Front. Econ. China 2021, 16(4): 607–627
https://doi.org/10.54605/fec20210402

RESEARCH ARTICLE

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New Nosocomephobia? Changes in Hospitalizations during the COVID-19 Pandemic

Abstract While the coronavirus disease-2019 (COVID-19) pandemic directly caused millions of hospitalizations and deaths, its indirect impacts on people with other illnesses can be of equal importance. Using discharge records in a major Chinese megacity where there was a limited number of COVID-19 cases, we find significant declines in the number of hospital admissions for a whole spectrum of disease categories during the pandemic. The declines were larger in COVID-19 designated hospitals and top-grade hospitals. In-hospital mortality and length of stay (LOS) were higher for stroke, ischaemic heart diseases, and malignant neoplasms, while women delivering in hospitals had fewer C-sections and shorter LOS. Our results suggest that people avoided necessary hospitalization out of fear of being infected by COVID-19. To prevent the adverse impacts of delaying health care, policymakers should establish clear guidelines encouraging people to seek necessary care, especially during the reopening period.

Keywords COVID-19, hospitalization, fear of infection
JEL Classification I11, I12, I18

Received May 12, 2021

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1 Introduction

The coronavirus disease 2019 (COVID-19) pandemic has caused 180 million hospitalizations, and approximately 4 million deaths worldwide.[1] However, the indirect health consequences of a pandemic may be as impactful as the outbreak itself (Elston, 2017). Studies focusing on areas with overloaded health care systems (e.g., Northern Italy) have found significant declines in hospital admissions for specific diseases during the pandemic (De Filippo et al., 2020; Solomon et al., 2020). This study examines a major megacity in China with a population above 16 million that has reported a limited number of COVID-19 cases, and examines the impact of the pandemic on non-COVID-19 hospitalizations for a whole spectrum of illnesses.

As the first country to report cases of COVID-19, China was also one of the first to flatten the epidemic curve (Verma et al., 2020). In most cities outside Hubei Province, the pandemic was largely contained and only a small percentage of health care resources were diverted to treat COVID-19 patients. In our sample city, 456 confirmed cases and three deaths were reported as of December 31, 2020. This provides an attractive setting to investigate whether and how people's fear and avoidance behavior instead of shortages of medical resources changed the patterns of hospitalizations during the pandemic.

Utilizing a unique data set of all inpatient discharge records in the sample city, we identify the effects of the pandemic on non-COVID-19 hospitalizations. Specifically, as the outbreak of the pandemic coincided with the 2020 Chinese New Year (CNY), we use two dimensions of differences: a) year 2019 vs. 2020 and b) the pre-CNY vs. post-CNY periods of each year. We find that the pandemic led to declines in the daily number of hospital admissions for a whole spectrum of disease categories, and the magnitudes of the declines varied substantially across categories. The declines in hospitalizations were smaller during the "reopening" period than the "stay-at-home" period, and the declines were larger for COVID-19-designated hospitals than other health care facilities and larger for top-grade hospitals than other health care facilities. Moreover, we particularly examine stroke, ischemic heart diseases, and malignant neoplasms, which are leading causes of death in China (Zhou et al., 2019), and find that the pandemic led to higher in-hospital mortality and longer length of stay (LOS) for the three diseases. Finally, we investigate hospitalizations for child deliveries,

[1] The World Health Organization (WHO) frequently updates the numbers of confirmed cases and deaths of COVID-19 on an online dashboard: https://covid19.who.int/ (accessed on June 30, 2021).

which are hard to postpone and reschedule, and find that parturient women were less likely to have a C-section and had shorter LOS during the pandemic.

Our study contributes to the literature on the impacts of the pandemic on the health care utilization. Chatterji and Li (2020) find that the pandemic caused lower utilization of outpatient services in the U.S. In comparison, our study focuses on inpatients who are more severely ill and more vulnerable to lack of timely care. In addition, medical research finds declines in stroke evaluation and hospital admissions for acute cardiovascular conditions in western countries (De Filippo et al., 2020; Solomon et al., 2020). Our study comprehensively examines a whole spectrum of illnesses and uses discharge data from the largest developing country. Lastly and more broadly speaking, our study is part of the literature on the impacts of the pandemic on various aspects of society, such as air pollution, financial markets, small businesses, labor markets, and schooling (Almond et al., 2021; Corbet et al., 2020; Fairlie, 2020; Forsythe et al., 2020; Goulas and Megalokonomou, 2020).

2 Data and Variables

We obtained the inpatient discharge records of all health care facilities from the local Health Commission in a megacity in southwestern China (city population 16.3 million in 2019).[2] The dataset covers all hospitalizations for the first three months of 2019 and the first three months of 2020 in the megacity.

The outbreak of the COVID-19 pandemic coincided with the Chinese New Year (CNY; January 25, 2020). During the CNY holiday, people head home for family reunions and most social-economic activities are paused. Our sample city enacted "Level I" public health emergency responses, the highest of four possible levels, on the evening of January 24. To facilitate our empirical analysis to identify the impact of the COVID-19 pandemic, we focus on inpatients who were admitted in the three weeks before and five weeks after the CNY in 2019 and 2020 (January 15 to February 4 and February 5 to March 11 in 2019, and January 4 to 24 and January 25 to February 28 in 2020).[3] Figure 1 compares the daily numbers of hospital admissions between the

[2] Due to our data agreement, we are not able to disclose the name of the sample city.

[3] Our raw data cover all inpatients discharged in the first three months of 2019 and 2020. However, we exclude the patients admitted in the last three weeks of each three-month period in our baseline analysis, because patients who were admitted closer to the end of each three-month period are less likely to be observed in the data set, since they may well have been discharged after March 31 of each year. To further balance our sample, we use the sample period of the three weeks before and five weeks after the CNY in 2019 and 2020.

sample periods of 2019 and 2020.

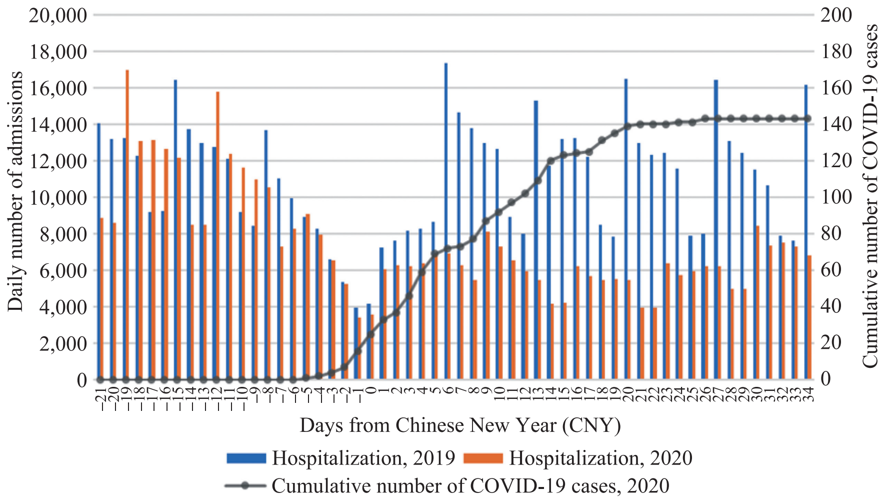

Figure 1 Daily Number of Hospital Admissions before and during the COVID-19 Pandemic in 2020 and during the Same Period in 2019, Relative to the Cumulative Number of Confirmed Cases of COVID-19

Note: The horizontal axis refers to the lunar calendar dates. Date 0 is the Chinese New Year. The CNY dates change every year because the festival is based on the Chinese lunar calendar. The CNY of 2019 falls on February 5 and the CNY of 2020 falls on January 25.

Our sample includes 1.037 million non-COVID-19 hospitalizations in 816 health care facilities. From the data set, we obtain information on the characteristics of hospitalizations and patients' demographic characteristics. We first construct our key dependent variable (the number of hospital admissions) to illustrate the impact of the pandemic on hospitalization volume. We then construct three outcome variables to reflect other aspects of hospitalization (quality, choice of procedure and, LOS). Finally, we included a set of control variables. Table 1 provides detailed information on variable construction, and table 2 presents the statistics of these variables.

Table 1 Variable Definitions

Variable name	Description	Data source
Admissions	The daily number of non-COVID-19 hospital admissions, constructed by counting the number of patients admitted on each day in the sample city	Discharge records

(To be continued)

(Continued)

Variable name	Description	Data source
In-hospital mortality	A dummy indicating in-hospital mortality	Discharge records
LOS	The number of days from hospital admission to discharge or death (if occurring during hospitalization)	Discharge records
C-section	A dummy indicating C-sections for parturient women	Discharge records
Age	The age of the inpatient	Discharge records
Male	A dummy indicating whether the patient is male	Discharge records
Number of comorbidities	The number of diagnoses that the patient has	Discharge records
COVID	A dummy indicating the post-CNY 2020 period (after the outbreak of COVID-19)	/
Reopen	A dummy indicating the reopening period (32 days after the CNY in 2020)	/
PM2.5	The concentration of fine particulate matter	The local environmental monitoring center
Physicians and nurses assigned	The cumulative number of physicians and nurses assigned by the government from the sample city to Hubei Province to treat COVID-19 patients	Hospital webpages and online news reports
Designated	A dummy indicating COVID-19-designated hospitals	Official government directions
Top-grade	A dummy indicating Grade 3 hospitals	Hospital webpages

Table 2 Summary Statistics

VARIABLES	(1) N	(2) Mean	(3) SD
Panel A. Daily number of admissions			
All causes except COVID-19	112	9259.8	3534.6
Respiratory system	112	2949.7	1154.8

(To be continued)

(Continued)

VARIABLES	(1) N	(2) Mean	(3) SD
Digestive system	112	921.1	341.2
Circulatory system	112	817.9	309.3
Musculoskeletal system and connective tissue	112	785.3	421.3
Pregnancy, childbirth, and puerperium	112	710.3	123.4
Genitourinary system	112	555.9	242.6
Neoplasms	112	415.8	289.2
Injury, poisoning, and external causes	112	348.1	122.1
Endocrine, nutritional, and metabolic	112	171.1	94.5
Nervous system	112	170.5	74.5
Panel B. Daily-level control			
PM2.5	112	142.8	28.4
Panel C. Patient characteristics			
In-hospital mortality, %	1,037,100	0.8	8.7
LOS	1,037,100	9.0	6.5
Age	1,037,100	50.9	24.2
Male, %	1,036,972	45.4	49.8
Number of comorbidities	1,037,100	1.9	1.2
Panel D. Patient characteristics for child deliveries			
C-section, %	47,448	44.1	49.7
LOS	47,448	5.7	2.3
Age	47,448	29.1	4.4
Number of comorbidities	47,448	2.6	0.7

Note: The table shows the summary statistics of the daily number of hospital admissions, daily-level control, and patient characteristics. Panel A shows the daily-level number of admissions for various disease categories. Panel B shows the daily-level control, PM2.5. Panel C shows the individual-level patient characteristics and panel D shows the characteristics of patients admitted for child deliveries.

3 Empirical Specifications

To identify the effects of the COVID-19 pandemic, we account for two dimensions of differences, following Almond et al. (2020): a) year 2019 vs. 2020 and; b) pre-CNY vs. post-CNY periods of each year. Specifically, we compare the difference between the pre-CNY 2020 and post-CNY 2020 periods and the difference between the pre-CNY 2019 and post-CNY 2019 periods. To examine the effects of the pandemic on the daily number of admissions, we use the following model:

$$ln(H_{g,t}) = \beta COVID_{g,t} + \alpha Treat_g + Week_t + DoW_{g,t} + \theta P_{g,t} + \epsilon_{g,t}, \quad (1)$$

where $H_{g,t}$ is the number of hospital admissions on day t ($t \in [-21, 34]$) from the CNY of year g ($g \in \{2019, 2020\}$) in the sample city.[4] The CNY dates change every year because the festival is based on the Chinese lunar calendar. The CNY of 2019 falls on February 5 and the CNY of 2020 falls on January 25. $COVID_{g,t}$ indicates the period of post-CNY 2020 (after the outbreak of COVID-19), which is also our variable of interest. $Treat_g$ is a dummy indicating the year 2020. $Week_t$ includes a set of dummies indicating each week of the three weeks before and five weeks after the CNY. $DoW_{g,t}$ is day-of-week (in the Gregorian calendar) fixed effects. To control for potential confounding variations in air pollution (He et al., 2020), we include $P_{g,t}$, which is the concentration of fine particulate matter, PM2.5, on day t of year g. To examine whether a shortage of physicians and nurses explains the impact of the pandemic on hospital admissions, we also include the cumulative number of physicians and nurses assigned to Hubei Province from the sample megacity as an additional control in an alternative specification. Furthermore, we explore the effects of the reopening and use hospital-daily-level admission data for more detailed analyses, such as the heterogeneous impacts of the pandemic across different hospitals and facilities. We first identify the COVID-19-designated hospitals and examine whether the impacts of the pandemic on hospital admissions are heterogeneous across the designated and non-designated hospitals, then repeat the investigation for top-grade hospitals and other health care facilities.[5]

Besides hospital admissions, we analyze patient-level hospitalization outcomes using the following model:

$$Y_{i,g,t} = \beta COVID_{g,t} + \alpha Treat_g + Week_t + DoW_{g,t} + \boldsymbol{X}_{i,g,t}\boldsymbol{\gamma} + \epsilon_{i,g,t}, \quad (2)$$

[4] As a robustness check, we use an alternative model (the negative binomial model) . See Appendix B for details.

[5] The government classifies hospitals into three grades: Grade 1 (primary), Grade 2 (secondary), and Grade 3 (tertiary), with increasing quality and scale. We regard Grade 3 hospitals as top-grade hospitals having the most patients and physicians. See Supplementary Appendix A for detailed regression specifications.

where $Y_{i,g,t}$ denotes the outcome of concern of patient i admitted on day t from the CNY of year g, including the in-hospital mortality, LOS, and C-section.[6] $\boldsymbol{X}_{i,g,t}$ is a vector of the patient characteristics, including age, gender, primary diagnosis code (3-digit ICD-10 code), and number of comorbidities.[7] We also include the cumulative number of physicians and nurses assigned to Hubei Province as an additional control for in-hospital mortality in an alternative specification. Standard errors are clustered at the hospital level. The other notations are the same as in Equation 1.

4 Results

Hospitalizations for a whole spectrum of disease categories Table 3, column 1 shows that the pandemic led to a 41.1% decrease in the number of admissions.[8,9] Next, we find that the pandemic led to significant declines in hospital admissions, ranging from 16.2% to 62.1% for the top ten (volume-based) categories of diseases according to the ICD-10 (Table 4).[10] The variations in the magnitudes of the declines could be explained by the difficulty of deferring treatment and illness severity. For example, pregnancy, childbirth, and the puerperium can hardly be rescheduled or delayed and the decline in admissions for these was the smallest across disease categories. Lastly, Table SA.2 shows that the pandemic led to a 27.4% decrease in the daily number of admissions, holding the number of physicians and nurses assigned away to Hubei Province constant.

Reopening and heterogeneous effects Table 5 shows that compared with 2019, the number of admissions sharply declined due to the pandemic, but the decline became significantly smaller after the reopening, indicating the effectiveness of reopen-

[6] As robustness checks, we use alternative models (the logit and negative binomial model). See Supplementary Appendix B for details.

[7] ICD-10 stands for International Statistical Classification of Diseases and Related Health Problems – 10th Revision.

[8] In the baseline, we use the log of the daily number of hospital admissions as our dependent variable (Equation 1). To interpret the coefficient β, we take the exponential of β and then subtract one ($exp(\beta) - 1$) to calculate the percentage change.

[9] As robustness checks, we also estimate the model based on hospital-daily-level hospital admission data and obtain similarly significant results (Table SA.1). In addition to the OLS estimation, we also use the negative binomial model and obtain similar results (Table 3, column 2).

[10] We check the validity of our empirical method with the parallel trend test (see Appendix B for details).

ing policies in affecting people's behaviors. After the reopening signal, implying a reduced risk of infection, people's avoidance of hospital admissions was significantly alleviated. Table 6 shows that the declines in hospital admissions during the pandemic were significantly greater in COVID-19-designated hospitals than other health care facilities and significantly greater in top-grade hospitals than other facilities. Visits to COVID-19-designated hospital were perceived to have higher risk of infection because COVID-19 patients were more likely to be sent to these hospitals. Similarly, people tended to believe that the risk of infection was higher in top-grade hospitals, which treated more patients and hence were more crowded. To conclude, we find that the pandemic led to significantly larger declines in admissions in the hospitals that people believed to be riskier.

Table 3 Impact of the Pandemic on the Daily Number of Hospital Admissions for All Causes

	(1)	(2)
VARIABLES	ln(admissions)	Admissions
COVID	−0.529***	−0.541***
	(0.085)	(0.070)
% change	−41.1%	−41.8%
Method	OLS	Negative binomial
Observations	112	112

Note: The table shows the impact of the COVID-19 pandemic on the daily number of hospital admissions for all causes except COVID-19. In column 1, we use the OLS model and in column 2, we use the negative binomial model. The controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and air pollution (see Equation 1 for details of estimation). Robust standard errors are in parentheses. *** denotes significance at the 1 percent level.

In-hospital mortality and LOS We examine the impact of the pandemic on the probability of in-hospital death and LOS of each patient, especially for three common diseases, stroke, ischemic heart diseases, and malignant neoplasms, which are the leading causes of death in China (Zhou et al., 2019). Table 7, panel A shows that the pandemic significantly increased the likelihood of in-hospital mortality. For all non-COVID-19 admissions, the probability of in-hospital mortality increased by 0.36 percentage points (45 percent of the sample average in-hospital mortality rate). The increases were 2.12, 0.96, and 3.69 percentage points for stroke, ischemic heart diseases, and malignant neoplasms, respectively. The effects are still significant when we control the number of physicians and nurses assigned away to Hubei Province (table SA.3). In addition, table 7, panel B shows that during the pandemic, LOS increased by 0.159 days for all non-COVID-19 admissions, and increased by 0.814, 0.764, and 0.863 days for stroke, ischemic heart diseases, and malignant neoplasms, respectively.

Table 4 Impact of the Pandemic on Hospital Admissions for the Top 10 Disease Categories

Dependent variable: ln(admissions)	Subsample				
	(1) Respiratory system	(2) Digestive system	(3) Circulatory system	(4) Musculoskeletal system and connective tissue	(5) Pregnancy, childbirth, and puerperium
COVID	−0.365***	−0.655***	−0.641***	−0.712***	−0.177***
	(0.068)	(0.080)	(0.089)	(0.169)	(0.050)
% change	−30.6%	−48.1%	−47.3%	−50.9%	−16.2%
Observations	112	112	112	112	112
	(6) Genitourinary system	(7) Neoplasms	(8) Injury, poisoning, and external causes	(9) Endocrine, nutritional, and metabolic	(10) Nervous system
COVID	−0.567***	−0.820***	−0.738***	−0.971***	−0.746***
	(0.122)	(0.183)	(0.065)	(0.128)	(0.103)
% change	−43.3%	−56.0%	−52.2%	−62.1%	−52.6%
Observations	112	112	112	112	112

Note: The table shows the impact of the COVID-19 pandemic on the daily number of hospital admissions for the top 10 categories (ranked by volume) in the International Classification of Diseases, Tenth Revision. The controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and air pollution. Robust standard errors are in parentheses. *** denotes significance at the 1 percent level.

Table 5 Impact of the Reopening on Hospital Admissions

VARIABLES	(1) ln(admissions)
Reopen	0.170**
	(0.0784)
COVID	−0.545***
	(0.0873)
Observations	120

Note: The table shows the whether the effects of the pandemic on the daily number of hospital admissions are different after the reopening. The controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and air pollution. See Equation SA.1 for specification details. Robust standard errors are in parentheses. *** denotes significance at the 1 percent level, and ** at the 5 percent level.

Table 6 Impact of the Heterogeneous Effects of the Pandemic on Hospital Admissions

VARIABLES	(1) ln(admissions)	(2) ln(admissions)
COVID * Designated	−0.320***	
	(0.030)	
COVID * Topgrade		−0.279***
		(0.028)
COVID	−0.351***	−0.340***
	(0.008)	(0.008)
Observations	91,280	91,280

Note: The table shows the heterogeneous effects of the COVID-19 pandemic on the daily number of hospital admissions for different types of hospitals. Column 1 shows whether the effects of the pandemic are different in COVID-19-designated hospitals and other health care facilities. Column 2 shows whether the effects are different in top-grade hospitals and other health care facilities. The controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, air pollution, and hospital fixed effects. See Equation SA.3 for specification details. Robust standard errors are in parentheses. *** denotes significance at the 1 percent level.

Table 7 Impact of the Pandemic on In-Hospital Mortality and LOS

		Subsample		
	(1)	(2)	(3)	(4)
	All causes	Stroke	Ischemic heart diseases	Malignant neoplasms
Panel A. In-hospital mortality				
COVID	0.0036***	0.0212***	0.0096**	0.0369***
	(0.0006)	(0.0060)	(0.0039)	(0.0085)
Observations	1,025,679	19,829	22,651	27,009
Panel B. LOS				
COVID	0.159*	0.814***	0.764***	0.863*
	(0.091)	(0.310)	(0.289)	(0.456)
Observations	1,025,679	19,829	22,651	27,009

Note: The table shows the impact of the COVID-19 pandemic on in-hospital mortality and length of stay (LOS) for all causes except COVID-19 and three common diseases (i.e., stroke, ischemic heart diseases, and malignant neoplasms). Panel A shows the results for in-hospital mortality and Panel B shows the results for LOS. We control a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and patient characteristics such as age, gender, primary diagnosis code, and number of comorbidities. Robust standard errors clustered at the hospital level are in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Child deliveries As discussed above, the decline in hospital admissions for pregnancy, childbirth, and the puerperium was the smallest among the whole spectrum of disease categories. For a more detailed analysis, we identify 47,448 hospitalizations for child delivery in 100 health care facilities. Table 8 shows that the pandemic reduced the probability of C-sections by 1.9 percentage points. In addition, there was a modest but significant decrease in LOS of 0.151 day. The decrease remained significant (0.116 day) after controlling the delivery method (whether the patient had a C-section).

Table 8 Impact of the Pandemic on Hospitalizations for Child Deliveries

VARIABLES	(1) C−section	(2) LOS	(3) LOS
COVID	−0.019**	−0.151**	−0.116*
	(0.009)	(0.069)	(0.061)
C-section			1.881***
			(0.077)
Observations	47,448	47,448	47,448

Note: The table shows the impact of the COVID-19 pandemic on hospitalizations for child deliveries. Column 1 shows the impact of the pandemic on the likelihood of C-sections. Column 2 and 3 show the impact on LOS for child deliveries. We control a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and patient characteristics such as age and number of comorbidities. Robust standard errors clustered at the hospital level are in parentheses. In column 3, we additionally control for a dummy indicating C-section. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

5 Discussion

There are four candidate explanations for the declines in hospitalizations during the pandemic. First, the health care system may have been overloaded by COVID-19 patients and hospitals were unable to take in patients with other conditions. However, this was not the case in the sample city, where only fewer than 150 cumulative confirmed COVID-19 cases were reported until the end of our sample period in 2020.

Second, a shortage of physicians and nurses may lead to fewer admissions. In the sample city, around 500 physicians and nurses were sent to Hubei Province to treat COVID-19 patients. However, the impact of the pandemic on hospital admissions remains significant after we control for the number of sent-away physicians and nurses (Table SA.2). This shows that changes in the number of physicians and nurses alone cannot explain our findings of the impact of the pandemic.

The third possible explanation is that the COVID-19 pandemic and related government policies (e.g., “stay-at-home” and “social-distancing” guidance) may have made people adjust their daily behaviors, build healthy habits, and in turn become healthier.

This may explain the declines in hospitalizations for diseases of the respiratory system to some extent. However, people getting healthier at home cannot explain the declines in hospitalizations for many other diseases. We find a sharp fall in hospitalizations for neoplasms (56.0%), but patients with neoplasms are unlikely to get better by just resting at home.

The last possible explanation is that people who were sick avoided hospitals because they feared getting the COVID-19 virus. Our findings support this explanation in three ways. First, we find that the declines in hospital admissions during the pandemic were greater in the COVID-19-designated hospitals and top-grade hospitals that were perceived to be more dangerous (i.e., presenting a higher risk of infection). Second, if people delay hospital visits out of fear, it is likely that they will miss the ideal time window for treatment, resulting in worse treatment outcomes. Our findings of treatment outcomes confirm that this is the case (Table 7). Third, we find that women delivering in hospitals had fewer C-sections and shorter LOS. If parturient women fear COVID-19 infection, they want shorter stays and are less likely to choose a C-section, which typically requires longer LOS.

6 Conclusion

In conclusion, the COVID-19 pandemic led to substantial declines in hospital admissions for a whole spectrum of disease categories in a city barely affected by COVID-19. The decline became smaller during the reopening period, and the decline was larger in COVID-19-designated hospitals and top-grade hospitals. Patient outcomes were worse for the three common diseases. Women delivering in hospitals had fewer C-sections and shorter LOS. Our results suggest that people avoided hospitals out of fear of COVID-19 infection. To prevent the adverse impacts of delaying health care, policymakers should establish clear guidelines encouraging people to seek necessary care during the pandemic.

Acknowledgments The authors thank Aria Yan for excellent research assistance. Zhigang Tao would like to thank the University of Hong Kong where most of his contributions to this paper were carried out.

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Appendices

A Extensions

We extend our baseline analysis by exploring the effects of the "reopening" during the pandemic on non-COVID-19 admissions. On February 26, 2020 (32 days after the 2020 CNY), the government announced a downgrade from the "Level I" emergency response to "Level II," which served as an official signal for reopening. The model we use is as follows:

$$\begin{aligned} ln(H_{g,t}) = {} & \phi Reopen_{g,t} + \beta COVID_{g,t} + \alpha Treat_g + \delta Post\_sub_t \\ & + Week_t + DoW_{g,t} + \theta P_{g,t} + \epsilon_{g,t}, \end{aligned} \tag{SA.1}$$

where $Reopen_{g,t}$ indicates whether day t from the CNY of year g falls in the reopening period (that is, $t \geqslant 32$ and $g = 2020$). To increase the statistical power of the analysis of the "reopening" effects, we include four more days ($t \in [35, 38]$) to lengthen the reopening period in our sample to an entire week. $Post\_sub_t$ is a dummy variable indicating a subperiod of the post-CNY period, which starts 32 days after the CNY ($t \geqslant 32$). In the model, we effectively control for all the two-way interactions among $Post\_sub_t$, $Treat_g$, and a dummy indicating the post-CNY period. The interaction between $Post\_sub_t$ and the dummy indicating the post-CNY period is the same as $Post\_sub_t$. The interaction between $Post\_sub_t$ and $Treat_g$ is the same as $Reopen_{g,t}$. Other notations are the same as in Equation 1.

For robustness checks and also more detailed analyses, we examine the impact of the pandemic on hospital admissions at the more disaggregated level, that is, the hospital-daily level. The model used is as follows:

$$ln(H_{h,g,t}) = \beta COVID_{g,t} + \alpha Treat_g + Week_t + DoW_{g,t} + \theta P_{g,t} + \lambda_h + \epsilon_{g,t}, \quad \text{(SA.2)}$$

where $H_{h,g,t}$ is the number of hospital admissions in hospital h on day t ($t \in [-21, 34]$) from the CNY of year g ($g \in \{2019, 2020\}$). λ_h is hospital fixed effects. Other notations are the same as in Equation 1.

Based on the hospital-daily-level data, we also examine the heterogeneous effects of the pandemic on hospitalizations across a) COVID-19-designated hospitals and non-designated health care facilities; and b) top-grade hospitals and other health care facilities. The model we use is as follows:

$$\begin{aligned} ln(H_{h,g,t}) = {} & \xi COVID_{g,t} \cdot Type_h + \beta COVID_{g,t} + \kappa Treat_g \cdot Type_h \\ & + \delta Post_t \cdot Type_h + \alpha Treat_g + Week_t + DoW_{g,t} + \theta P_{g,t} + \lambda_h + \epsilon_{d,g,t}, \quad \text{(SA.3)} \end{aligned}$$

where $Type_h$ is a) a dummy, $Designated_h$, which equals 1 for COVID-19-designated hospitals, and 0 otherwise; and b) a dummy, $Topgrade_h$, which equals 1 for top-grade hospitals, and 0 otherwise. $Post_t$ is a dummy indicating the post-CNY period ($t \geqslant 0$). The other notations are the same as in Equations 1 and SA.2.

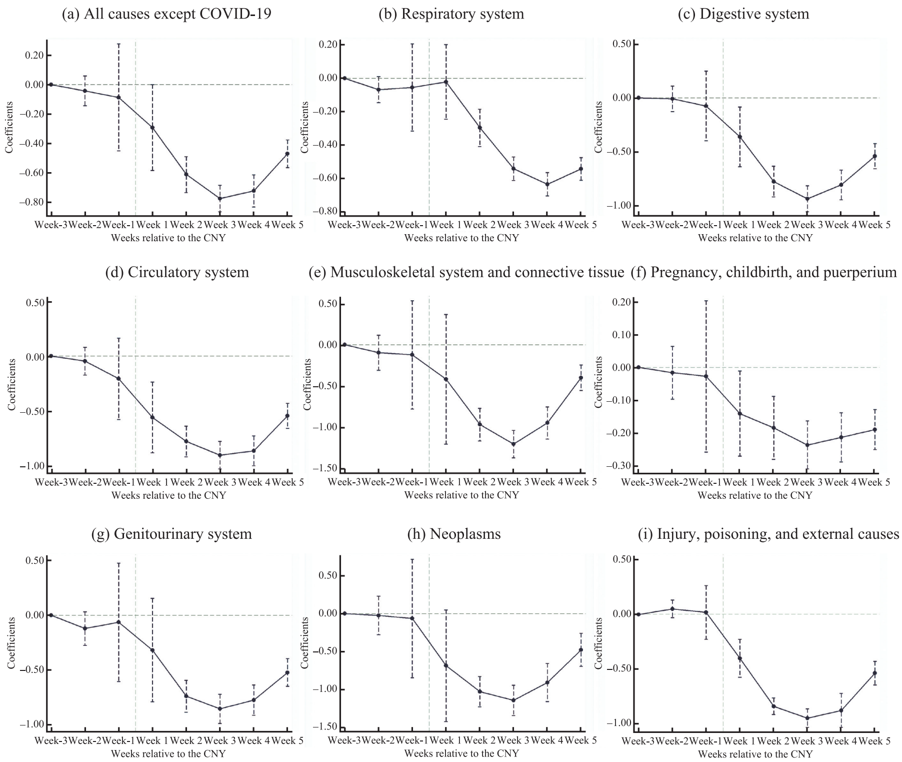
B Robustness Checks

Alternative models First, when examining the effects of the pandemic on the daily number of hospital admissions, we additionally use the negative binomial model to better account for the fact that the number of hospital admissions is a count variable. Table 3, column 2 shows that similar results as in the baseline are obtained. Second, we additionally use the logit model for in-hospital mortality (Table SA.4) and the negative binomial model for LOS to take into account the fact that LOS is a count variable (Table SA.5). Third, we use the logit model for C-sections (Table SA.6). To conclude, all our findings are robust to alternative model choices.

Parallel Trend Assumption The validity of this two-difference analysis lies in the assumption that in the absence of treatment, the difference between the treatment and control group is constant over time. To test this assumption, we compare the trend of hospital admissions in 2020 with that in 2019. More specifically, we run the following regression:

$$ln(H_{g,t}) = \sum_j \beta_j TreatWeek_{g,j,t} + \alpha Treat_g + Week_t + DoW_{g,t} + \theta P_{g,t} + \epsilon_{g,t}, \quad \text{(SA.4)}$$

where $TreatWeek_{g,j,t}$ is a set of dummy variables indicating the j^{th} week relative to the CNY in 2020. Other notations are the same as in Equation 1. We then plot the coefficients β_j in Figure SA.1. The differences between the admissions in 2020 and 2019 are not significant before the CNY and are significantly negative after the CNY. This provides evidence of the validity of our analysis.



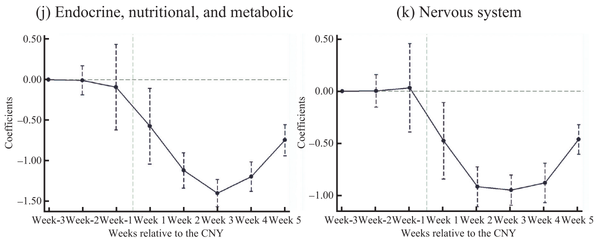


Figure SA.1 Parallel Trend Check

Note: The figures compare the hospital admissions in 2020 with those in 2019 to check for the parallel trend assumption required in the two-difference analysis. We plot the coefficients β_j in Equation SA.4. The first figure shows the admissions for all causes except COVID-19, and the remaining figures show those for the top 10 disease categories (ranked by volume) in the International Classification of Diseases, Tenth Revision.

Table SA.1 Impact of the Pandemic on the Number of Hospital Admissions for All Causes Using Hospital-Daily-Level Data

	(1)
VARIABLES	ln(admissions)
COVID	−0.359***
	(0.008)
% change	−30.2%
Observations	91,280

Note: The table shows the impact of the COVID-19 pandemic on the daily number of hospital admissions for all causes except COVID-19 using hospital-daily-level data. The controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, air pollution, and hospital fixed effects. See Equation SA.2 for specification details. Robust standard errors are in parentheses. *** denotes significance at the 1 percent level.

Table SA.2 Impact of the Pandemic on the Daily Number of Hospital Admissions Controlling for the Cumulative Number of Physicians and Nurses Assigned to Hubei Province

VARIABLES	(1) ln(admissions)
COVID	−0.320**
	(0.148)
Physicians and nurses assigned	−0.000619**
	(0.000298)
% change	−27.4%
Observations	112

Note: The table shows the impact of the pandemic on the daily number of hospital admissions when the cumulative number of physicians and nurses assigned to Hubei Province is included as another control. Other controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and air pollution. Robust standard errors are in parentheses. ** denotes significance at the 5 percent level.

Table SA.3 Impact of the Pandemic on In-Hospital Mortality Controlling for the Cumulative Number of Physicians and Nurses Assigned to Hubei Province

		Subsample		
	(1) All causes	(2) Stroke	(3) Ischemic heart diseases	(4) Malignant neoplasms
COVID	0.0031***	0.0235***	0.0156**	0.0642***
	(0.0009)	(0.0090)	(0.0075)	(0.0193)
Physicians and nurses assigned	0.000001	0.000007	0.000017	0.000073*
	(0.000002)	(0.000017)	(0.000017)	(0.000043)
Observations	1,025,679	19,829	22,651	27,009

Note: The table shows the impact of the COVID-19 pandemic on in-hospital mortality for all causes except COVID-19 and three common diseases (i.e., stroke, ischemic heart diseases, and malignant neoplasms), when the cumulative number of physicians and nurses assigned to Hubei Province is included as another control. Other controls include a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and patient characteristics such as age, gender, primary diagnosis code, and number of comorbidities. Robust standard errors clustered at the hospital level are in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table SA.4 Robustness Check: Logit Model for In-Hospital Mortality

	Subsample		
	(1)	(2)	(3)
Dependent variable: in-hospital mortality	Stroke	Ischemic heart diseases	Malignant neoplasms
COVID	0.688***	0.511**	0.558***
	(0.190)	(0.208)	(0.137)
% change in odds	99.0%	66.7%	74.7%
Observations	19,829	22,651	27,009

Note: The table shows the impact of the COVID-19 pandemic on in-hospital mortality for the three leading causes of deaths in China (i.e., stroke, ischemic heart diseases, and malignant neoplasms). We use the logit model and control a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and patient characteristics such as age, gender, primary diagnosis code, and number of comorbidities. Robust standard errors clustered at the hospital level are in parentheses. *** denotes significance at the 1 percent level, and ** at the 5 percent level.

Table SA.5 Robustness Check: Negative Binomial Model for Length of Stay

	Subsample		
	(1)	(2)	(3)
Dependent variable: LOS	Stroke	Ischemic heart diseases	Malignant neoplasms
COVID	0.069***	0.081**	0.067*
	(0.025)	(0.034)	(0.036)
% change	7.1%	8.4%	6.9%
Observations	19,829	22,651	27,009

Note: The table shows the impact of the COVID-19 pandemic on patients' length of stay (LOS) for three common diseases (i.e., stroke, ischemic heart diseases, and malignant neoplasms). We use the negative binomial model and control a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and patient characteristics such as age, gender, primary diagnosis code, and number of comorbidities. Robust standard errors clustered at the hospital level are in parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table SA.6 Robustness Check: Logit Model for C-Section

	(1)
VARIABLES	C-section
COVID	−0.084**
	(0.040)
% change in odds	8.8%
Observations	47,448

Note: The table shows the impact of the COVID-19 pandemic on the likelihood of C-sections. We use the logit model and control a set of dummies indicating each week of the three weeks before and five weeks after the CNY, day-of-week fixed effects, and patient characteristics such as age and number of comorbidities. Robust standard errors clustered at the hospital level are in parentheses. ** denotes significance at the 5 percent level.