Information Provision and Healthcare Quality

Online Appendix

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Contents

Appendix A The Chinese Healthcare System

China developed its healthcare system after the establishment of the People's Republic of China in 1949. One of the major achievements was an innovative three-tier system of public hospitals. The three-tier classification of hospitals is based on weighted scores that measure the number of beds, level of service provision, medical technology, medical equipment, and quality of management and medical care. In practice, the three tiers are further subdivided into 3 subsidiary levels (Ministry of Health, 1989). The first tier generally consists of community health stations and clinics that have fewer than 100 beds and are tasked with providing primary care, preventive care, and rehabilitation services at the community level. The second tier is generally represented by township hospitals in mid-size cities. They are equipped with 100 to 500 beds, and are responsible for more comprehensive health services and medical training for health workers in tier-one facilities. The third tier contains general hospitals at the city, provincial, or national level with a bed capacity exceeding 500. They provide the most sophisticated acute care and specialist services. They also play a dominant role in medical education and research, and serve as medical hubs for multiple regions.

Backed by government funding, the three-tier system was successful in improving the population's health and life expectancy across the country from 1949 to the 1980s. Between 1952 and 1982, life expectancy increased from 45 years to 68 years, the infant mortality rate fell from 200 to 34 per 1,000 live births, and longstanding scourges such as schistosomiasis were largely eradicated (Blumenthal and Hsiao, 2005). In 1984, the "China Model" was highly praised by the World Bank and the World Health Organization as an effective model for other developing countries (World Bank, 1984).

The main reason for the success of the three-tier hospital system during the 1950s to 1980s was the referral system and strong fiscal support from the government. During this period, patients had to enter the healthcare system through the first tier and were then funnelled into higher tiers for more severe cases. Patients whose diseases required more comprehensive care or intensive care were transferred from community health facilities to higher-tier hospitals. Moreover, all public hospitals were fully financed by the government.

Following the economic reforms initiated in December 1978, however, the market-oriented healthcare reforms of the 1980s and 1990s moved the Chinese healthcare system onto a different track (Blumenthal and Hsiao, 2015; Yip and Hsiao, 2008). The three-tier structure remained intact, but the reforms gave more autonomy to hospitals and dramatically cut government financing. Government funding had fallen to a mere 10% of a hospital's total revenues by the early 1990s and has stayed low ever since (Yip and Hsiao, 2008). Since the government cut fiscal support to public hospitals in the 1980s, public hospitals became responsible for their own financing. They relied increasingly on profits from the prescription of expensive medicines and use of advanced technologies, which contributed to escalating medical spending and imposed a financial burden on patients.

In parallel, the medical referral system that funnelled patients from lower-tier health facilities to higher-tier hospitals based on patients' disease severity had collapsed in the midst of the increasing autonomy of public hospitals. Patients were no longer required to enter the healthcare system from the first tier, and hospitals across different tiers started competing for patients and medical revenue. Because the higher-tier hospitals had the advantage of having more advanced medical equipment and better trained physicians, they provided better quality medical services and captured an increasing share of the local healthcare market.

The disparity between hospital tiers has rapidly widened. Tier-three hospitals have grown quickly in size and captured the lion's share of skilled physicians, patient flow, and revenue. For example, in 2014 the average tier-three hospital in China employed 26 times more physicians and nurses, treated 27 times more patients, and received 60 times more revenue than their tier-one counterparts (National Bureau of Statistics, 2015). (For additional comparisons between Chinese hospitals in different tiers, see Table 1.) In contrast, lower-tier facilities are increasingly understaffed and underfunded.[1] This has created a downward spiral in the quality and reputation of lower-tier facilities, and motivates patients to flock to tier-three hospitals regardless of the severity of their illness.

The three-tier hospital system has two important problems. First, resources are misallocated across tiers. Tier-three hospitals are overcrowded, and lower-tier hospitals are underutilized. By 2014, the bed occupancy rate in tier-three hospitals was overwhelmingly 101.8%, in contrast to only 60.1% in tier-one hospitals (National Bureau of Statistics, 2015). In comparison, the most commonly targeted bed occupancy rate is 85% in US hospitals (Green, 2006). Second, tier-three hospitals face large inefficiency. Due to overcrowding, the problems of waiting and rationing quickly escalated in tier-three hospitals—which has deterred patients with acute conditions from receiving timely care, and drives many patients to forfeit treatment without being seen. Cancellation rates, defined as the share of registered consultations that are not completed, are usually above 10% in tier-three hospitals (Chen et al., 2016). This represents a waste of limited medical resources in tier-three hospitals.

The Chinese government has recognized these challenges. In the government news outlet, the government stated in 2008 that "A wrong concept in the socialist market economy is that the medical and health care system should be market-oriented depending on market forces to meet the medical care needs of the people" (Tang et al., 2008).

In 2009, the Chinese government launched a nationwide systemic health reform, pledging to provide more affordable and equitable access to healthcare for all citizens by 2020. The reform marked a departure from the market-oriented strategy used since 1978, and reinstated the government's role in the financing of healthcare and the provision of public goods (Chen, 2009; Eggleston et al., 2008). The 2009 health reform has five objectives. First, expand public health insurance to gradually cover more than 95% of the Chinese population, including improved

1. China has a large shortage of general practitioners (GPs): In 2014, there were only 0.13 GPs per 1,000 population. GPs only account for 5.6% of all physicians across China (National Bureau of Statistics, 2015). In contrast, in the UK there are 0.8 GPs per 1,000 population, which account for 28.7% of all physicians (OECD, 2016).

coverage for urban residents, the new rural cooperative Medicare scheme for rural residents, and the improved Medicaid scheme for the poor. Second, establish a nationwide drug system with dedicated high reimbursement rates for a list of essential drugs to provide an affordable drug supply. Third, provide more public financing and infrastructure support to grassroots health facilities and county hospitals to expand health service networks in rural areas and reduce the workload for urban hospitals. Fourth, promote basic public health services. Fifth, launch the pilot reform in public hospitals. See Chen (2009) for more details.

Although the 2009 healthcare reform has made great progress in expanding insurance coverage, much work remains to improve healthcare delivery. Three long-lasting problems stand out, which also mark the main differences between the Chinese healthcare system and most Western healthcare systems: (1) there is no effective referral system in outpatient settings that directs traffic to primary-care or acute-care hospitals. (2) The price differential in registration fee is too narrow to serve as a screening device to enforce more appropriate use of different levels of healthcare services. (3) The traditional walk-in outpatient registration system presents additional information barriers for patient choice of hospitals. Information on crowdedness in the hospital and the availability of physicians is revealed to patients only after they have visited the hospital and registered for the consultation. As a result, many patients—especially those visiting crowded tier-three hospitals—were deterred by unexpectedly long queues and abandoned their registrations (Blumenthal and Hsiao, 2015).

Despite lackluster development on the supply side, the demand for health and health services is booming in China, driven by the growing middle class and an aging population. The total number of annual hospital consultations tripled from 2005 to 2014 (from 51.8 million to 153.7 million), and average hospital revenue has increased almost five times during the same period (from 55.7 million to 273.4 million) (National Bureau of Statistics, 2015). A report by the McKinsey Global Institute predicts that healthcare spending in China will reach 1 trillion USD by 2020, up from 350 billion in 2012 (Le Deu et al., 2012). Facing this ever-growing demand, improving healthcare delivery has become the top priority for both the government and the society as a whole to ensure the most effective development of China's healthcare system.

Appendix B Tables and Figures

TABLE A1
Heterogeneous Effect by Age Groups

	(1)	(2)	(3)	(4)	(5)	(6)
		Total			Offline	
VARIABLES	Consultations	Registrations	Cancellation Rate	Consultations	Registrations	Cancellation Rate
Panel A: Age below 20						
App	0.158***	0.163***	0.004*	0.028	0.029	0.000
	(0.021)	(0.021)	(0.002)	(0.021)	(0.020)	(0.002)
Observations	29,728	29,728	29,728	29,728	29,728	29,728
R-squared	0.846	0.855	0.649	0.846	0.854	0.650
Panel B: Age between 20 and 40						
App	0.105***	0.071***	-0.024***	-0.007	-0.043***	-0.027***
	(0.014)	(0.014)	(0.004)	(0.014)	(0.014)	(0.004)
Observations	29,731	29,731	29,731	29,731	29,731	29,731
R-squared	0.827	0.837	0.739	0.824	0.835	0.737
Panel C: Age between 40 and 60						
App	0.057***	0.016	-0.032***	0.024**	-0.018*	-0.033***
	(0.013)	(0.011)	(0.005)	(0.012)	(0.011)	(0.005)
Observations	29,727	29,727	29,727	29,727	29,727	29,727
R-squared	0.770	0.780	0.716	0.775	0.784	0.715
Panel D: Age above 60						
App	0.083***	0.041***	-0.031***	0.056***	0.017	-0.032***
	(0.015)	(0.013)	(0.006)	(0.014)	(0.012)	(0.006)
Observations	29,717	29,717	29,717	29,717	29,717	29,717
R-squared	0.783	0.790	0.627	0.784	0.792	0.626

Notes: Dependent variables are the logarithm of total consultations, total registrations, and total cancellation rates, respectively, in Columns (1) to (3), and the logarithm of offline consultations, offline registrations, and offline cancellation rates in Columns (4) to (6). Panel A is for patients aged below 20, Panel B for age between 20 and 40, Panel C for age between 40 and 60, and Panel D for age above 60. All regressions include hospital fixed effects and month-by-year fixed effects. Robust standard errors are clustered at the hospital level. $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$

TABLE A2
Comparing the Dynamic Response Between Adopting and Non-Adopting Hospitals Before and After the Treatment

	(1)	(2)	(3)	(4)	(5)	(6)
		Total			Offline	
Dependent Variable	Consultations	Registrations	Cancellation Rate	Consultations	Registrations	Cancellation Rate
App^0	0.050***	0.036***	-0.025***	-0.008	-0.035**	-0.022***
	(0.011)	(0.010)	(0.006)	(0.012)	(0.013)	(0.005)
App^1	0.119***	0.073***	-0.040***	0.026	-0.018	-0.036***
	(0.028)	(0.021)	(0.012)	(0.022)	(0.022)	(0.010)
App^2	0.106***	0.064***	-0.040**	0.008	-0.037	-0.035***
	(0.031)	(0.022)	(0.014)	(0.028)	(0.027)	(0.012)
App^3	0.107***	0.061**	-0.045***	-0.001	-0.048	-0.037***
	(0.030)	(0.023)	(0.013)	(0.029)	(0.028)	(0.011)
App^4	0.148***	0.072**	-0.058**	0.001	-0.063*	-0.050**
	(0.040)	(0.034)	(0.025)	(0.040)	(0.035)	(0.020)
App^{-2}	0.002	-0.002	-0.004	0.003	-0.001	-0.003
	(0.014)	(0.008)	(0.003)	(0.010)	(0.009)	(0.002)
App^{-3}	0.016	0.007	-0.005	0.014	0.010	-0.004
	(0.016)	(0.009)	(0.005)	(0.012)	(0.011)	(0.004)
App^{-4}	-0.003	-0.002	-0.001	0.001	0.002	-0.001
	(0.020)	(0.012)	(0.005)	(0.014)	(0.013)	(0.004)
App^{-5}	-0.004	-0.009	-0.007	0.005	-0.004	-0.007
	(0.021)	(0.013)	(0.007)	(0.015)	(0.013)	(0.005)
App^{-6}	0.021	0.006	-0.003	0.023	0.017	-0.003
	(0.021)	(0.016)	(0.010)	(0.015)	(0.015)	(0.008)
Observations	29,452	29,452	29,452	29,452	29,452	29,452
R-squared	0.934	0.973	0.786	0.960	0.963	0.848
Month-by-Year FE	YES	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES	YES

Notes: This table estimates the dynamic effect of the app launch. The regression model is $y_{it} = \alpha_0 + \sum_{T=-6,\neq-1}^{4} \alpha_1^T App_{it}^T + \lambda_i + \lambda_t + \epsilon_{it},$ where $T \in \{-6, -5, ..., 4\}$. App^{-1} is the last quarter before the app launch (the omitted reference quarter); App^0 represents the first quarter after the app launch; and App^4 is the fifth and all subsequent quarters. All quarter dummies of App^T are zero for control hospitals. All regressions include hospital fixed effects and month-by-year fixed effects. Robust standard errors are clustered at the hospital level. $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$

TABLE A3
Testing Parallel Trends Between Adopting and Non-Adopting Hospitals Before the Treatment

	(1) Apr 2013	(2) May 2013	(3) Jun 2013	(4) Jul 2013	(5) Aug 2013	(6) Sep 2013	(7) Oct 2013	(8) Nov 2013	(9) Dec 2013	(10) Jan 2014
Panel A: Total Consultations										
App	0.015	0.021	0.021	0.019	0.016	0.019	0.038***	0.024	0.017	0.019
	(0.019)	(0.018)	(0.013)	(0.011)	(0.011)	(0.012)	(0.013)	(0.015)	(0.015)	(0.020)
Observations	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392
R-squared	0.934	0.934	0.934	0.934	0.934	0.934	0.935	0.934	0.934	0.934
Month-by-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Panel B: Total Registrations										
App	0.003	0.008	0.009	0.006	0.003	0.005	0.018*	0.010	0.008	0.012
	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.011)	(0.015)
Observations	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392
R-squared	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975
Month-by-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Panel C: Total Cancellation Rates										
App	-0.007	-0.005	-0.004	-0.008	-0.007	-0.008	-0.006	-0.006	-0.003	-0.000
	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
Observations	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392	7,392
R-squared	0.920	0.920	0.920	0.921	0.921	0.921	0.920	0.920	0.920	0.920
Month-by-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table tests whether there exist differential preexisting trends between adopting and non-adopting hospitals in the pre-app period from January 2013 to July 2014. This table reports regression results for Figure A1. The regression specification is $y_{it} = \alpha + \beta App_{it}^{M} + \lambda_i + \lambda_t + \epsilon_{it}$, where $M \in \{Apr2013, May2013, ..., Jan2014\}$, and App_{it}^{M} is a placebo dummy that switches to one for adopting hospitals after month M. All regressions include hospital fixed effects and month-by-year fixed effects. Robust standard errors are clustered at the hospital level. $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$

TABLE A4
Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
		Total			Offline	
VARIABLES	Consultations	Registrations	Cancellation Rate	Consultations	Registrations	Cancellation Rate
Robustness 1: Adding city-specific time trend						
App	0.109***	0.063***	-0.041**	-0.001	-0.046*	-0.036***
	(0.030)	(0.021)	(0.015)	(0.027)	(0.024)	(0.012)
Observations	29,452	29,452	29,452	29,452	29,452	29,452
R-squared	0.934	0.973	0.781	0.960	0.963	0.843
Robustness 2: Adding interaction between pre-app cancellation rates and time trend						
App	0.104***	0.068***	-0.033***	-0.005	-0.041	-0.029***
	(0.033)	(0.021)	(0.007)	(0.027)	(0.025)	(0.006)
Observations	29,452	29,452	29,452	29,452	29,452	29,452
R-squared	0.935	0.974	0.825	0.960	0.963	0.876
Robustness 3: Subsample of adopter hospitals						
App	0.117**	0.071**	-0.041**	0.029	-0.014	-0.035**
	(0.051)	(0.029)	(0.015)	(0.032)	(0.031)	(0.013)
Observations	11,351	11,351	11,351	11,351	11,351	11,351
R-squared	0.959	0.984	0.839	0.973	0.977	0.880
Robustness 4: Subsample of non-specialty hospitals						
App	0.119***	0.066**	-0.043**	0.005	-0.043	-0.038**
	(0.034)	(0.023)	(0.016)	(0.030)	(0.027)	(0.013)
Observations	26,691	26,691	26,691	26,691	26,691	26,691
R-squared	0.945	0.978	0.781	0.966	0.969	0.843
Robustness 5: Subsample of weekday observations						
App	0.102***	0.049**	-0.041**	-0.006	-0.052*	-0.036***
	(0.032)	(0.022)	(0.015)	(0.028)	(0.026)	(0.012)
Observations	21,033	21,033	21,033	21,033	21,033	21,033
R-squared	0.962	0.984	0.788	0.976	0.978	0.847
Robustness 6: Subsample of provincial capital hospitals						
App	0.105**	0.073***	-0.024**	-0.015	-0.038	-0.021***
	(0.036)	(0.018)	(0.008)	(0.034)	(0.029)	(0.006)
Observations	19,973	19,973	19,973	19,973	19,973	19,973
R-squared	0.940	0.975	0.528	0.964	0.964	0.650
Robustness 7: Subsample of balanced panel						
App	0.096***	0.064***	-0.033***	-0.008	-0.044**	-0.030***
	(0.029)	(0.015)	(0.011)	(0.023)	(0.020)	(0.009)
Observations	24,980	24,980	24,980	24,980	24,980	24,980
R-squared	0.937	0.974	0.776	0.961	0.964	0.839

Notes: This table checks the robustness by re-estimating Equation 1 with modified specifications. All regressions include hospital fixed effects and month-by-year fixed effects. Robust standard errors are clustered at the hospital level. $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$

TABLE A5
Descriptive Statistics by Days of the Week Before App Launch

VARIABLES	**Daily Consultations**		**Daily Registrations**		**Daily Cancellation Rate**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Monday	1,872	1,590	2,232	1,845	0.139	0.0980
Tuesday	1,643	1,417	1,966	1,638	0.141	0.105
Wednesday	1,565	1,314	1,870	1,535	0.138	0.102
Thursday	1,551	1,278	1,854	1,503	0.136	0.102
Friday	1,564	1,287	1,883	1,522	0.139	0.105
Saturday	1,329	1,061	1,591	1,278	0.129	0.105
Sunday	1,013	700.0	1,213	914.5	0.125	0.106
Weekdays	1,640	1,388	1,962	1,620	0.139	0.102
Weekends	1,170	910.8	1,400	1,125	0.127	0.106

Notes: This table shows hospital summary statistics broken down by days of the week for the year 2013.

TABLE A6
Heterogeneous Effect by Days of the Week

	(1)	(2)	(3)	(4)	(5)	(6)
		Total			Offline	
Dependent Variable	Consultations	Registrations	Cancellation Rate	Consultations	Registrations	Cancellation Rate
App×Mon	0.086**	0.038	-0.044***	-0.013	-0.061*	-0.038***
	(0.039)	(0.029)	(0.015)	(0.031)	(0.032)	(0.012)
App×Tue	0.080*	0.036	-0.040***	-0.024	-0.067*	-0.034***
	(0.046)	(0.035)	(0.014)	(0.037)	(0.039)	(0.011)
App×Wed	0.070**	0.031	-0.040**	-0.026	-0.073**	-0.038***
	(0.032)	(0.024)	(0.015)	(0.029)	(0.029)	(0.012)
App×Thu	0.083**	0.038	-0.040**	-0.021	-0.066**	-0.036***
	(0.035)	(0.026)	(0.015)	(0.030)	(0.030)	(0.012)
App×Fri	0.102***	0.051**	-0.042**	-0.005	-0.052*	-0.038***
	(0.032)	(0.024)	(0.015)	(0.028)	(0.028)	(0.012)
App×Weekends	0.169***	0.124***	-0.040**	0.041	-0.001	-0.033**
	(0.044)	(0.022)	(0.015)	(0.034)	(0.026)	(0.012)
Observations	29,452	29,452	29,452	29,452	29,452	29,452
R-squared	0.959	0.984	0.787	0.974	0.977	0.847
Month-by-Year FE	YES	YES	YES	YES	YES	YES
Tier by DOW FE	YES	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES	YES

Notes: This table reports estimated effects of the app by days of the week from Equation 2. Dependent variables are in logarithm terms except for cancellation rates. All regressions include hospital fixed effects, month-by-year fixed effects, and day of the week fixed effects. Robust standard errors are clustered at the hospital level. $***\, p < 0.01, **\ p < 0.05, *\, p < 0.1$

TABLE A7
Effect of the App in Non-categorized Departments by Hospital Tier

	(1)	(2)	(3)	(4)	(5)	(6)
		Total			Offline	
Dependent Variable	Consultations	Registrations	Cancellation Rate	Consultations	Registrations	Cancellation Rate
$App \times TierTwo$	0.128**	0.116**	-0.009	0.045	0.035	-0.007
	(0.050)	(0.052)	(0.014)	(0.055)	(0.057)	(0.008)
$App \times TierThree$	0.066**	-0.010	-0.049*	0.034	-0.043	-0.054**
	(0.025)	(0.030)	(0.027)	(0.034)	(0.025)	(0.022)
Observations	27,076	27,076	27,076	27,076	27,076	27,076
R-squared	0.987	0.985	0.827	0.987	0.987	0.922

Notes: This table shows the effect of the appointment app on non-categorized departments—that is, all departments excluding the more severe and less severe departments defined in Table 6. *App* is the dummy that switches to one after the app is launched in treatment hospitals. $TierThree$ and $TierTwo$ are dummies for tier-three and tier-two hospitals, respectively. All regressions include hospital fixed effects and month-by-year fixed effects. Robust standard errors are clustered at the hospital level. $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$

TABLE A8
Patient Sorting and Drug Spending: IV Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			Log(Drug Spending)			
Disease	Severe	Diabetes	Hypertension	CHD	COPD& Asthma	
Panel A: Using *Pre. Tier 2 * Post* as excluded instrument						
Tier 3 Adopter	0.031*	0.063*	0.037*	0.028	0.014	
	(0.016)	(0.034)	(0.019)	(0.040)	(0.012)	
Observations	170,469	56,980	100,108	20,595	24,243	
R-squared	0.015	0.019	0.020	0.011	0.015	
Demographic Controls	Yes	Yes	Yes	Yes	Yes	
Comorbidity Controls	Yes	Yes	Yes	Yes	Yes	
Individual FE	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	
Disease	Nonsevere	Common Cold	Pharyngitis	Rhinitis	Arthritis & Back Pain	Mild Skin Conditions
Panel A: Using *Per. Tier 3 Adopter * Post* as excluded instrument						
Tier 2	-0.269***	-0.207***	-0.191**	-0.188***	-0.237**	-0.182**
	(0.036)	(0.049)	(0.071)	(0.050)	(0.108)	(0.070)
Observations	110,066	23,716	23,959	7,574	30,081	31,331
R-squared	-0.010	-0.018	-0.021	0.039	0.030	0.025
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Comorbidity Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

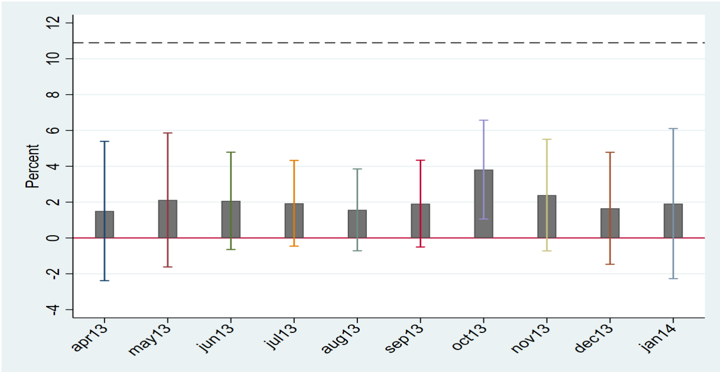
Notes: This table reports IV estimated effects of patient sorting on drug medical spending. Panel A reports estimation results for Equation 6 on the sample of patients with severe conditions, using the logarithm of total medical spending as dependent variable and $Tier2^{Pre} * Post$ as the IV for $Tier3Adopter$. Similarly, Panel B reports estimation results for Equation 7 on the sample of patients with nonsevere conditions, using the logarithm of total medical spending as dependent variable and $Tier3Adopter^{Pre} * Post$ as the IV for $Tier2$. See Subsection 6.2 for details on regression specification and sample construction. Robust standard errors are clustered at individual level. $***\ p < 0.01, **\ p < 0.05, *\ p < 0.1$

TABLE A9
App Launch and Reduction in Scheduled Waiting Time

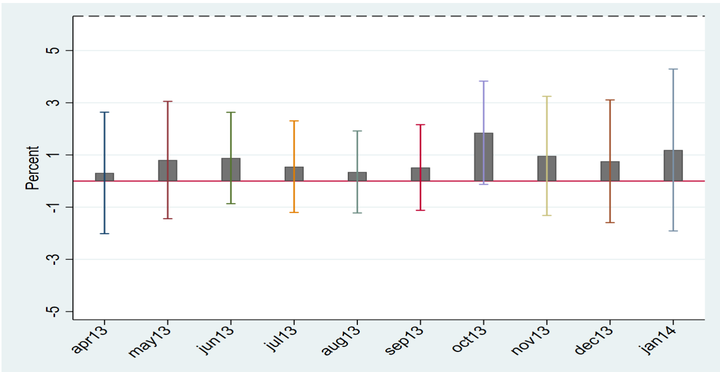
Dependent Variable	Waiting Time
NewApp×Mon	-2.081***
	(0.153)
NewApp×Tue	-2.022***
	(0.167)
NewApp×Wed	-2.441***
	(0.165)
NewApp×Thu	-2.737***
	(0.164)
NewApp×Fri	-2.882***
	(0.157)
NewApp×Weedends	-3.440***
	(0.140)
Observations	1,705,283
R-squared	0.008
Number of Individuals	278,909
Individual FE	YES
Year-by-Month FE	YES
Day of the Week FE	YES

Notes: This table reports estimated effects of subsequent app launches on the scheduled waiting time of existing app users by day of the week. We estimate $Waiting_{ijt} = \phi_0 + \sum_{d=1}^{6} \phi_1^d NewApp_{ijt} \times DOW_d + \lambda_i + \lambda_t + \epsilon_{ijt}$, where $Waiting_{ijt}$ is the duration of scheduled waiting for patient i in city j when she makes the booking on time t; $NewApp_{ijt}$ denotes the number of new apps adopted in city j on time t since patient i's first online booking; DOW_d indicates the dth day of the week and DOW_6 represents Saturday and Sunday; λ_i are individual fixed effects; and λ_t are year-by-month fixed effects and day of week fixed effects. Robust standard errors are clustered at the individual level. $*** \; p < 0.01, ** \; p < 0.05, * \; p < 0.1$

(A) Total Consultations



(B) Total Registrations



(C) Total Cancellation Rate

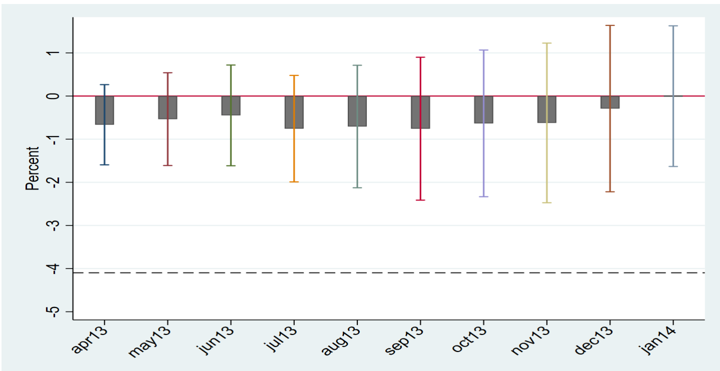


FIGURE A1
Testing Parallel Trends before App Adoption

Notes: This figure tests whether there exist differential preexisting trends between adopting and non-adopting hospitals in the pre-app period from Jan 2013 to April 2014. The regression specification is $y_{it} = \alpha + \beta App_{it}^{M} + \lambda_i + \lambda_t + \epsilon_{it}$, where $M \in \{apr2013, may2013, ..., jan2014\}$, and App_{it}^{M} is a placebo dummy that switches to one for adopting hospitals after month M. Each shaded bar represents the estimated β from a separate regression, coupled with the the 95% confidence interval. Detailed regression results are reported in Appendix Table A3. The dashed horizontal line in each panel represents the estimated effect of actual app adoption in the baseline sample, obtained from Table 4.

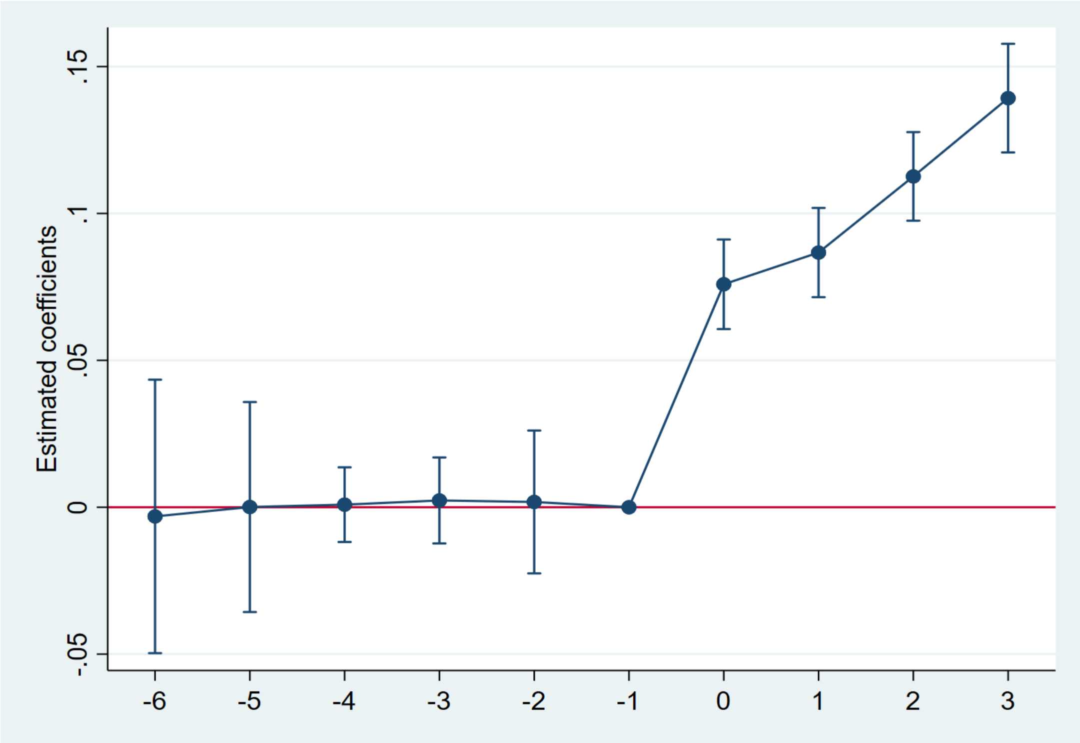


FIGURE A2
Dynamic DD Estimation of Effect of the App on Patient Sorting in Patients with Severe Conditions

Notes: This figure presents the dynamic effects of app adoption on the probability of switching from tier-two hospital to the tier-three new adopter hospital. The figure plots coefficient estimates of β_ds in from Equation $Tier3Adopter_{i,t} = \alpha + \sum_{d=-6,\neq-1}^{3} \beta_d \cdot Tier2_i^{Pre} \cdot visit_{i,d} + X_{i,t}\gamma + \lambda_i + \lambda_t + \epsilon_{i,t}$ with the 95% confidence interval. See further discussion of the specification in Section 5.2.

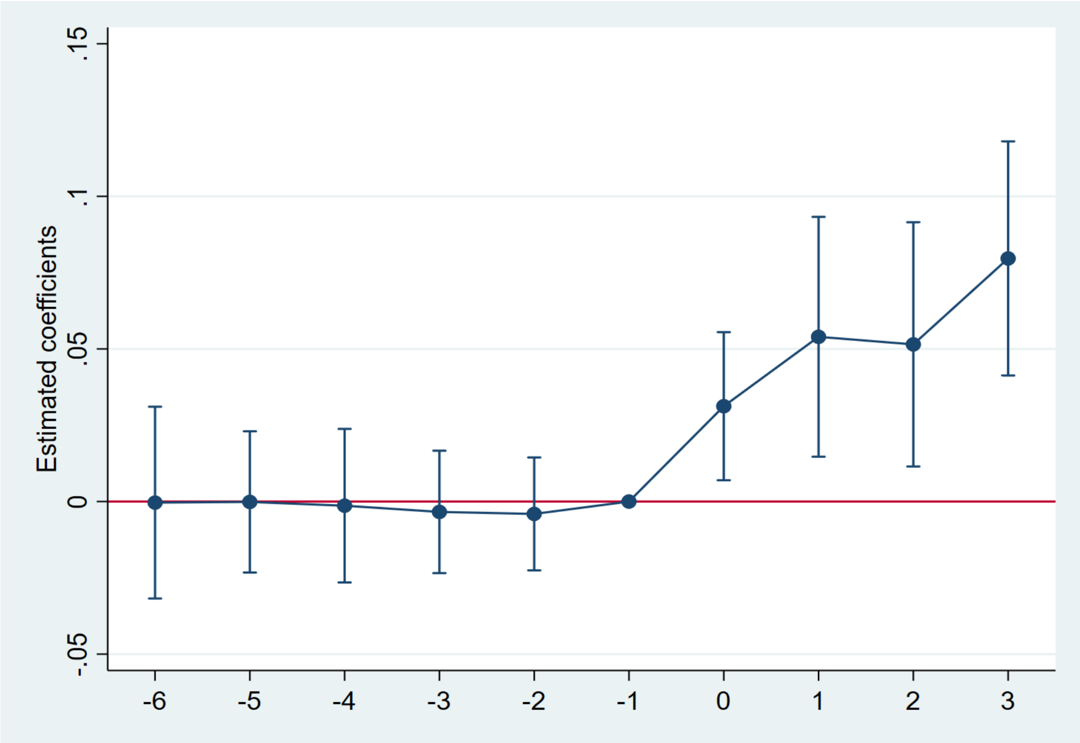


FIGURE A3
Dynamic DD Estimation of Effect of the App on Patient Sorting in Patients with Nonsevere Conditions

Notes: This figure presents the dynamic effects of app adoption on the probability of switching from the tier-three adopter hospital to a tier-two hospital. The figure plots coefficient estimates of β_ds in from Equation $Tier2_{i,t} = \alpha + \sum_{d=-6,\neq-1}^{3} \beta_d \cdot Tier3Adopter_i^{Pre} \cdot visit_{i,d} + X_{i,t}\gamma + \lambda_i + \lambda_t + \epsilon_{i,t}$ with the 95% confidence interval. See further discussion of the specification in Section 5.2.

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