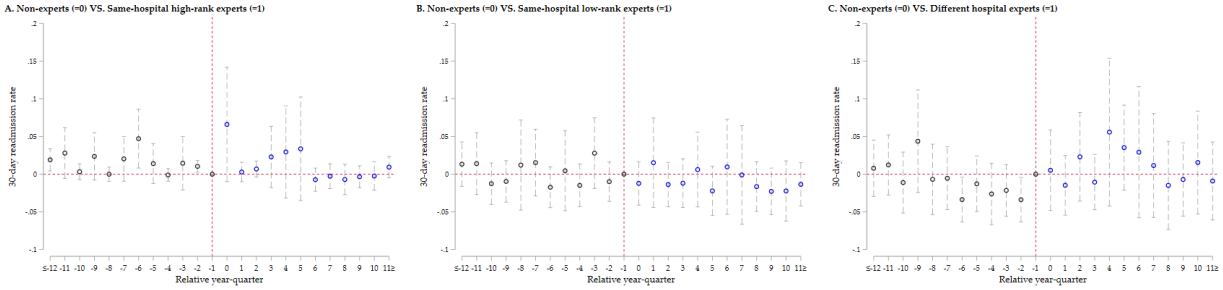
Figure 8: Expertise, Connection, and Rank: Length of Stay and Readmission Rates



(a) Length of stay



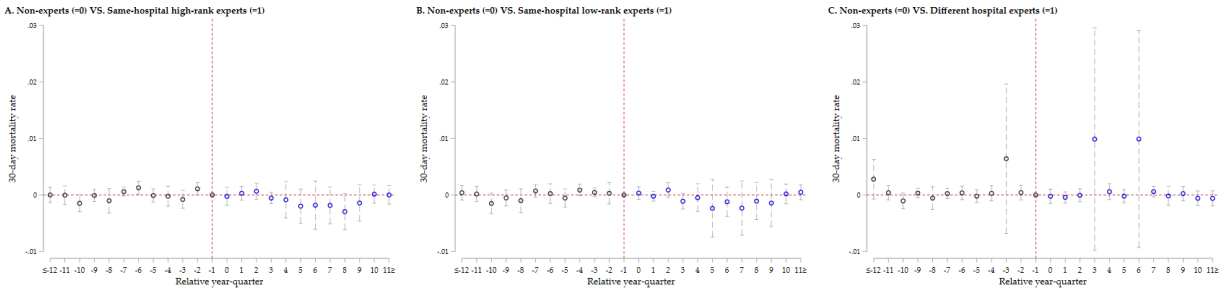
(b) Readmission within 7 days



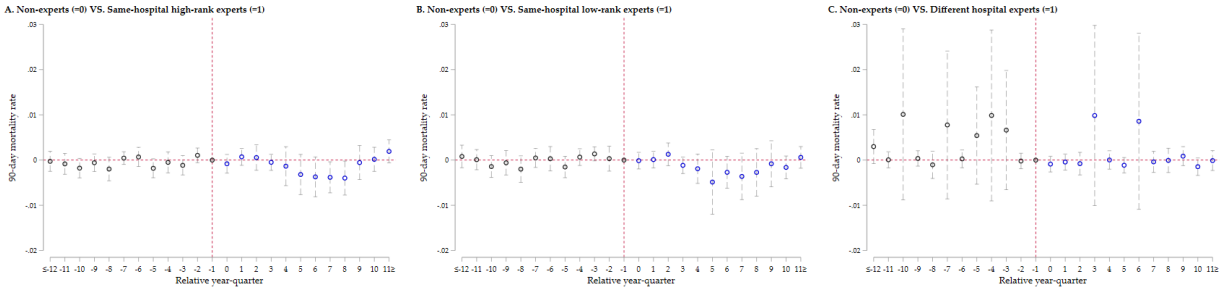
(c) Readmission within 30 days

Notes: These figures compare length of stay and readmission rates in three subgroups of experts to non-experts before and after ZDMP in public hospitals. The three expert subgroups are: (1) same-hospital higher-ranked expert patients; (2) same-hospital lower-ranked expert patients; (3) non-same hospital expert patients. Higher rank is defined as having a cadre status in the administrative ranking of public employees in China. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Figure 9: Expertise, Connection, and Rank: Mortality Rates



(a) 30-Day Mortality rate



(b) 90-Day Mortality rate

Notes: These figures compare mortality rates in three subgroups of experts to non-experts before and after ZDMP in public hospitals. The three expert subgroups are: (1) same-hospital higher-ranked expert patients; (2) same-hospital lower-ranked expert patients; (3) non-same hospital expert patients. Higher rank is defined as having a cadre status in the administrative ranking of public employees in China. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Tables

Table 1: Test of patient sorting

	(1) **1**(public)	(2) **1**(public)	(3) **1**(high drug pct)	(4) **1**(high drug pct)	(5) Age	(6) Female	(7) Rural *hukou*
Non-expert*post	0.0117	-0.0163	-0.0597	-0.0022	0.0648	-0.0296	-0.0037
	(0.0389)	(0.0250)	(0.0374)	(0.0187)	(0.6878)	(0.0195)	(0.0121)
Individual FE	No	Yes	No	Yes	No	No	No
Hospital FE	No	No	No	No	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	419,626	419,626	225,625	225,625	225,625	225,625	225,625
Mean of Y (Pre-ZDMP)	0.5350	0.5350	0.2959	0.2959	57.076	0.6579	0.0511

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. Non-expert*post takes 1 if a patient is a non-expert patient and the time is after ZDMP. All columns include year-quarter fixed effects. Columns (2) and (4) additionally include individual fixed effects because the sorting is based on hospitals' characteristics; while columns (5)–(7) additionally include hospital fixed effects because the sorting is based on patients' characteristics. 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 2: Outcomes of ZDMP: Public vs. Private Hospitals, Orthopedics Patients

	Panel A. Health care utilization (costs)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drug	Surgical	Diagnostic test	Imaging test	Medical service	Material	Nursing & bed	Total
Public*post	-496.65***	260.30***	153.49***	195.35***	536.18***	566.62**	126.54***	1,364.36***
	(122.86)	(72.22)	(28.94)	(38.83)	(168.19)	(223.31)	(29.28)	(349.57)
Observations	428,814	428,814	428,814	428,814	428,814	428,814	428,814	428,814
Mean of Y (Pre-ZDMP)	2153.94	135.96	401.27	505.61	1,454.05	824.97	287.51	5,800.13

	Panel B. LOS and health outcomes				
	(9)	(10)	(11)	(12)	(13)
	LOS	7-day read.	30-day read.	30-day death	90-day death
Public*post	0.966***	0.0034*	0.0128***	-0.0000	-0.0004
	(0.272)	(0.0019)	(0.0046)	(0.0002)	(0.0004)
Observations	428,814	428,814	428,814	428,814	428,814
Mean of Y (Pre-ZDMP)	9.194	0.0092	0.0387	0.0010	0.0025

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 ZDMP, as specified in Equation (1). All specifications include 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 3: Outcomes of ZDMP: Non-expert vs. Expert Orthopedics Patients

	Panel A. Health care utilization (costs)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drug	Surgical	Diagnostic test	Imaging test	Medical service	Material	Nursing & bed	Total
Non-expert*post	-364.35***	115.15*	135.62***	162.74***	599.10***	387.50*	105.09***	1,174.91***
	(104.14)	(58.70)	(31.60)	(33.50)	(184.49)	(210.60)	(18.57)	(308.25)
Observations	226,467	226,467	226,467	226,467	226,467	226,467	226,467	226,467
Mean of Y (Pre-ZDMP)	2517.58	221.38	483.70	698.81	1,707.45	1,474.08	375.83	7,526.23

	Panel B. LOS and health outcomes				
	(9)	(10)	(11)	(12)	(13)
	LOS	7-day readm.	30-day readm.	30-day death	90-day death
Non-expert*post	1.857***	-0.0037	-0.0044	0.0001	0.0015
	(0.241)	(0.0038)	(0.0063)	(0.0009)	(0.0012)
Observations	226,467	226,467	226,467	226,467	226,467
Mean of Y (Pre-ZDMP)	10.855	0.0128	0.0396	0.0015	0.0036

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. In this analysis, we keep public hospitals only. Non-expert*post takes 1 if a patient is an non-expert and the time is after ZDMP, as specified in Equation (2). All specifications include 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: Expertise, Connection, and Rank: Health Care Utilization (costs) of Orthopedics Patients

	Panel A. Same-hospital higher-ranked expert patients vs Non-expert patients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drug	Surgical	Diagnostic test	Imaging test	Medical service	Material	Nursing & bed	Total
Expert 1*post	507.02***	-244.79*	-286.57***	-369.19***	-977.30***	-699.77*	-145.22***	-2,230.48***
	(163.89)	(143.47)	(62.42)	(60.07)	(94.32)	(373.31)	(36.91)	(667.33)
Observations	221,858	221,858	221,858	221,858	221,858	221,858	221,858	221,858
Mean of Y (Pre-ZDMP)	2,532.02	222.09	483.32	698.68	1,705.08	1,479.58	376.14	7,544.33
	Panel B. Same-hospital lower-ranked expert patients vs Non-expert patients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drug	Surgical	Diagnostic test	Imaging test	Medical service	Material	Nursing & bed	Total
Expert 2*post	383.05**	-220.06***	-206.48***	-206.20***	-793.82***	-448.05*	-115.33***	-1,622.46***
	(151.09)	(78.28)	(41.01)	(54.12)	(123.82)	(262.49)	(30.55)	(451.22)
Observations	222,002	222,002	222,002	222,002	222,002	222,002	222,002	222,002
Mean of Y (Pre-ZDMP)	2,531.92	221.61	482.34	696.21	1,708.44	1,478.86	375.36	7,542.10
	Panel C. Different-hospital expert patients vs Non-expert patients							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drug	Surgical	Diagnostic test	Imaging test	Medical service	Material	Nursing & bed	Total
Expert 3*post	224.79**	-39.98	-58.63**	-80.18**	-427.53***	-360.47	-88.25***	-850.75**
	(88.23)	(72.75)	(26.40)	(33.53)	(84.47)	(290.68)	(19.46)	(422.23)
Observations	223,817	223,817	223,817	223,817	223,817	223,817	223,817	223,817
Mean of Y (Pre-ZDMP)	2,535.75	222.76	482.90	698.91	1,705.88	1487.62	376.12	7,557.59

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. In this analysis, we keep public hospitals only. Expert 1*post takes 1 if a patient is a same-hospital higher-ranked expert and the time is after ZDMP, as specified in Equation (3). Expert 2*post takes 1 if a patient is a same-hospital lower-ranked expert and the time is after ZDMP, as specified in Equation (3). Expert 3*post takes 1 if a patient is a non-same hospital expert and the time is after ZDMP, as specified in Equation (3). All specifications include 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.

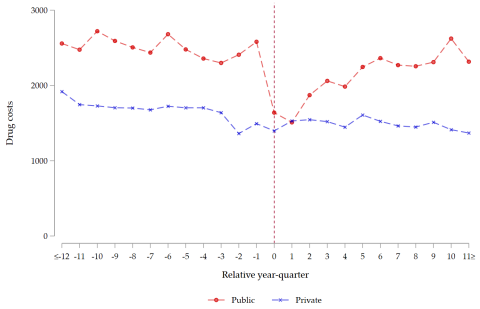
Table 5: Expertise, Connection, and Rank: Length of Stay and Health Outcomes of Orthopedics Patients

	Panel A. Same-hospital higher-ranked expert patients vs Non-expert patients				
	(1)	(2)	(3)	(4)	(5)
	LOS	7-day readm.	30-day readm.	30-day death	90-day death
Expert 1*post	-2.695***	0.0068	-0.0005	-0.0007	-0.0005
	(0.464)	(0.0052)	(0.0079)	(0.0004)	(0.0006)
Observations	221,858	221,858	221,858	221,858	221,858
Mean of Y (Pre-ZDMP)	10.828	0.0129	0.0399	0.0015	0.0036
	Panel B. Same-hospital lower-ranked expert patients vs Non-expert patients				
	(1)	(2)	(3)	(4)	(5)
	LOS	7-day readm.	30-day readm.	30-day death	90-day death
Expert 2*post	-2.248***	-0.0038	-0.0144*	-0.0009	-0.0017
	(0.372)	(0.0033)	(0.0075)	(0.0008)	(0.0011)
Observations	222,002	222,002	222,002	222,002	222,002
Mean of Y (Pre-ZDMP)	10.821	0.0129	0.0399	0.0015	0.0036
	Panel C. Different hospital expert patients vs Non-expert patients				
	(1)	(2)	(3)	(4)	(5)
	LOS	7-day readm.	30-day readm.	30-day death	90-day death
Expert 3*post	-1.377***	0.0055	0.0130	0.0002	-0.0021
	(0.326)	(0.0056)	(0.0108)	(0.0015)	(0.0019)
Observations	223,817	223,817	223,817	223,817	223,817
Mean of Y (Pre-ZDMP)	10.824	0.0130	0.0399	0.0015	0.0037

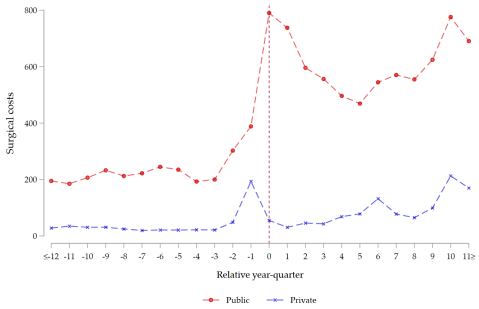
Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. In this analysis, we keep public hospitals only. Expert 1*post takes 1 if a patient is a same-hospital higher-ranked expert and the time is after ZDMP, as specified in Equation (3). Expert 2*post takes 1 if a patient is a same-hospital lower-ranked expert and the time is after ZDMP, as specified in Equation (3). Expert 3*post takes 1 if a patient is a non-same hospital expert and the time is after ZDMP, as specified in Equation (3). All specifications include 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

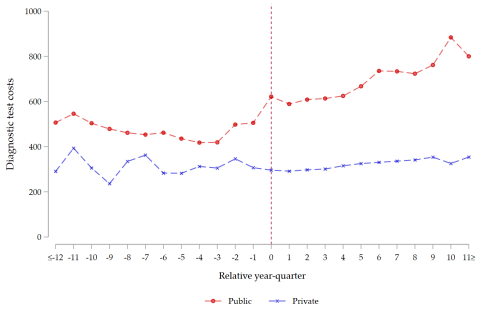
Figure A1: Public vs. Private Hospitals: Health Care Utilization Raw Trends



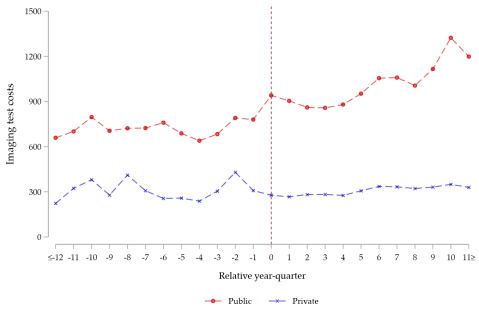
(a) Drug costs



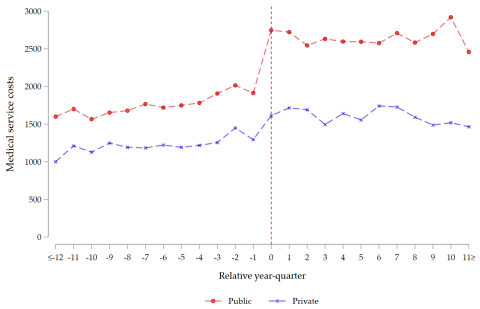
(b) Surgical costs



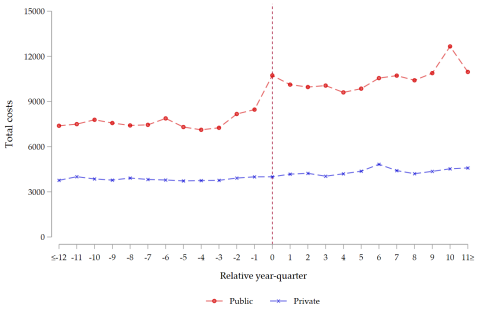
(c) Diagnostic test costs



(d) Imaging test costs

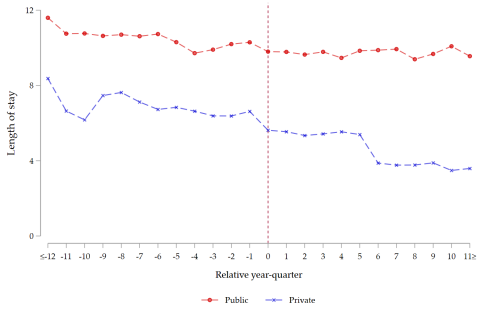


(e) Medical services costs

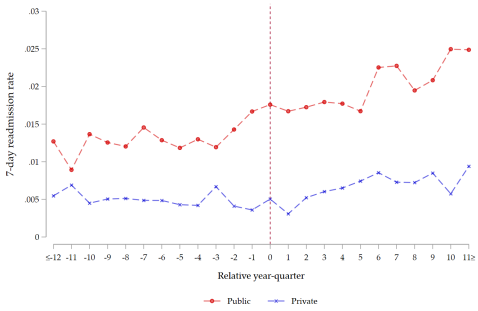


(f) Total costs

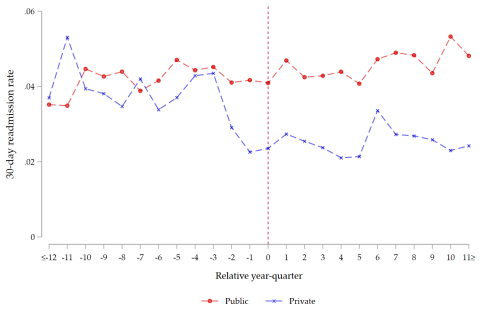
Figure A2: Public vs. Private Hospitals: Length of Stay and Health Outcomes Raw Trends



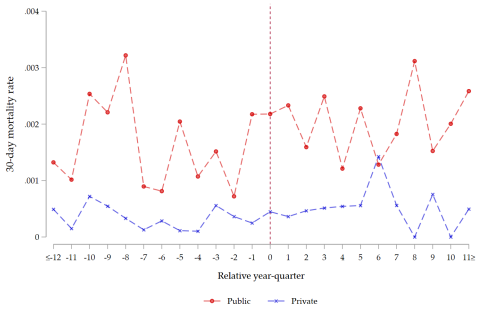
(a) Length of stay



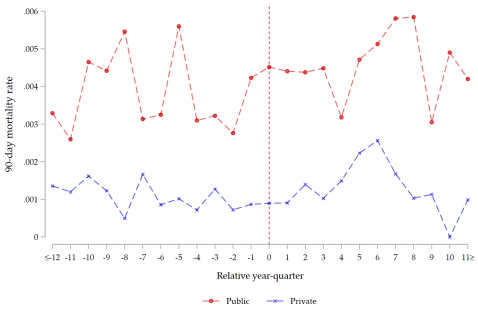
(b) Readmission within 7 days



(c) Readmission within 30 days

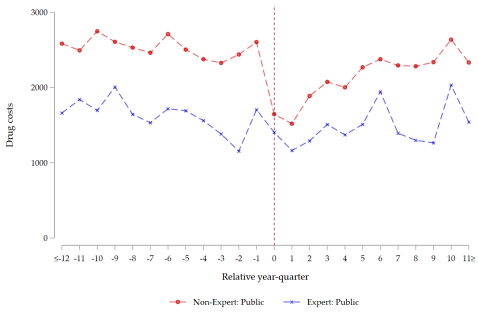


(d) 30-day mortality rate

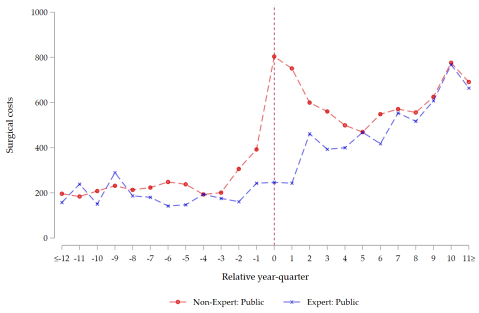


(e) 90-day mortality rate

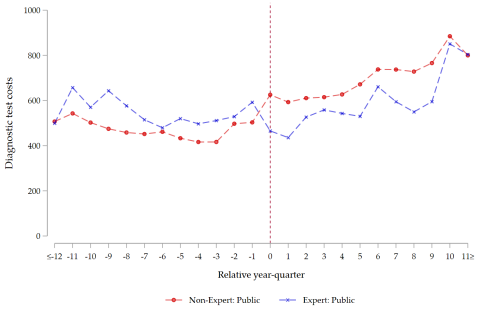
Figure A3: Non-expert vs. Expert Patients: Health Care Utilization Raw Trends



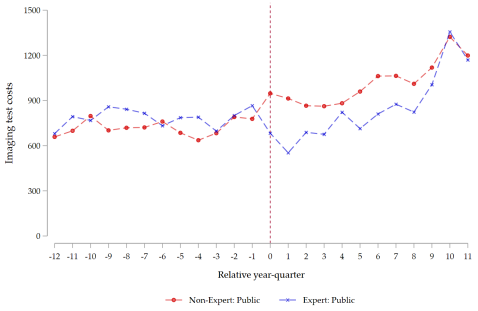
(a) Drug costs



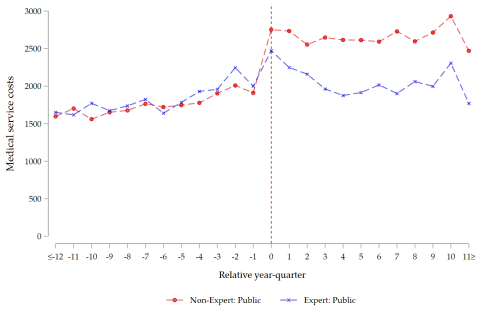
(b) Surgical costs



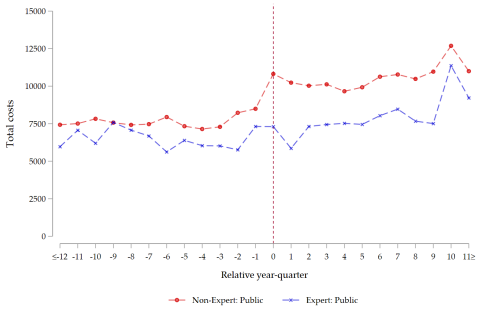
(c) Diagnostic test costs



(d) Imaging test costs



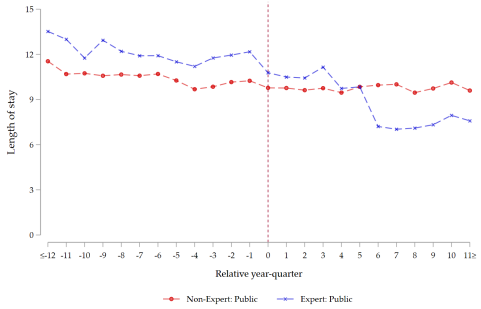
(e) Medical services costs



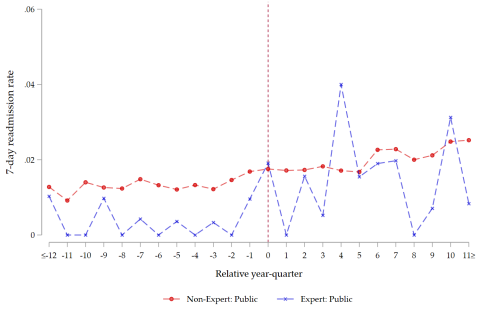
(f) Total costs

Notes: relative to experts, how non-experts' medical utilization changes over time.

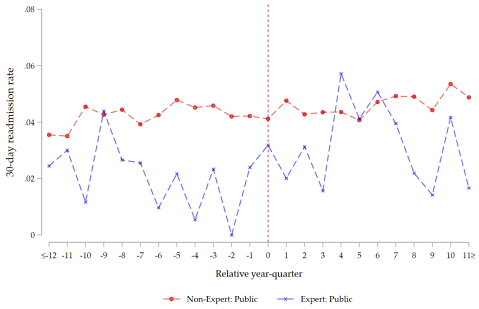
Figure A4: Non-expert vs. Expert Patients: Length of Stay and Health Outcomes Raw Trends



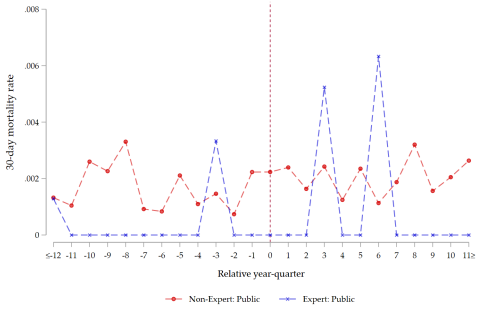
(a) Length of stay



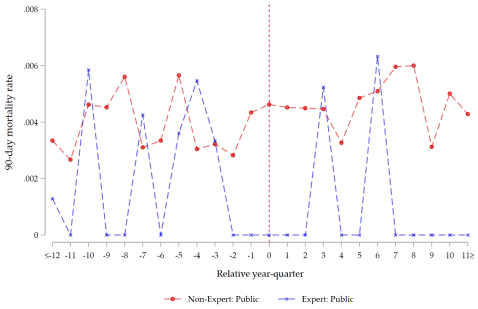
(b) Readmission within 7 days



(c) Readmission within 30 days

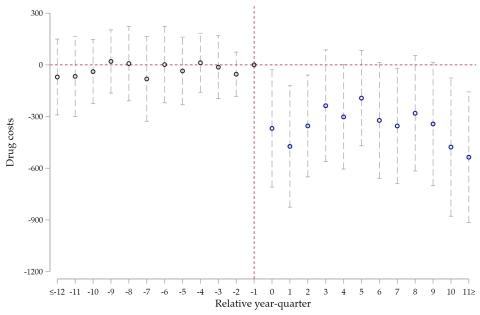


(d) 30-day mortality rate

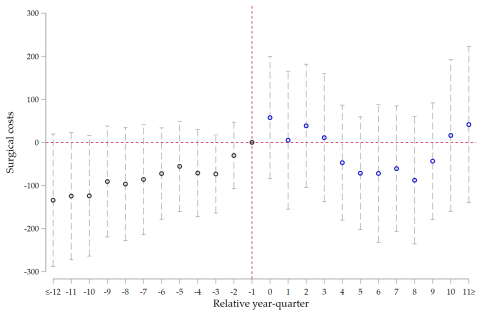


(e) 90-day mortality rate

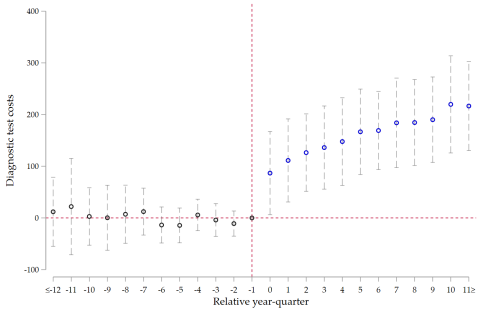
Figure A5: Event Study for DDD Results: Health Care Utilization



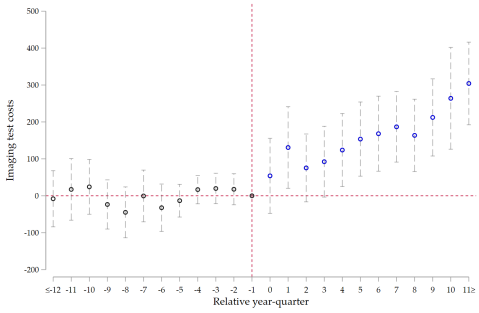
(a) Drug costs



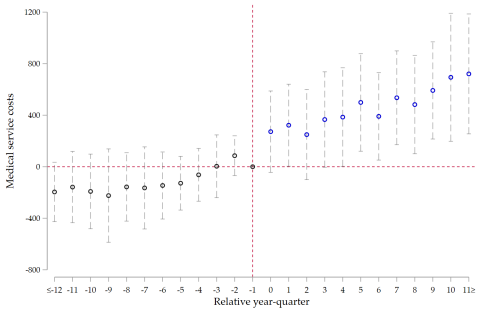
(b) Surgical costs



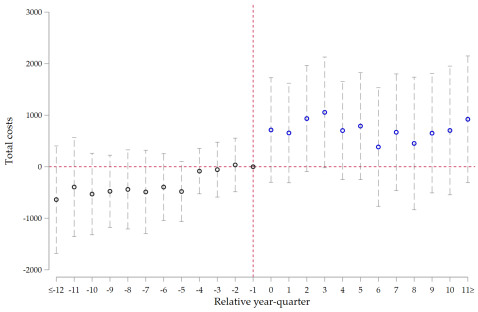
(c) Diagnostic test costs



(d) Imaging test costs



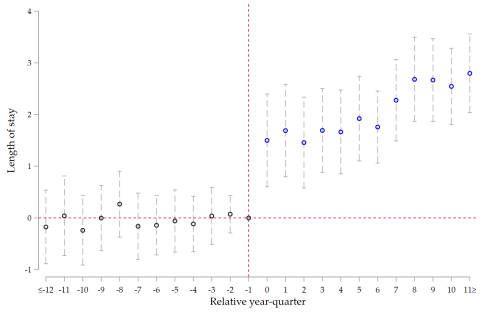
(e) Medical services costs



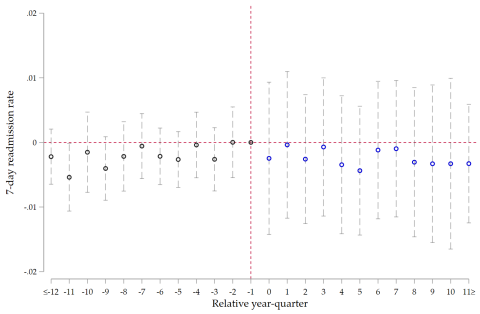
(f) Total costs

Notes: These figures show health care utilization of expert orthopedic patients, relative to non-expert orthopedic patients in public hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

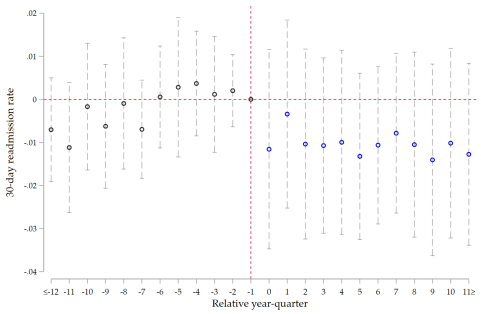
Figure A6: Event Study for DDD Results: Length of Stay and Health Outcomes



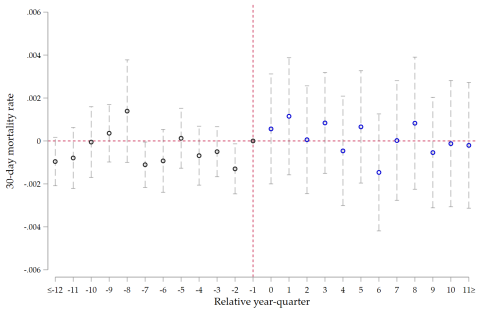
(a) Length of stay



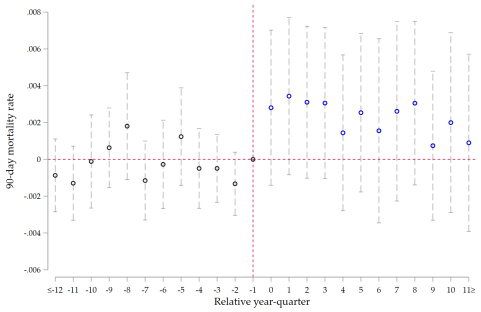
(b) Readmission within 7 days



(c) Readmission within 30 days



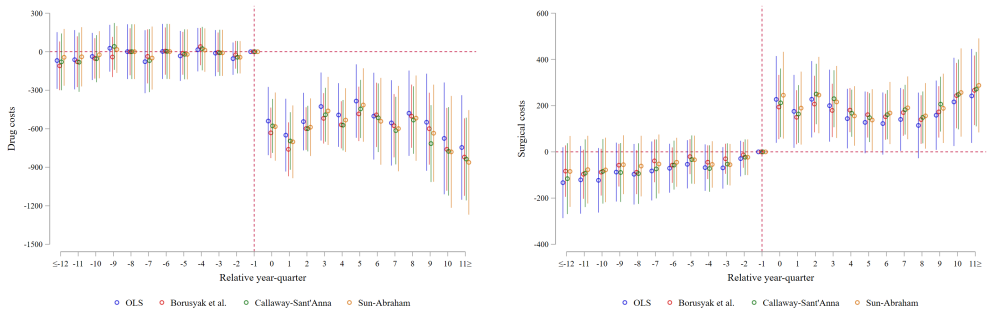
(d) 30-day mortality rate



(e) 90-day mortality rate

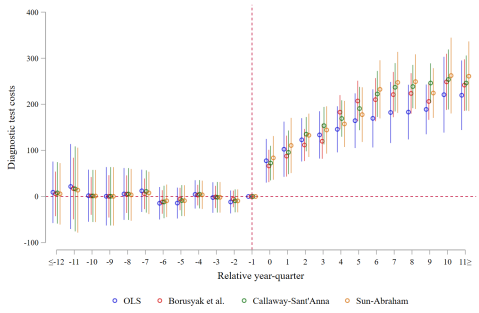
Notes: These figures show length of stay and total expenditures of expert orthopedic patients, relative to non-expert orthopedic patients in public hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Figure A7: Public vs. Private Hospitals: Health Care Utilization (Costs) – Staggered DID

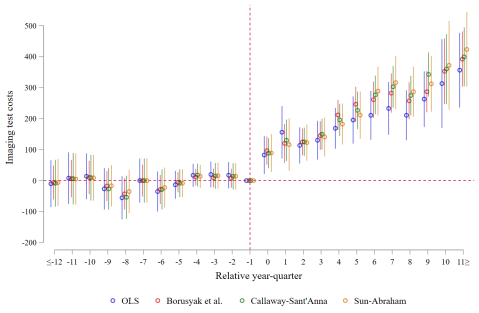


(a) Drug costs

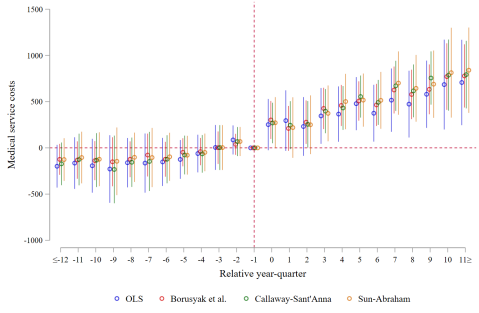
(b) Surgical costs



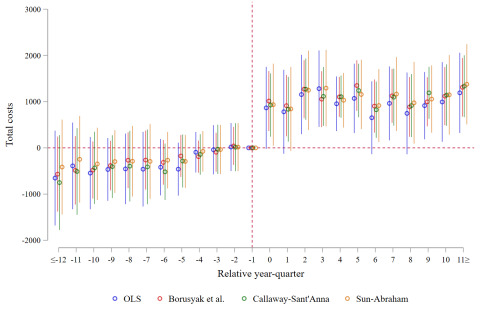
(c) Diagnostic test costs



(d) Imaging test costs



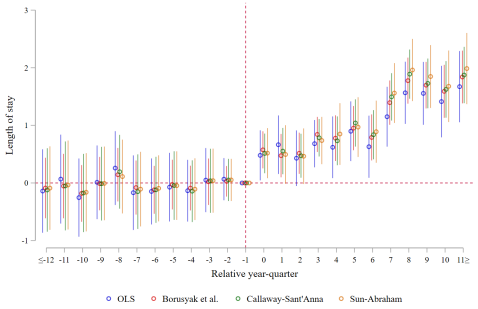
(e) Medical services costs



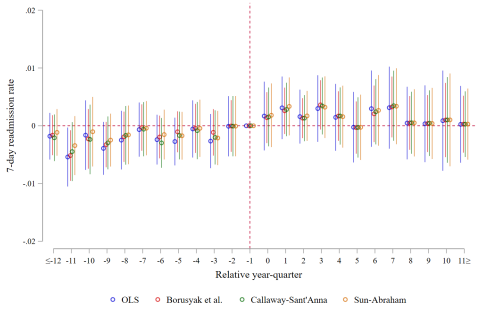
(f) Total costs

Notes: These figures show health care utilization of orthopedic patients in public hospitals relative to private hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

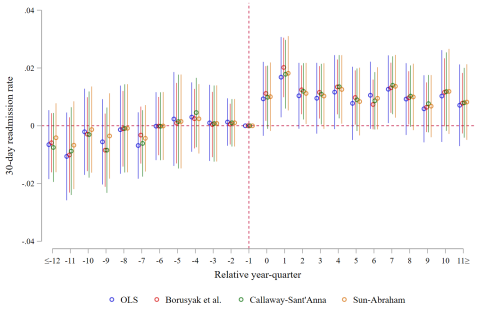
Figure A8: Public vs. Private Hospitals: Length of Stay and Health Outcomes – Staggered DID



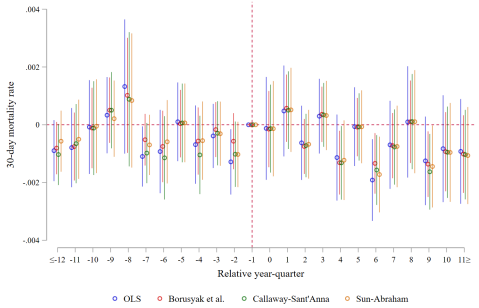
(a) Length of stay



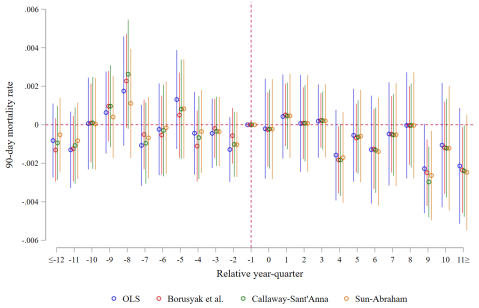
(b) Readmission within 7 days



(c) Readmission within 30 days



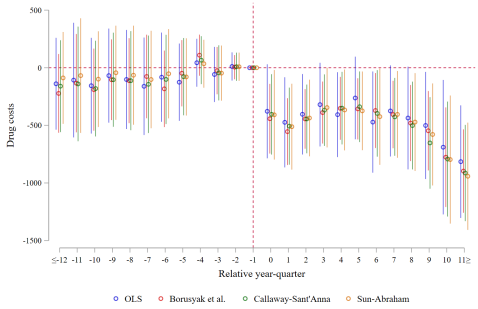
(d) 30-day mortality rate



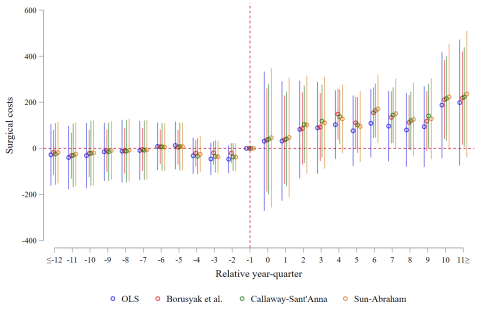
(e) 90-day mortality rate

Notes: These figures show health outcomes of orthopedic patients in public hospitals relative to private hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

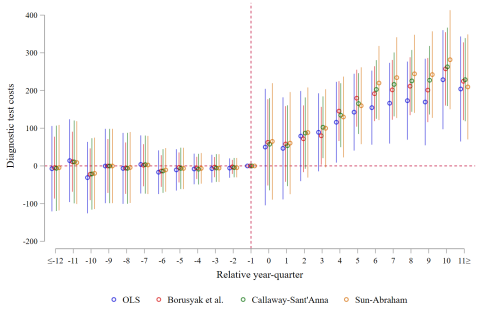
Figure A9: Non-expert vs. Expert Patients in Public Hospitals: Health Care Utilization (Costs) – Staggered DID



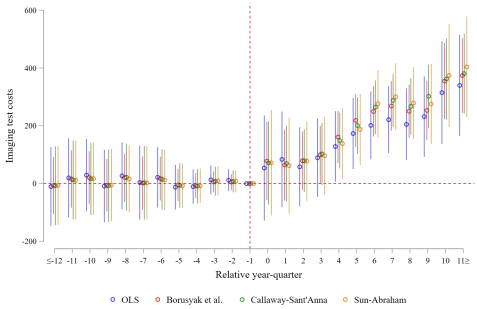
(a) Drug costs



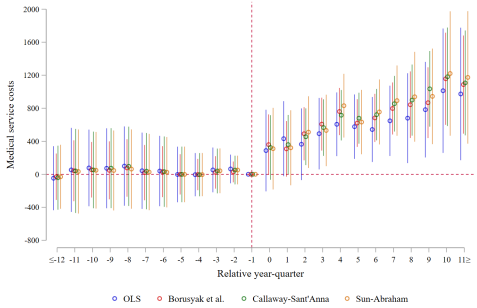
(b) Surgical costs



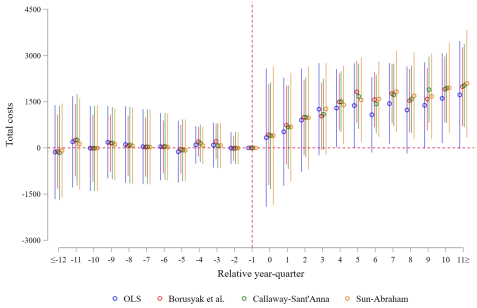
(c) Diagnostic test costs



(d) Imaging test costs



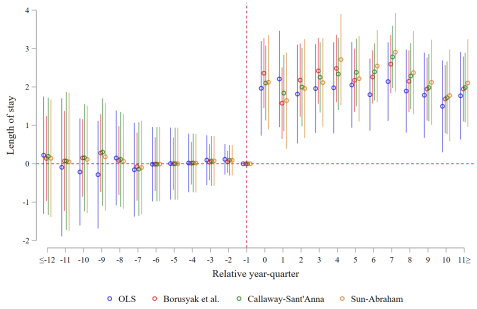
(e) Medical services costs



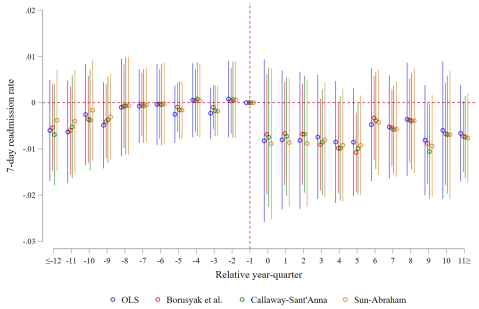
(f) Total costs

Notes: These figures show health care utilization of orthopedic patients in public hospitals relative to private hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

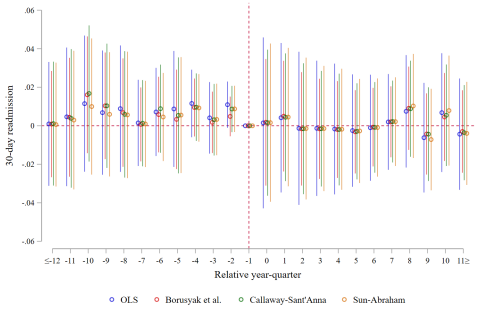
Figure A10: Non-expert vs. Expert Patients in Public Hospitals: Length of Stay and Health Outcomes – Staggered DID



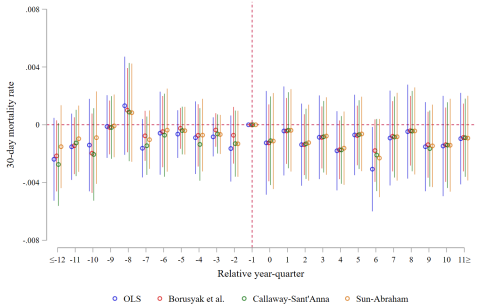
(a) Length of stay



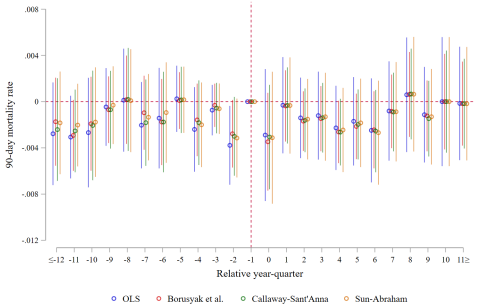
(b) Readmission within 7 days



(c) Readmission within 30 days



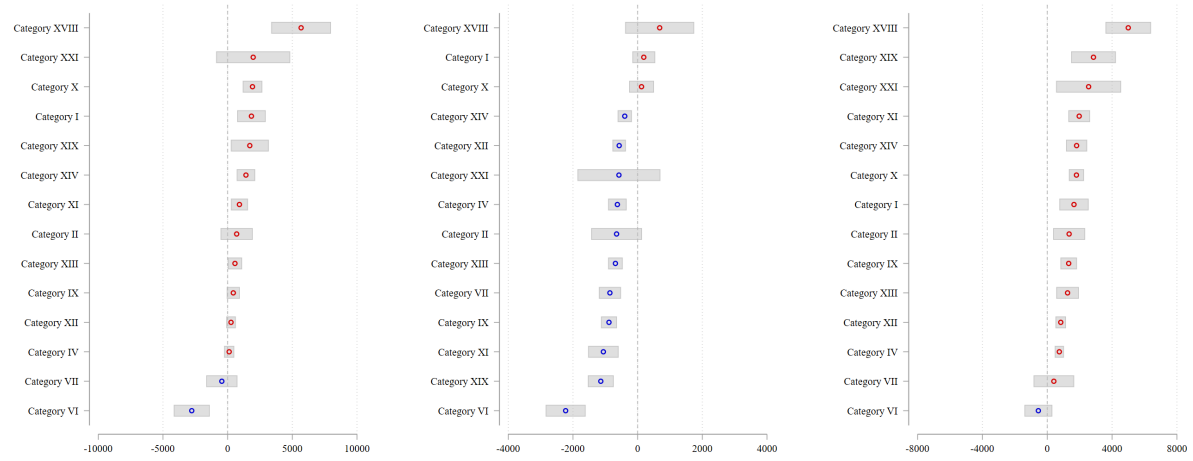
(d) 30-day mortality rate



(e) 90-day mortality rate

Notes: These figures show health outcomes of orthopedic patients in public hospitals relative to private hospitals before and after ZDMP. Event study results are shown in the figures. Dots represent point estimates. Caps indicate 95% confidence intervals. The number in the parentheses of Y-axis represents the mean of Y in relative year -1. Hospital fixed effects and year-quarter fixed effects are included in regressions. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

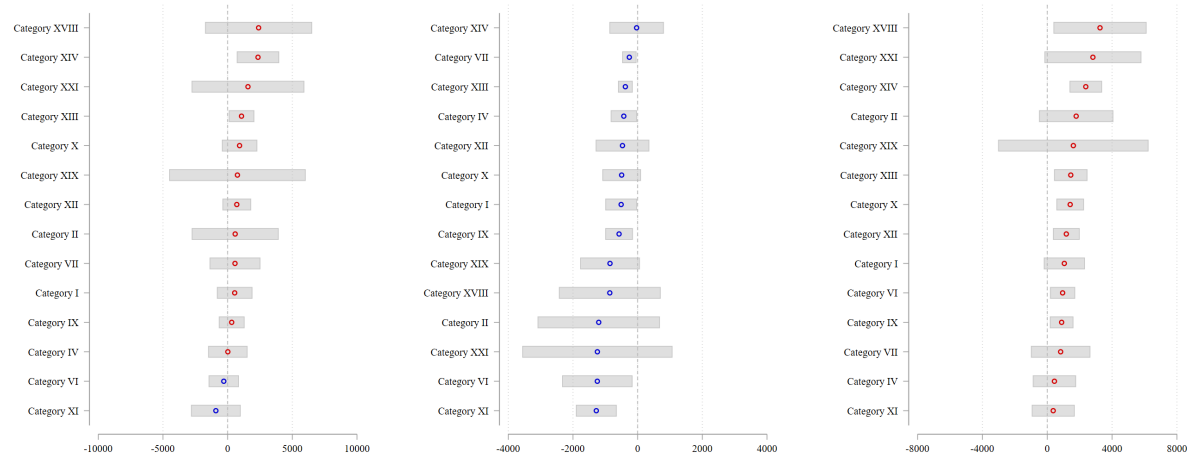
Figure A11: Public (=1) vs. Private (=0) Hospitals by Disease



(a) Total costs (b) Drug costs (c) Non-drug costs

Notes: These figures compare the effects of ZDMP on health care utilization outcomes between public and private hospitals by diseases. Categories of disease (ICD-10 version) include: I. Certain infectious and parasitic diseases; II. Neoplasms; III. Diseases of the blood and immune mechanism; IV. Endocrine, nutritional and metabolic diseases; V. Mental and behavioural disorders; VI. Diseases of the nervous system; VII. Diseases of the eye and adnexa; VIII. Diseases of the ear and mastoid process; IX. Diseases of the circulatory system; X. Diseases of the respiratory system; XI. Diseases of the digestive system; XII. Diseases of the skin and subcutaneous tissue; XIII. Diseases of the musculoskeletal system and connective tissue; XIV. Diseases of the genitourinary system; XV. Pregnancy, childbirth and the puerperium; XVI. Certain conditions originating in the perinatal period; XVII. Congenital malformations, deformations and chromosomal abnormalities; XVIII. Symptoms, signs and abnormal clinical and laboratory findings; XIX. Injury and results of external causes; XX. External causes of morbidity and mortality; XXI. Factors influencing health status and contact with health services; XXII. special purposes. Dots represent point estimates **(with blue color for negative estimates and red color for positive estimates)**. Shadow bars indicate 90% confidence intervals. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Figure A12: Non-expert Patients (=1) vs. Expert Patients (=0) in Public Hospitals by Disease



(a) Total costs (b) Drug costs (c) Non-drug costs

Notes: These figures compare the effects of ZDMP on health care utilization outcomes between expert patients and non-expert patients in public hospitals by diseases. Categories of disease (ICD-10 version) include: I. Certain infectious and parasitic diseases; II. Neoplasms; III. Diseases of the blood and immune mechanism; IV. Endocrine, nutritional and metabolic diseases; V. Mental and behavioural disorders; VI. Diseases of the nervous system; VII. Diseases of the eye and adnexa; VIII. Diseases of the ear and mastoid process; IX. Diseases of the circulatory system; X. Diseases of the respiratory system; XI. Diseases of the digestive system; XII. Diseases of the skin and subcutaneous tissue; XIII. Diseases of the musculoskeletal system and connective tissue; XIV. Diseases of the genitourinary system; XV. Pregnancy, childbirth and the puerperium; XVI. Certain conditions originating in the perinatal period; XVII. Congenital malformations, deformations and chromosomal abnormalities; XVIII. Symptoms, signs and abnormal clinical and laboratory findings; XIX. Injury and results of external causes; XX. External causes of morbidity and mortality; XXI. Factors influencing health status and contact with health services; XXII. special purposes. Dots represent point estimates **(with blue color for negative estimates and red color for positive estimates)**. Shadow bars indicate 90% confidence intervals. Standard errors are clustered at the hospital level, adjusted for within-cluster correlation and heteroskedasticity.

Table A1: Descriptive Statistics: Public Hospitals vs Private Hospitals, Orthopedics Patients

	Public hospitals		Private hospitals	
	(1)	(2)	(3)	(4)
	Pre	Post	Pre	Post
	Panel A. Outcome variables			
Health care utilization (costs)				
Drug	2,517.54	2,084.23	1,735.62	1,492.24
	(3,116.82)	(2,812.71)	(933.46)	(948.33)
Surgery	221.37	614.93	37.69	66.08
	(825.96)	(1,935.66)	(419.24)	(512.05)
Diagnostic test	483.69	685.08	306.43	314.77
	(452.76)	(679.37)	(216.51)	(191.14)
Imaging test	698.80	995.18	283.34	295.80
	(771.83)	(1,123.31)	(327.24)	(318.92)
Medical service	1,707.43	2,642.26	1,162.51	1,622.80
	(1,360.34)	(2,222.68)	(1,031.79)	(1,146.77)
Materials	1,474.06	2,793.04	78.24	212.68
	(6,923.31)	(9,669.02)	(1,029.62)	(1,946.08)
Nursing and bed	375.82	575.85	185.92	225.08
	(335.54)	(532.82)	(148.52)	(202.54)
Total	7,526.14	10,457.56	3,814.43	4,243.00
	(10,731.74)	(15,358.81)	(2,239.93)	(3,390.46)
LOS and health outcomes				
Length of stay	10.855	9.731	7.283	4.953
	(5.082)	(4.878)	(3.434)	(2.333)
7-day readmission rate	0.0128	0.0196	0.0051	0.0061
	(0.1125)	(0.1386)	(0.0715)	(0.0779)
30-day readmission rate	0.0396	0.0452	0.0377	0.0252
	(0.1950)	(0.2078)	(0.1904)	(0.1567)
30-day death rate	0.0015	0.0020	0.0004	0.0005
	(0.0388)	(0.0451)	(0.0194)	(0.0224)
90-day death rate	0.0036	0.0045	0.0012	0.0013
	(0.0600)	(0.0670)	(0.0340)	(0.0360)
	Panel B. Individual and hospital characteristics			
Demographic characteristics				
Age (in years)	57.076	57.639	58.198	59.035
	(12.200)	(12.703)	(10.419)	(10.482)
Gender (1 = female)	0.658	0.634	0.702	0.689
	(0.474)	(0.482)	(0.457)	(0.463)
Hukou status (1 = rural)	0.051	0.063	0.040	0.051
	(0.220)	(0.244)	(0.196)	(0.221)
Expertise (1 = health related employment)	0.026	0.025	0.018	0.018
	(0.160)	(0.156)	(0.134)	(0.135)
Rank (1 = Cadre)	0.160	0.140	0.077	0.062
	(0.367)	(0.347)	(0.266)	(0.242)
Hospital tier				
Share of Tier 1	0.132	0.176	0.688	0.626
	(0.339)	(0.381)	(0.463)	(0.484)
Share of Tier 2	0.312	0.171	0.294	0.356
	(0.463)	(0.376)	(0.456)	(0.479)
Share of Tier 3	0.556	0.653	0.018	0.018
	(0.497)	(0.476)	(0.134)	(0.133)
Observation	150,363	76,107	130,710	71,641

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. Means of variables are reported with standard deviations in parentheses.

Table A2: Descriptive Statistics: Non-expert vs Expert Orthopedics Patients in Public Hospitals

	Non-expert patients		Expert patients	
	(1)	(2)	(3)	(4)
	Pre	Post	Pre	Post
	Panel A. Outcome variables			
Health care utilization (costs)				
Drug	2,541.26	2,100.71	1,638.75	1,444.70
	(3,139.67)	(2,824.66)	(1,903.90)	(2,208.85)
Surgery	222.55	619.04	177.61	455.15
	(829.25)	(1,945.49)	(691.70)	(1,497.04)
Diagnostic test	482.41	687.94	531.27	574.002
	(450.67)	(680.32)	(522.22)	(631.53)
Imaging test	697.48	999.98	747.73	809.03
	(769.58)	(1,124.17)	(849.71)	(1,073.08)
Medical service	1,705.95	2,657.37	1,762.18	2,056.13
	(1,361.41)	(2,233.535)	(1,319.11)	(1,647.05)
Materials	1,486.10	2,816.48	1,027.66	1,883.39
	(6,956.73)	(9,720.83)	(5,526.51)	(7,327.24)
Nursing and bed	375.89	579.11	373.32	449.403
	(335.91)	(534.84)	(321.76)	(428.63)
Total	7,559.18	10,528.21	6,301.94	7,716.25
	(10,788.85)	(15,433.10)	(8,252.27)	(11,810.84)
LOS and health outcomes				
Length of stay	10.807	9.747	12.612	9.106
	(5.046)	(4.871)	(5.991)	(5.101)
7-day readmission rate	0.0130	0.0197	0.0058	0.0146
	(0.1133)	(0.1391)	(0.0761)	(0.1202)
30-day readmission rate	0.0401	0.0456	0.0223	0.0319
	(0.1961)	(0.2086)	(0.1476)	(0.1758)
30-day death rate	0.0015	0.0021	0.0008	0.0010
	(0.0391)	(0.0454)	(0.0275)	(0.0323)
90-day death rate	0.0037	0.0046	0.0018	0.0010
	(0.0600)	(0.0670)	(0.0421)	(0.0323)
	Panel B. Individual and hospital characteristics			
Demographic characteristics				
Age (in years)	57.243	57.803	50.895	51.293
	(12.047)	(12.584)	(15.711)	(15.403)
Gender (1 = female)	0.655	0.630	0.759	0.762
	(0.475)	(0.483)	(0.428)	(0.426)
Hukou status (1 = rural)	0.051	0.064	0.049	0.055
	(0.220)	(0.244)	(0.215)	(0.229)
Rank (1 = Cadre)	0.152	0.134	0.467	0.360
	(0.359)	(0.341)	(0.499)	(0.480)
Hospital tier				
Share of Tier 1	0.131	0.175	0.163	0.211
	(0.338)	(0.380)	(0.369)	(0.408)
Share of Tier 2	0.313	0.170	0.272	0.223
	(0.464)	(0.375)	(0.445)	(0.416)
Share of Tier 3	0.556	0.655	0.565	0.566
	(0.497)	(0.475)	(0.496)	(0.496)
Observation	146,412	74,195	3,951	1,912

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. Means of variables are reported with standard deviations in parentheses.

Table A3: Descriptive Statistics: Non-expert vs Subgroups of expert Orthopedics Patients in Public Hospitals

	Non-expert		Same-hospital high rank expert		Same-hospital low rank expert		Different hospital expert	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Panel A. Outcome variables								
Health care utilization (costs)								
Drug	2,541.26	2,100.71	1,057.25	767.88	995.38	640.46	2,156.64	2,033.90
	(3,139.67)	(2,824.66)	(887.48)	(1,003.15)	(1,119.67)	(598.85)	(2,290.71)	(2,724.24)
Surgery	222.55	619.04	147.68	280.74	67.03	117.49	236.55	668.36
	(829.25)	(1,945.49)	(595.23)	(892.85)	(350.65)	(635.12)	(819.33)	(1,857.20)
Diagnostic test	482.41	687.94	627.26	514.00	469.93	401.53	515.61	673.85
	(450.67)	(680.32)	(547.98)	(540.36)	(519.41)	(381.00)	(506.54)	(725.89)
Imaging test	697.48	999.98	889.02	729.80	486.16	413.32	796.08	1,019.92
	(769.58)	(1,124.17)	(890.44)	(918.83)	(674.73)	(598.16)	(874.04)	(1,225.57)
Medical service	1,705.95	2,657.37	1,565.15	1,631.42	2,114.72	1,848.92	1,699.85	2,285.86
	(1,361.41)	(2,233.535)	(1,117.61)	(1,331.34)	(1,307.86)	(1,391.31)	(1,375.61)	(1,801.67)
Materials	1,486.10	2,816.48	437.53	747.12	287.84	344.23	1,589.46	2,961.49
	(6,956.73)	(9,720.83)	(2,439.66)	(3,279.31)	(2,545.97)	(2,094.64)	(7,103.03)	(9,360.70)
Nursing and bed	375.89	579.11	414.62	436.21	287.82	297.46	391.23	525.01
	(335.91)	(534.84)	(276.84)	(341.07)	(271.37)	(249.22)	(351.45)	(495.51)
Total	7,559.18	10,528.21	5,171.75	5,141.33	4,729.95	4,084.30	7,442.53	10,227.12
	(10,788.85)	(15,433.10)	(4,015.70)	(5,869.63)	(4,286.73)	(4,229.47)	(10,406.78)	(14,661.85)
LOS and health outcomes								
Length of stay	10.807	9.747	13.995	9.724	12.885	8.229	11.903	9.327
	(5.046)	(4.871)	(6.396)	(5.404)	(5.617)	(4.474)	(5.851)	(5.231)
7-day readmission rate	0.0130	0.0197	0.0022	0.0120	0.0011	0.0020	0.0093	0.0214
	(0.1133)	(0.1391)	(0.0467)	(0.1089)	(0.0335)	(0.0445)	(0.0962)	(0.1449)
30-day readmission rate	0.0401	0.0456	0.0120	0.0179	0.0099	0.0150	0.0285	0.0475
	(0.1961)	(0.2086)	(0.1088)	(0.1328)	(0.0991)	(0.1216)	(0.1664)	(0.2129)
30-day death rate	0.0015	0.0021	0	0	0	0	0.0014	0.0019
	(0.0391)	(0.0454)	(0)	(0)	(0)	(0)	(0.0374)	(0.0432)
90-day death rate	0.0037	0.0046	0	0	0	0	0.0033	0.0019
	(0.0600)	(0.0670)	(0)	(0)	(0)	(0)	(0.0571)	(0.0432)
Panel B. Individual and hospital characteristics								
Demographic characteristics								
Age (in years)	57.243	57.803	49.853	53.517	46.626	46.312	53.122	52.945
	(12.047)	(12.584)	(13.810)	(12.443)	(15.125)	(14.555)	(16.300)	(16.102)
Gender (1 = female)	0.655	0.630	0.803	0.817	0.767	0.788	0.736	0.732
	(0.475)	(0.483)	(0.398)	(0.387)	(0.423)	(0.409)	(0.441)	(0.443)
Hukou status (1 = rural)	0.051	0.064	0.017	0.021	0.066	0.074	0.055	0.058
	(0.220)	(0.244)	(0.131)	(0.143)	(0.249)	(0.261)	(0.227)	(0.233)
Hospital tier								
Share of Tier 1	0.131	0.175	0.096	0.102	0.239	0.372	0.160	0.170
	(0.338)	(0.380)	(0.294)	(0.303)	(0.427)	(0.484)	(0.367)	(0.375)
Share of Tier 2	0.313	0.170	0.144	0.165	0.402	0.360	0.272	0.176
	(0.464)	(0.375)	(0.351)	(0.371)	(0.491)	(0.481)	(0.445)	(0.381)
Share of Tier 3	0.556	0.655	0.761	0.734	0.359	0.267	0.568	0.654
	(0.497)	(0.475)	(0.427)	(0.443)	(0.480)	(0.443)	(0.496)	(0.476)
Observation	146,412	74,195	919	334	892	505	2,140	1,073

Notes: Individuals' claim-level data from November 2010 to December 2018. Means of variables are reported with standard deviations in parentheses.

Table A4: Effects of ZDMP on Health Care Utilization (Quantity)

	Panel A. Public vs. Private hospitals				
	(1)	(2)	(3)	(4)	(5)
	# of unique drugs	# of surgeries	# of diagnostic tests	# of imaging tests	# of medical services
Public*post	-2.414***	0.082***	5.617***	1.851**	42.474**
	(0.379)	(0.025)	(1.429)	(0.811)	(19.585)
Observations	428,814	428,814	428,814	428,814	428,814
Mean of Y (Pre-ZDMP)	9.768	0.137	21.564	10.257	123.022
	Panel B. Non-expert patients vs. Expert patients				
	(1)	(2)	(3)	(4)	(5)
	# of unique drugs	# of surgeries	# of diagnostic tests	# of imaging tests	# of medical services
Non-expert*post	-3.638***	0.094***	3.855***	3.091***	47.852**
	(0.451)	(0.032)	(0.889)	(0.805)	(19.087)
Observations	226,467	226,467	226,467	226,467	226,467
Mean of Y (Pre-ZDMP)	10.578	0.222	21.298	13.964	108.057
	Panel C. Same-hospital higher-ranked expert patients vs Non-expert patients				
	(1)	(2)	(3)	(4)	(5)
	# of unique drugs	# of surgeries	# of diagnostic tests	# of imaging tests	# of medical services
Expert1*post	4.331***	-0.108**	-5.998***	-4.300***	-73.410***
	(0.781)	(0.050)	(1.591)	(1.414)	(14.808)
Observations	221,858	221,858	221,858	221,858	221,858
Mean of Y (Pre-ZDMP)	10.603	0.222	21.318	13.985	106.580
	Panel D. Same-hospital lower-ranked expert patients vs Non-expert patients				
	(1)	(2)	(3)	(4)	(5)
	# of unique drugs	# of surgeries	# of diagnostic tests	# of imaging tests	# of medical services
Expert2*post	3.571***	-0.101*	-4.441***	-3.495***	-60.778
	(0.776)	(0.057)	(1.570)	(1.142)	(58.073)
Observations	222,002	222,002	222,002	222,002	222,002
Mean of Y (Pre-ZDMP)	10.602	0.222	21.319	13.960	107.234
	Panel E. Different hospital expert patients vs Non-expert patients				
	(1)	(2)	(3)	(4)	(5)
	# of unique drugs	# of surgeries	# of diagnostic tests	# of imaging tests	# of medical services
Expert3*post	3.147***	-0.094**	-2.923***	-2.687**	-38.357***
	(0.384)	(0.039)	(0.896)	(1.138)	(5.404)
Observations	223,817	223,817	223,817	223,817	223,817
Mean of Y (Pre-ZDMP)	10.613	0.223	21.317	13.995	106.981

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 ZDMP, as specified in Equation (1). Non-expert*post takes 1 if a patient is an non-expert and the time is after ZDMP, as specified in Equation (2). Expert 1*post takes 1 if a patient is a same-hospital higher-ranked expert and the time is after ZDMP, as specified in Equation (3). Expert 2*post takes 1 if a patient is a same-hospital lower-ranked expert and the time is after ZDMP, as specified in Equation (3). Expert 3*post takes 1 if a patient is a non-same hospital expert and the time is after ZDMP, as specified in Equation (3). All specifications include 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 A5: Outcomes of ZDMP: DDD Results

	Panel A. Health care utilization (costs)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drug	Surgical	Diagnostic test	Imaging test	Medical service	Material	Nursing & bed	Total
Public*Non-expert*post	-311.54**	77.73	153.65***	157.49***	574.07***	368.66*	108.96***	1,140.55***
	(129.07)	(69.31)	(32.46)	(38.39)	(108.71)	(211.27)	(20.39)	(331.76)
Observations	428,814	428,814	428,814	428,814	428,814	428,814	428,814	428,814
Mean of Y (Pre-ZDMP)	2,153.94	135.96	401.27	505.61	1,454.05	824.97	287.51	5,800.13

	Panel B. LOS and health outcomes				
	(9)	(10)	(11)	(12)	(13)
	LOS	7-day readm.	30-day readm.	30-day death	90-day death
Public*Non-expert*post	2.087***	-0.0003	-0.0071	0.0007	0.0027
	(0.289)	(0.0044)	(0.0092)	(0.0012)	(0.0020)
Observations	428,814	428,814	428,814	428,814	428,814
Mean of Y (Pre-ZDMP)	9.194	0.0092	0.0387	0.0010	0.0025

Notes: Individuals' claim-level data from November 2010 to December 2018 are used for analysis with a DID model. In this analysis, we keep public hospitals only. Public*Non-expert*post takes 1 if a patient in a public hospital is an non-expert and the time is after ZDMP, as specified in Equation (2). All specifications include 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.