COVID-19 Outbreak and Voluntary Demand for Non-COVID-19 Healthcare:
Evidence from Taiwan

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Abstract

This paper examines the impact of the COVID-19 outbreak on voluntary demand for Non-COVID-19 healthcare. We use 2014-2020 weekly county-level data from Taiwan National Health Insurance alongside a difference-in-differences design. Our results indicate that even if there are no government restrictions on human mobility, people spontaneously reduce their demand for healthcare due to fears of infection or improved health status. On average, the number of outpatient visits (inpatient admissions) decreased by 18% (9%) after COVID-19 outbreak. Furthermore, the demand response of healthcare for infectious diseases (e.g. flu) is much greater and more persistent than for other diseases, suggesting that the substantial decline in healthcare use is induced by positive public-health externality of prevention measures for COVID-19.

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NOTE: This preprint reports new research that has not been certified by peer review and should not be used to guide clinical practice.
1 Introduction

The coronavirus disease 2019 (COVID-19) has raged through most countries around the world, but an effective and accessible vaccine or treatment is still far away. Previous studies have pointed out that the pandemic response of restricting the movements of a population, such as lockdowns or stay-at-home orders, may indeed slow down the spread of the virus (Lin and Meissner, 2020; Abouk and Heydari, 2020; Dave et al., 2020; Fang et al., 2020). However, these prevention measures have also changed many aspects of people’s lives and could have negative impacts on macroeconomic activities (Atkeson, Atkeson; Baker et al., 2020; Eichenbaum, 2020; Guerrieri et al., 2020; Altig et al., 2020), household consumption (Baker et al., 2020; Cicala et al., 2020), and the labor market (Beland et al., 2020; Rojas et al., 2020; Forsythe et al., 2020).

Although these timely studies provide invaluable evidence that can help us understand the effects of these measures on COVID-19 transmission and their economic consequences, there is scant empirical evidence regarding the impact of the outbreak and these pandemic responses on people voluntarily demanding healthcare. Particularly, the healthcare system is one of the most affected sectors during this pandemic, since COVID-19 is essentially a public health crisis. Recent studies have shown that there have been large declines in healthcare utilization for non-COVID-19 diseases (Ziedan et al., 2020; Birkmeyer et al., 2020; Chatterji and Li, 2020; Mehrotra et al., 2020; Hartnett, 2020). However, it is not clear that this observed decline is due to voluntary responses to the pandemic or to other inevitable issues, such as government restrictions on mobility (Chatterji and Li, 2020; Sands et al., 2020; Ziedan et al., 2020), the availability of health resources (Søreide et al., 2020; Hamel et al., 2020) or loss of healthcare coverage and unaffordable medical care costs (Stephenson, 2020; Hamel et al., 2020; Karpman et al., 2020).¹

In this paper, we fill this gap by examining the effect of the COVID-19 outbreak and pandemic responses on the voluntary demand for non-COVID-19 healthcare. Specifically, we investigate this issue by using a difference-in-differences design and weekly county-level data from Taiwan’s National Health Insurance (NHI). The case of Taiwan is well-suited for this analysis for three important reasons. First, its

¹The Urban Institute Coronavirus Tracking Survey indicates that one-third of adults report that they or their family have encountered an “unmet need for medical care,” due to coronavirus (Gonzalez et al., 2020). Furthermore, the KFF Health Tracking Poll reveals that during the COVID-19 outbreak, half of the US population skipped or postponed their medical care, even though one-third of them did try to access medical treatment over a 3-month period (Hamel et al., 2020).
NHI is a compulsory single-payer system, in which everyone has to enroll; thus, the NHI data cover the population-wide healthcare utilization of both outpatient care and inpatient care. This feature allows us to investigate the pandemic effect on different types of healthcare use. Second, up to this point, Taiwan has only experienced seven deaths and 550 COVID-19 cases, so the pandemic has had a very limited impact on healthcare capacity in Taiwan, helping us rule out unmet demand due to supply-side factors. Finally, Taiwan did not implement any lockdown or self-isolation policies; the Taiwanese for their part carried on with their normal lives alongside relatively looser regulation. Therefore, our estimated change in demand for healthcare can persuasively represent the spontaneous response to the COVID-19 pandemic rather than government restrictions on activity/mobility.

We obtain three key findings from our research. Firstly, using Google Trends data, we determine that the Taiwanese responded to the first COVID-19 case by immediately seeking information about the virus and personal protective equipment such as face masks. Consistent with this finding, a cross-country survey suggests that more than 80% of Taiwanese wear face masks in the beginning of the pandemic (i.e. February, 2020).

Secondly, our results suggest that the COVID-19 outbreak led to an 18% decline in the total number of outpatient visits and a 9% decline in the total number of inpatient admissions. The decline in voluntary demand for healthcare during the pandemic period is likely to be mixed with two effects. On one hand, the fear of contracting COVID-19 in hospitals could make people reduce or postpone the use of health care services. Such effect should fade away when the virus disappear from the community. On the other hand, the COVID-19 prevention measures, such as wearing face mask, might have had an unintended effect by reducing the transmission of infectious diseases and then decreased the demand for healthcare. This effect could be large and persistent since these prevention measures indeed make people healthy.

Thirdly, in order to explore possible mechanisms of our findings, we perform subgroup analyses based on the type of diseases. We find that the demand response of healthcare for infectious diseases (e.g. flu, other types of pneumonia or Enterovirus) is much greater and more persistent than for other diseases. On average, the number of outpatient visits and inpatient admissions for infectious diseases decreased by 38%.

2 For example, there were crowd control efforts in popular spots and national parks beginning mid-April, but no bans on domestic travel were initiated.
and 44%, respectively. Furthermore, we also find that the mortality due to influenza-like illness (i.e. flu and other pneumonia) declines by at least 10% after the COVID-19 outbreak. Finally, our event study design indicates that the decline in outpatient visits (inpatient admissions) for infectious diseases remained substantial (i.e. a 30% to 50% decrease) even if there have been no new confirmed local cases since mid-April. In contrast, the reduction in healthcare utilization for other diseases died away during the period when COVID-19 pandemic slowed down.

This paper stands apart from previous literature in the following ways. Firstly, we contribute to the fast-growing body of literature analyzing the impacts of the COVID-19 pandemic on healthcare systems. Several recent studies (Ziedan et al., 2020; Birkmeyer et al., 2020; Chatterji and Li, 2020; Mehrotra et al., 2020; Hartnett, 2020) indicate that there was a large decline in healthcare utilization during the pandemic period in the US. For example, Ziedan et al. (2020) analyzes how state closure policy affects non-COVID-19 health utilization. The result suggests that through March and early April, outpatient visits in the US declined by around 40%, and one-third of this reduction (i.e. 15% decline in outpatient visits) could be explained by states’ closure policies. Our paper provides novel evidence by showing that even if there are no government restrictions on human mobility (e.g. lockdowns or stay-at-home orders), the voluntary response to the pandemic can reduce demand for healthcare substantially and the size of voluntary response (i.e. 18% decline in outpatient visits) is comparable to the effect of state closure policies on healthcare utilization found in Ziedan et al. (2020). Further, our analysis sheds light on the mechanisms through which pandemics affect voluntary demand for Non-COVID-19 healthcare.

Secondly, the spontaneous response to COVID-19 risk broadly relates to “prevalence response” in the literature on economic epidemiology (Ahituv et al., 1996; Gersovitz and Hammer, 2003; Lakdawalla et al., 2006; Paula et al., 2014; Delavande and Kohler, 2012; Bennett et al., 2015). This paper complements this line of research by showing that people could still take preventive actions proactively to reduce the transmission of the virus even if prevalence of the disease is low.3

Thirdly, this paper is also related to the literature on the health effects of non-pharmaceutical interventions (NPIs). Most of the recent research points out that such interventions can indeed effectively reduce

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3Based on the cumulated number of COVID-19 cases reported on October 28th, 2020, the incidence of COVID-19 per 100,000 population is about 2.3 in Taiwan and 2,696 in US.
COVID-19 transmission (Lin and Meissner, 2020; Chernozhukov et al., 2020; Mitze et al., 2020; Abouk and Heydari, 2020; Dave et al., 2020), but they might have negative impacts on mental health (Armbruster and Klotzbücher, 2020; Lu et al., 2020). We contribute to this stream of the literature by showing that the NPIs for COVID-19 has unintended health effects on reducing the incidence of non-COVID-19 diseases such as flu and other pneumonia-based conditions.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of Taiwan’s response to the COVID-19 pandemic. In Section 3, we discuss our data and sample selection. Section 4 provides the graphical evidence of healthcare demand responses to the COVID-19 outbreak. In Section 5, we discuss our empirical strategy and then display the results on healthcare utilization. Finally, Section 7 provides a general discussion of our results and the concluding remarks.

2 Taiwan’s Response to the COVID-19 Pandemic

Given its geographic proximity to and close economic relationship with China, where the COVID-19 outbreak began, Taiwan has been considered one of the most affected countries. Surprisingly, as of October 24th, 2020, Taiwan had recorded only seven deaths and 550 confirmed cases – 502 of which have recovered. Note that the total population of Taiwan is around 23 million, and the country’s infection rate is very low. In addition, no severe local transmissions have had occurred in Taiwan up to that point. Fewer than 10% of confirmed cases are local ones, and there have been no new confirmed local cases since April 14th. Figure B.1 in the Online Appendix displays the number of new confirmed cases for each week of 2020. In general, three key strategies have helped the nation successfully prevent the spread of the virus: 1) Early border control and quarantine policies; 2) Distributing and producing face masks and 3) Disclosing COVID-19 information to the public.

2.1 Early Border Control and Quarantine Policies

As of the first confirmed case, the Taiwan government initiated quarantine policies requiring people returning from ‘high-risk’ COVID-19 countries (e.g. China), and those who had come into contact with confirmed cases, had to enter self-quarantine for 14 days. From March 19th, the Taiwan government restricted
all foreigners from entering the country, and on the very same day, all citizens returning from oversea had to take 14 days’ quarantine. Nevertheless, Taiwan maintained normal life, with no lockdowns or shutdowns, no closure of public spaces or the transportation system and no bans on domestic travel.

2.2 Universal Use of Face Masks

In contrast to European and American countries, the Taiwan government considered face masks one of the most important items of personal protective equipment (PPE) for reducing COVID-19 transmission. In order to make sure every resident had access to face masks, at the beginning of the outbreak (i.e. January 24th) the Taiwan government banned their export and requisitioned a huge increase in local production. The daily production capacity of face mask manufacturers in Taiwan before the outbreak was 1.88 million pieces, but currently, Taiwan is able to produce more than 15 million per day. Moreover, starting from February 6th, the government implemented a name-based rationing system for face masks to curb panic-buying and to ensure the universal face-covering of all residents in Taiwan.

2.3 Public Disclosure of COVID-19 Information

Besides its universal masking policy, border controls and quarantine policies, Taiwan’s success in terms of controlling the epidemic can also be attributed to its information dissemination and disclosure strategies. On January 20th, the Central Epidemic Command Center (CECC) was initiated. When the first confirmed case was corroborated on January 22nd, the CECC held press conferences every day to report on the epidemic and to offer self-protection information to citizens.

Specifically, the CECC reported newly confirmed cases, cumulative confirmed cases, new death cases and recovered cases every day. The CECC also set up an on-line system for citizens to find out daily data on COVID-19 cases relevant to different counties. In addition, when specific symptoms (such as loss of taste, stroke, etc.) were noted, the CECC also released this information to the public, and whenever any

4https://www.moea.gov.tw/MNS/populace/news/News.aspx?kind=1&menu_id=40&news_id=88545, Accessed 5 Sep. 2020
5https://www.moea.gov.tw/MNS/populace/news/News.aspx?kind=9&menu_id=22333&news_id=89290, Accessed 5 Sep. 2020
6The frequency of these briefings was reduced to once a week from June 8th following a cumulative 8 weeks of no local confirmed cases.
7https://nidss.cdc.gov.tw/ch/NIDSS_DiseaseMap.aspx?dc=1&dt=5&disease=19CoV
local cases were discovered, it highlighted these during the press conferences with particular emphasis on the source and route of infection. The above information made citizens aware of the severity of the epidemic and helped them monitor their personal health status carefully.\footnote{More detailed review on Taiwan’s pandemic responses can be found in \textcite{Wang2020}.
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### 2.4 Behavioral Responses to COVID-19 Information

Using Google Trends data, we find that the Taiwanese people responded to the announcement of the first confirmed case immediately by searching for information about the virus and personal protective equipment (PPE), such as face masks and sanitiser.\footnote{Google Trends, powered by Google, provides the relative search interests of a given keyword made to Google at a given time period and location. Readers can get data from this website: \url{https://trends.google.com.tw/}.}

Note that instead of showing absolute search volume, Google Trends only provides a relative measure for daily search volume ranging from 0–100, where the numbers represent the search volume relative to the highest point. A value of 100 is the peak popularity of the term, and a value of 50 means half as popular. In order to match the frequency of healthcare data, we aggregate daily data to the weekly level.

Figures 1a suggests that the search intensity of the keywords “Coronavirus” nearly reached 250 in the week of the first confirmed case announcement.\footnote{We use the equivalent term in Chinese for Coronavirus as the keywords.} Moreover, this search intensity jumped more than double and reached its peak when the first local COVID-19 case was reported. We also find that PPE-related (i.e. face mask and sanitizer) searches also peaked after the announcement of the first local COVID-19 case (See Figure 1c and 1e).\footnote{We use the equivalent term in Chinese for mask and sanitizer as the keywords.} Due to the painful experience of the 2003 outbreak of SARS (\textcite{Bennett2015}), both the Taiwanese government and its people responded to the first COVID-19 case very quickly indeed.\footnote{SARS severely hurt Taiwan in 2003, with a total of 668 reported cases and 181 death cases (\textcite{Chen2005}).}

Not every country responded to the first COVID-19 case in such a way, with the United States being a counterexample. Consistent with \textcite{Bento2020}, Figures 1b, 1d and 1f indicates that the information-seeking behavior of the American people was in fact immediate following the first COVID-19 case, which was reported on January 21\textsuperscript{st}, 2020. However, in contrast to Taiwan, the peak of the relative search volume for COVID-19 and PPE-related key words happened on the 7\textsuperscript{th} week (i.e. March 8\textsuperscript{th} to 14\textsuperscript{th}) after the first confirmed case, because the US government verified this case was COVID-19 on March 1\textsuperscript{st}. In addition, the
search intensity for face masks (see Figure 1d) peaked after the Center for Disease Control and Prevention (CDC) recommended that people wearing a face mask (April 3rd) would be an effective way to prevent COVID-19 transmission on April 5th to April 11th (i.e. 11 weeks after first confirmed case). Figure B.2 of the Online Appendix shows the daily trends in search index. The patterns are similar to the weekly trends. Since the United States is a large country, it is possible that people only responded to local cases. In Figure B.3 of the Online Appendix, we also find a similar pattern in search behavior, using Google Trends data for Washington State or Seattle, where the first COVID-19 cases happened.

According to a survey conducted by the National Taipei University of Nursing and Health Sciences in April, 97.5% of Taiwanese thought that coronavirus is a serious disease, and over 90% of the interviewees correctly answered questions regarding how the virus spreads and prevention measures. Figure B.4 in the Online Appendix shows the percentage of people who say they are wearing face mask when in public places across time, surveyed by YouGov (Smith, 2020). The figure shows that as early as in February, over 80% of Taiwanese said that they were wearing a face mask in a public space. Further, the portion of people wearing masks remains high through the time. In contrast, only 7% of Americans said they had worn a face mask in early March, and the proportion began raised to half only until mid-April. All of these results are consistent with the patterns seen in Google Trends data, suggesting that the Taiwanese people have responded to COVID-19 in a rapid and proactive way.

3 Data and Sample

3.1 Data

Our healthcare utilization data come from the Taiwan National Infectious Disease Statistics System, which is accessed via the Taiwan Center for Disease Control’s (TCDC) Open Data Portal. This database originates from NHI claim data, so it covers almost the entire population and healthcare utilization in Taiwan. In order to investigate the outbreak of infectious diseases in a timely manner, the TCDC provides to the public weekly data on the number of outpatient visits and inpatient admissions by county, age group and category of

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13 https://www.livescience.com/cdc-recommends-face-masks-coronavirus.html, accessed 20 Aug. 2020
14 https://news.sina.com.tw/article/20200509/35111198.html, Accessed 10 Aug. 2020
15 https://data.cdc.gov.tw/
infectious disease. Note that the definition of “week” in this database follows the World Health Organization (WHO)’s definition, which always begins on a Sunday and ends on a Saturday but does not definitely start from January 1st.

### 3.2 Sample

The estimated sample is at the weekly-county level. The sample period is from 2014 to 2020, and we use the first 31 weeks of each year. Thus, the estimated sample includes 22 counties × 31 weeks × 7 years (2014 to 2020), leading to a sample size of 4,774.

To construct our outcome variables – the incidence rate of outpatient visits/inpatient admissions per 100,000 population for specific types of diseases – we divide the number of outpatient visits and inpatient admissions by the population of each corresponding county per year. Population information comes from the population statistics database provided by the Ministry of Interior, Taiwan. In our estimated sample, we also include time-varying factors, such as weather, that may affect health utilization in each county. Thus, we acquire daily weather information from the Central Weather Bureau’s (CWB) observation data inquiry system, in order to calculate the weekly average temperature and rainfall of each county.

Finally, in order to understand the mechanisms behind COVID-19 effects, we categorize diseases into infectious diseases (e.g. influenza-like illness and diarrhea) and other diseases. Table 1 displays the summary statistics for the outcome variables and covariates in the treatment group (i.e. 2020) and control group (i.e. 2014–2019).

### 4 Graphical Evidence

The top panel of Figure 2 displays trends in the numbers of outpatient visits in the first 31 weeks of the year for 2020 (see Figure 2a) and 2014–2019 (see Figure 2b). The solid line represents infectious disease-related visits, and the dashed line represents visits for other diseases. Since the first confirmed COVID-19

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16 The 31st week refers to about the last week in July or the first week in August.

17 https://www.ris.gov.tw/app/portal/346

18 https://e-service.cwb.gov.tw/HistoryDataQuery/index.jsp

19 The ICD-9 codes used for infectious diseases are as follows: 009.0, 034.1, 052, 074.0, 074.3, 480–487, 558.9, 787. The ICD-10 codes used for infectious diseases are: A08, A09, A22, A37, A38, B01, B08.4, B08.5, B25, B44, J06.9, J09-J18, K52, R19.7. The definition of other diseases is the diseases excluding the above ICD-9 and ICD 10 codes.
case was announced in the 4th week of 2020 (i.e. the week of January 21st), the vertical line in the graph separates that week from the following weeks. The vertical axis of Figure 2 stands for the percentage change in the number of outpatient visits from the baseline weeks. We use the average number of outpatient visits in the first three weeks of each year as the baseline.

Figure 2a shows that there is a large decline in visits for other diseases during the lunar new year (i.e. the 5th week of 2020) and a rebound after the holiday. This pattern can also be found in 2014–2019 (see Figure 2b). The difference between 2020 and the past few years is that the average number of visits for other diseases in 2020 did not rebound back to the baseline level, and in fact they declined by around 10% in the post-outbreak period. However, in a sharp deviation from the usual seasonal patterns of 2014–2019, the number of visits for infectious diseases in 2020 did not even rebound after the lunar new year and fell by almost 60% until the end of the sample period. This is quite unusual, as January to April (i.e. the first 16 weeks) is normally flu season in Taiwan.

The bottom panel of Figure 2 suggests that the same pattern can be found in inpatient care (i.e. more severe conditions). Again, we find that inpatient admissions for other diseases drop sharply during the week of the lunar new year and quickly reach baseline level after the holiday (see Figure 2c). Similar trends can be found in 2014–2019 (see Figure 2d). In sum, inpatient admissions for other diseases did not exhibit any decline after the announcement of the first COVID-19 case. In contrast to other diseases, the number of inpatient admissions for infectious diseases fell by near 50% during the post-outbreak period, which is very different from the trends in 2014–2019.

5 Empirical Strategy and Results

Our identification strategy is a difference-in-differences (DID) design. Since the first COVID-19 case in Taiwan was reported on January 21st 2020 (i.e. the 4th week of a year), we use 2020 data as the treatment group and define the weeks before (after) the 4th week of the year as the pre-outbreak (post-outbreak) period. To control the seasonal pattern of healthcare demand which is unrelated to the COVID-19 outbreak, we use 2014–2019 data as a control group to construct the counterfactual trend of health utilization in 2020.

We first use a conventional DID design to examine the average effects of the COVID-19 outbreak on
healthcare utilization, following which we extend to a DID event study design (Kleven et al., 2019; Chang et al., 2020; Ziedan et al., 2020), to investigate further the dynamic trajectory of the COVID-19 effects.

5.1 Effects of the COVID-19 Outbreak on Healthcare Utilization

In order to estimate the average effects of the COVID-19 outbreak on healthcare utilization, we specify the DID design as the following regression:

$$H_{idt} = \gamma_0 + \beta^{covid}Y_{2020} \times Post_d + \lambda_t + \eta_d + \theta_i + X_{idt}\psi + \epsilon_{idt}$$ (1)

Our estimation is implemented at the weekly-county level. $H_{idt}$ represents the outcomes of interest: numbers of outpatient visits (inpatient admissions) per 100,000 person-weeks in county $i$ in week $d$ of year $t$. We focus on three measures of the weekly volume of outpatient visits (inpatient admissions): 1) total visits/admissions; 2) visits/admissions for infectious diseases and 3) visits/admissions for other diseases. $Y_{2020}$ is a treatment-group dummy that takes one if the observation is in 2020, zero otherwise. $Post_d$ is a dummy indicating the post-outbreak period. We include the year fixed effect $\lambda_t$ to control for the general trend in healthcare utilization over time. In addition, $\eta_d$ represents the week-of-the-year fixed effect, which helps us control the seasonal pattern of healthcare demand within each year. To control any time-invariant confounding factors at the county-level, we also include a full set of county fixed effects $\theta_i$. $X_{idt}$ refers to a set of covariates, including various holiday dummies (e.g. Lunar new year week), average weekly temperature and average weekly rainfall. In order to account for possible within-group correlations of the errors, we use the multiway clustering approach proposed by Cameron et al. (2012) to calculate the standard errors clustered at both the year-week and county level in all regressions. Finally, all regressions are weighted by monthly population size of a county. In Section 5.2, we conduct robustness checks on the estimates by computing the standard errors at different cluster levels and using unweighted regressions.

The key variable used for identification in regression (1) is an interaction term between an indicator for treatment year $Y_{2020}$ and a dummy for post-outbreak period $Post_d$. The coefficients of interest are $\beta^{covid}$, measuring the difference in healthcare utilization before and after the COVID-19 outbreak in 2020 (i.e. the
treatment year), relative to the difference for the corresponding periods in 2014-2019 (i.e. the control years). \( \beta^{covid} \) can represent COVID-19 effects on healthcare utilization if the common trend assumption holds. That is, in the absence of the COVID-19 outbreak, the weekly trend in healthcare utilization should be similar in the treatment year and control years. We will examine this assumption by using the DID event study design and a placebo test.

The first three columns of Table 2 show the estimated \( \beta^{covid} \) (i.e. the coefficient on \( Y_{2020} \times Post_d \)) for outpatient care. The control variables are gradually included to test the sensitivity of the results to different specifications. Estimates across the specifications are fairly independent of the introduction of different sets of control variables. Our preferred specification is in Column (3) of Table 2, which includes a full set of covariates. The estimate in Column (3) of Panel A suggests that compared to the same weeks in 2014–2019, total outpatient visits per 100,000 person-weeks during the post-outbreak period in 2020 significantly decrease by 3,827 visits. This represents an 18% reduction in total outpatient visits from the baseline mean (i.e. 20,685 visits). Furthermore, the estimates in Column (3) of Panels B and C show that infectious diseases visits have a much larger decline (i.e. 38%) than other visits (i.e. 14%). According to the baseline mean, the visits for infectious diseases only account for 15% of outpatient utilization (i.e. \( \frac{3,261}{21,685} = 0.15 \)). However, more than 30% of reduction in total visits can be attributed to infectious diseases (i.e. \( \frac{1,243}{3,827} = 0.32 \)).

Columns (4) to (6) display the estimated \( \beta^{covid} \) for inpatient care. Column (6) of Table 2 is our preferred specification. The estimate in Column (6) of Panel A indicates that the COVID-19 outbreak reduces total inpatient admissions per 100,000 person-weeks by 15.4 (i.e. a 9% decrease). The estimates in Column (6) of Panels B and C show the results for infectious diseases admissions and other admissions, respectively. Compared to the trend in previous years, the number of infectious diseases admissions per 100,000 person-weeks declined by 7.21 during the post-outbreak period in 2020 (see Panel B). This is a sizeable change, thereby suggesting that the COVID-19 outbreak reduced inpatient admissions for infectious diseases by 44%. In contrast, inpatient admissions for other diseases decreased by only 5% (see Panel C).

Since the impact of the COVID-19 outbreak on healthcare utilization might have evolved over time, we need to trace out the full dynamic trajectory of the COVID-19 effects. Therefore, we implement a DID event study design by interacting treatment group dummy \( Y_{2020} \) with leads and lags time dummies \( W_d \).
\[ H_{idt} = \gamma_0 + \sum_d \beta_d Y_{2020} \times W_d + \lambda_t + \eta_d + \theta_i + X_{idt} \psi + \varepsilon_{idt} \]  

(2)

We use \( W_d \), where \( d = -3, -1, 0, 1, 2, 3, \ldots, 25, 26, 27 \), to denote dummy variables for the weeks before and after the 4th week of a year. For example, \( W_1 \) represents a dummy for the first week after the announcement of the first confirmed COVID-19 case. Note that we use the 2nd week of a year as the baseline week (i.e. \( d = -2 \)).

The key variables used for identification in regression (2) are a set of week dummies \( W_d \) interacted with the treatment group dummy \( Y_{2020} \). The coefficients of interest are \( \beta_d \), measuring the difference in healthcare utilization between week \( d \) and the baseline week for 2020 (i.e. the treatment year), relative to the difference for 2014–2019 (i.e. the control years). \( \beta_d \) can represent the causal effect of the COVID-19 outbreak on healthcare utilization during the pandemic period.

In order to obtain the relative change from the baseline mean, we divide the estimated \( \beta_d \) by the average outcome of the baseline week in the treatment year. We show these estimates and the corresponding 95% confidence intervals in Figure 3. The top (bottom) panel of Figure 3 displays the results for outpatient (inpatient) care. Three key insights emerge from the figures. Firstly, the estimates for the first three weeks of a year (i.e. \( d = -3, -2, -1 \)) in all figures are close to zero, suggesting that trends in the numbers of outpatient visits/inpatient admissions between the treatment year (i.e. 2020) and the control years (i.e. 2014–2019) are parallel before the COVID-19 outbreak. Therefore, the common trend assumption of our DID design is valid.

Secondly, Figure 3a indicates that the size of the reduction in visits for infectious diseases is very large. The COVID-19 outbreak reduces the utilization of outpatient care for infectious diseases by about 50% within the first four weeks of the pandemic, and the effects are persistent, thereby suggesting that infectious diseases visits still declined by at least 25% at the end of the sample period. For the visits for other diseases, Figure 3b suggests that the reduction in outpatient use is relatively smaller. The number of visits for other diseases declined by 15% in the 4th week after the first case was reported and shrink to zero in later-June (i.e. the 23rd week after first COVID-19 case) because there were no local COVID-19 cases in Taiwan for
more than a month.

Thirdly, Figure 3c suggests that the number of inpatient admissions for infectious diseases decreased by about 50% in the 4th week after the announcement of the first COVID-19 case. Consistent with outpatient care, the reduction in infectious diseases admissions never rebounded to the pre-outbreak level until the last week of our sample period (i.e. around the last week of July). Figure 3d indicates that inpatient admissions for other diseases significantly declined when the number of COVID-19 cases accumulated quickly and reached peak (i.e. the 6th week to the 13th week after the first COVID-19 case). Interestingly, the COVID-19-induced decline in the number of admissions for other diseases dropped immediately to zero when the number of COVID-19 cases started to decelerate (i.e. the 14th week after the first COVID-19 case).

5.2 Placebo Test and Robustness Checks

In this section, we first implement a placebo test by excluding the sample in 2020 and using instead the sample in 2019 as the treatment group, while those in other years are utilized as the control group. Table 3 shows that the estimated “COVID-19 effects” are much smaller than the ones in our main results. In addition, most of the estimates are either insignificant or positive. Figure 4 displays the DID event study estimates. In sharp contrast to Figure 3, almost all estimates are close to zero and insignificant. Again, this placebo result confirms the validity of the common trend assumption, suggesting that in the absence of a COVID-19 outbreak, the weekly trends in healthcare utilization are similar across different years.

Then, we conduct several robustness checks using various specifications. Table A.1 of the Online Appendix displays the estimated coefficients of $Y_{2020} \times Post$ using a Poisson fixed effect regression. The estimated coefficients in this specification can directly represent the percentage change in healthcare utilization induced by COVID-19 outbreak. We find that the estimated sizes of change in outpatient visits/inpatient admissions are largely similar to our main estimates. Table A.2 of the Online Appendix shows the results using the unweighted regression (1). We find that our estimates are robust to this change.

Finally, we calculate the standard errors based on different clustering levels to examine the robustness of statistical inference. Table A.3 and A.4 of the Online Appendix present statistical inferences using the standard errors clustered on the county or year-week, respectively. We find that our results are robust to this
5.3 Effects of the COVID-19 Outbreak on Influenza-Associated Mortality: Suggestive Evidence

Among infectious diseases, influenza-like illness (ILI) share many similarities with COVID-19 in terms of disease presentation and the ways of transmission. If the prevention measures for COVID-19, such as wearing a face mask, indeed leads to decline in healthcare use for infectious diseases, we should expect outpatient visits and inpatient admissions for ILI experience larger reductions.

In this section, we first examine the effect COVID-19 outbreak on healthcare utilization for ILI. Table A.5 of the Online Appendix indicates that the COVID-19 outbreak reduces outpatient visits (inpatient admissions) for ILI by 72% (49%) which is even larger than the size of decline in outpatient visits for infectious diseases.

Then, we provide suggestive evidence on the effect of the COVID-19 outbreak on ILI-related mortality. Different from healthcare utilization, the TCDC provides data on the number of ILI-related deaths at the national level from 2008 to 2020. The weakly ILI mortality rate is 1.54 per 100,000 population in the first three weeks during 2008 to 2019, and this number is slightly reduced to 1.49 in the 4th to the 31st week (a 3% decrease). For 2020, on the other hand, the mortality rate per 100,000 population is 1.93 in the first three weeks of 2020 (pre-outbreak period) and declines to 1.72 after the COVID-19 outbreak (an 11% decrease).

Figure B.5 of the Online Appendix displays the percentage change in the weekly number of ILI-related deaths per 100,000 population from the baseline mean (i.e. the average outcome of the first three weeks in each year). The solid line represents the trend of the ILI-related mortality rate in 2020. The dashed line represents the 12-year average of the ILI-related mortality rate during 2008–2019 and the corresponding interval within two standard deviations from the mean. Again, the vertical line in the graph denotes the 4th week of a year. Our result suggests that the trend for the ILI-related mortality rate in 2020 is quite unusual. Compared to the same period in the previous 12 years, the percentage change from the baseline mean for the ILI-related mortality rate fell by 10% to 20%. In addition, the magnitude of decline remains constant until the end of the sample period.
6 Discussion

6.1 Interpretation of the Results

So far, we have found that the COVID-19 outbreak is associated with a substantial reduction in both outpatient and inpatient utilization. In addition, the healthcare utilization for infectious diseases experienced a much larger decline than for other diseases during the pandemic period. Since COVID-19 had limited impacts on Taiwan’s healthcare system, and the government did not implement any mobility-restricted policy or close health facilities, the reduction in healthcare utilization is unlikely to have been caused by issues related to healthcare supply or human mobility restrictions.

Therefore, the decline in demand for healthcare during the pandemic period is likely to be mixed with two effects. First, people may have reduced healthcare utilization due to the fear of COVID-19 infection. As hospitals are usually a place with a high risk of contracting diseases, patients might postpone or cancel their visits, if receiving medical treatment is neither necessary nor urgent; we call this mechanism the “fear effect”. Second, the COVID-19 prevention measures, such as wearing face mask and hand-washing, might have had an unintended effect by reducing the transmission of infectious diseases (e.g. flu or other forms of pneumonia). Thus, the demand for healthcare could have decreased due to an improvement in health status. This particular mechanism is called the “prevention effect.”

In our main analysis, we find that the COVID-19 outbreak caused different impacts on healthcare utilization for infectious diseases and other diseases. Such differences can help us understand the mechanisms behind healthcare demand responses to the COVID-19 outbreak. If the decline in healthcare utilization were mainly driven by the fear effect, we should expect COVID-19 outbreak would have less negative impact on utilization of inpatient care (i.e. essential healthcare) than that of outpatient care (i.e. discretionary healthcare). In addition, the demand response to the fear of contracting COVID-19 might have disappeared when no new local COVID-19 cases being reported.

Our results indicate that the demand response of healthcare for other diseases could have been induced by the fear effect of contracting COVID-19. For other diseases, the COVID-19 outbreak led to a 14% reduction in outpatient visits but only reduced inpatient admissions by 5%. Furthermore, the DID event study
analysis suggests that the negative effect of the COVID-19 outbreak on the utilization of both outpatient care and inpatient care for other diseases faded when no new local COVID-19 cases were reported in Taiwan. Interestingly, we find that the demand response of inpatient care vanished earlier than for outpatient care (i.e. the 14\textsuperscript{th} week vs the 23\textsuperscript{rd} week after the first COVID-19 case).

On the other hand, if the reduction in healthcare utilization was mainly driven by the prevention effect, we should expect that the negative effect of the COVID-19 outbreak would have been sizable and persistent, because these measures basically helped stop the spread of infectious diseases and are still being implemented until now; for example, mask-wearing is still compulsory on public transport in Taiwan. Under this mechanism, we should also find corresponding evidence on the improvement in health status, such as a decline in mortality. Our results indicate that the prevention effect of COVID-19 encouraged a reduction in demand for infectious diseases healthcare. Firstly, we find that the COVID-19 outbreak led to a large decline in outpatient visits and inpatient admissions for infectious diseases (i.e. a 38% and a 44% decrease, respectively). Secondly, among the infectious diseases, the decline is even larger for ILI, which shares many similarities with COVID-19. Thirdly, the negative effect of the COVID-19 outbreak on the demand for infectious diseases healthcare is quite persistent. Finally, our results indicate that the COVID-19 outbreak reduced the ILI-related mortality rate by at least 10%, suggesting COVID-19 prevention measures indeed resulted in unintended health benefits.

6.2 Effects of COVID-19 Outbreak on Healthcare Expenditure

Using our results, we can provide the estimated effect of the COVID-19 outbreak on NHI healthcare expenditure. Note that the average expense per outpatient visit and the average expense per inpatient admission are around 1,387 NT$ (i.e. 47 US$) and 63,249 NT$ (i.e. 2,163 US$), respectively. Based on the above information, our DID estimates suggest that the COVID-19 outbreak could “save” NHI expenditure to the tune of 41.4 billion NT$ (i.e. 1.4 billion US$), which accounts for 5.7% of the annual NHI budget (713.9 billion NT$ in 2019).\textsuperscript{20}

\textsuperscript{20}Our calculation is based on the following information: 1) the estimate in Panel A of Table 2 indicates that on average, the COVID-19 outbreak reduces total outpatient visits (inpatient admissions) per 100,000 person-weeks by 3,827 (15.4) for 28 weeks; 2) the average expense per inpatient admission are around 1,387 NT$ and 63,249 NT$, respectively; 3) the total population in Taiwan is about 23,570,000.
7 Conclusion

This paper examines the effects of the COVID-19 outbreak on voluntary demand for healthcare in Taiwan. By comparing with the same period in the years before the COVID-19 outbreak (i.e. 2014–2019), we find a large decline in health utilization after the outbreak of COVID-19. On average, the COVID-19 outbreak reduced the number of outpatient visits and inpatient admissions by 18% and 9%, respectively. In addition, the demand response of healthcare for infectious diseases was much larger than for non-infectious diseases. Finally, we also find that the outbreak induced at least a 10% decline in the ILI-mortality rate.

There are two important limitations of this paper. First, our data source only provides total outpatient visits/inpatient admissions and subcategories of infectious diseases. Due to this limitation, we cannot analyze the impact of COVID-19 on other types of healthcare, such as mental health. It is possible that future researches will explore such issues after individual-level NHI claim data have been released. Second, our research design cannot untangle which prevention measures avoided the spread of infectious diseases and then reduced demand for associated healthcare. However, as universal masking has been the key element in Taiwan’s pandemic response, we believe that this practice should play an important role in this regard. Nevertheless, more studies are needed to understand the effect of different prevention measures on health utilization and health.
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## Tables

### Table 1: Summary Statistics for the Treatment and Control Groups

|                                | Treatment group | Control group |
|--------------------------------|-----------------|---------------|
|                                | 2020            | 2014–2019     |
|                                | Pre-outbreak    | Post-outbreak | Pre-outbreak | Post-outbreak |
| Number of total outpatient visits (per 100,000 population) | 21,685.9 (5,458.4) | 18,143.9 (4,858.2) | 20,915.7 (5,644.6) | 20,384.5 (5,822.7) |
| Number of outpatient visits for infectious diseases (per 100,000 population) | 3,261.5 (687.4) | 1,760.4 (680.8) | 3,259.8 (725.3) | 2,817.4 (799.5) |
| Number of outpatient visits for other diseases (per 100,000 population) | 18,424.4 (5,047.4) | 16,383.5 (4,607.4) | 17,655.9 (5,202.6) | 17,567.1 (5,374.8) |
| Number of total inpatient admissions (per 100,000 population) | 166.9 (87.6) | 161.5 (85.6) | 148.2 (85.9) | 157.9 (86.8) |
| Number of inpatient admissions for infectious diseases (per 100,000 population) | 16.5 (8.7) | 10.4 (5.8) | 13.9 (8.9) | 15.9 (9.4) |
| Number of inpatient admissions for other diseases (per 100,000 population) | 150.4 (83.5) | 151.1 (82.3) | 134.3 (80.0) | 142.1 (81.0) |
| Population | 1,072,904 (1,110,366) | 1,072,347 (1,102,909) | 1,068,317 (1,091,071) | 1,068,602 (1,090,631) |
| Temperature (°C) | 17.1 (2.1) | 22.5 (5.1) | 16.0 (2.6) | 22.2 (5.2) |
| Precipitation (mm) | 7.4 (10.9) | 4.2 (7.0) | 3.3 (5.9) | 6.0 (8.8) |
| Observations | 66 | 616 | 396 | 3,696 |

*Note:* Healthcare utilization data come from the Taiwan National Infectious Disease Statistics System, which originates from 2014–2020 NHI claim data. Population information comes from the population statistics database provided by the Ministry of Interior, Taiwan. Weather variables are from the Central Weather Bureau’s (CWB) observation data inquiry system. The all variables and their summary statistics are at county level. Standard deviations are in parentheses.
Table 2: Effects of COVID-19 Outbreak on Healthcare Utilization: DID Design

| Panel | Total Visits/Admissions |
|-------|-------------------------|
|       | (1) (2) (3) (4) (5) (6) |
|       | Outpatient Care          |
|       | Inpatient Care           |
| **Y_{2020} × Post** | -3,720.63*** | -3,445.71*** | -3,827.25*** | -16.32*** | -16.03** | -15.40*** |
| Baseline Mean   | (210.51)          | (402.78)       | (430.61)       | (3.83)   | (7.01)   | (5.41)   |
| Percent Change | -17.16%            | -15.89%        | -17.65%        | -9.78%   | -9.61%   | -9.23%   |
| **Panel B: Infectious Diseases** |
| **Y_{2020} × Post** | -1,191.01*** | -1,216.48*** | -1,243.02*** | -7.32*** | -7.86*** | -7.21*** |
| Baseline Mean   | (99.33)           | (101.89)       | (109.56)       | (0.68)   | (0.65)   | (1.03)   |
| Percent Change | -36.52%            | -37.30%        | -38.11%        | -44.43%  | -47.77%  | -43.79%  |
| **Panel C: Other Diseases** |
| **Y_{2020} × Post** | -2,529.62*** | -2,229.23*** | -2,584.24*** | -9.01**  | -8.17    | -8.19    |
| Baseline Mean   | (123.79)          | (298.59)       | (367.10)       | (3.43)   | (6.55)   | (5.09)   |
| Percent Change | -13.73%            | -12.10%        | -14.03%        | -5.99%   | -5.43%   | -5.45%   |

Observation: 4,774

Basic Control: ✓ ✓ ✓ ✓ ✓ ✓
Weather Variables: ✓ ✓ ✓ ✓
Fixed County Effect: ✓ ✓

Note: This table shows the estimated $\beta_{covid}$ (i.e., the coefficient on $Y_{2020} × Post_d$) in the equation (1). The outcomes of interest is numbers of outpatient visits (inpatient admissions) per 100,000 person-weeks. Sample period is 2014–2020. Basic Control includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). Weather Variables includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e., before the outbreak) for the treatment group (Year 2020). Robust standard errors clustered at the year-week and county levels are reported in parentheses.

*p < 0.1**  p < 0.05***  p < 0.01
### Table 3: Placebo Test: DID Design

|                | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       |
|----------------|-----------|-----------|-----------|-----------|-----------|-----------|
|                | Outpatient Care | Inpatient Care |           |           |           |           |
| **Panel A: Total Visits/Admissions** |           |           |           |           |           |           |
| $Y_{2019} \times Post$ | 799.03*** | 1,347.30*** | 898.98*  | -4.44**  | -2.43    | -3.11    |
| Baseline Mean   | 20,412.46 | 164.21    |           |           |           |           |
| Percent Change  | 3.91%    | 6.6%      | 4.4%      | -2.71%   | -1.48%   | -1.89%   |
| **Panel B: Infectious Diseases** |           |           |           |           |           |           |
| $Y_{2019} \times Post$ | 312.87*** | 289.03*** | 269.61*** | 0.00     | -0.49    | 0.10     |
| Baseline Mean   | 2,962.26 | 13.78     |           |           |           |           |
| Percent Change  | 10.56%   | 9.76%     | 9.1%      | 0.02%    | -3.25%   | 0.74%    |
| **Panel C: Other Diseases** |           |           |           |           |           |           |
| $Y_{2019} \times Post$ | 486.16*** | 1,058.27*** | 629.37 | -4.45*** | -1.98    | -3.21    |
| Baseline Mean   | 20,140.88 | 154.95    |           |           |           |           |
| Percent Change  | 2.79%    | 6.06%     | 3.61%     | -2.96%   | -1.32%   | -2.14%   |

**Observation**: 4,092

**Basic Control**: ✓ ✓ ✓ ✓ ✓ ✓ ✓

**Weather Variables**: ✓ ✓ ✓ ✓ ✓

**County Fixed Effect**: ✓ ✓

*Note: This table shows the estimated $\beta^{covid}$ (i.e. the coefficient on $Y_{2019} \times Post$) in the equation (1). The outcomes of interest is numbers of outpatient visits (inpatient admissions) per 100,000 person-weeks. Sample period is 2014–2019. **Basic Control** includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). **Weather Variables** includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e. before the outbreak) for the treatment group (Year 2019). Robust standard errors clustered at the year-week and county levels are reported in parentheses.*

*p < 0.1**  **p < 0.05***  **p < 0.01**
Figures

Figure 1: Google Search Intensity for COVID-19 Related Keywords: Taiwan and US

(a) Coronavirus, Taiwan
(b) Coronavirus, US
(c) Mask, Taiwan
(d) Mask, US
(e) Sanitizer, Taiwan
(f) Sanitizer, US

Notes: The figures are constructed by using Google Trends data. Google Trends only provides a relative measure for daily search volume ranging from 0–100. In order to match the frequency of healthcare data, we aggregate daily data to the weekly level. For Taiwan’s keywords, we use the equivalent term in Chinese for Coronavirus, mask, and sanitizer as the keywords.
Figure 2: Number of Outpatient Visits/Inpatient Admissions per 100,000 People

(a) Outpatient Visits, 2020

(b) Outpatient Visits, 2014-2019

(c) Inpatient Admissions, 2020

(d) Inpatient Admissions, 2014-2019

Notes: Sample period is 2014–2020. Figure 2a and Figure 2b (Figure 2c and Figure 2d) display trends in the numbers of outpatient visits (inpatient admissions) in the first 31 weeks of the year for 2020 and 2014–2019, respectively. The solid line represents infectious diseases visits (admissions), and the dashed line represents non-infectious diseases visits (admissions). Since the first confirmed COVID-19 case was announced in the 4th week of 2020 (i.e. the week of January 21st), the vertical line in the graph separates that week from the following weeks. The vertical axis of Figure 2 stands for the percentage change in the number of outpatient visits (inpatient admissions) from the baseline weeks. We use the number of outpatient visits (inpatient admissions) in the first three weeks of each year as the baseline.
Figure 3: Effects of COVID-19 Outbreak on Healthcare Utilization: DID Event Study Design

Notes: Sample period is 2014–2020. The vertical axis displays the estimated percentage change in number of outpatient visits/inpatient admissions from the baseline and the corresponding 95% confidence intervals. In order to get these numbers, we divide the estimated $\beta_d$ from the equation (2) by the average outcome of the baseline week in the treatment year. The horizontal axis denotes weeks from the 4th week of a year.
Figure 4: Placebo Test: DID Event Study Design

Notes: Sample period is 2014-2019. The vertical axis displays the estimated percentage change in number of outpatient visits/inpatient admissions from the baseline and the corresponding 95% confidence intervals. In order to get these numbers, we divide the estimated $\beta_d$ from the equation (2) by the average outcome of the baseline week in the treatment year. The horizontal axis denotes weeks from the 4th week of a year.
## Online Appendix

### A Tables

Table A.1: Robustness Check 1: Poisson Regressions

|                  | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       |
|------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| **Panel A: Total Visits/Admissions** |           |           |           |           |           |           |
| $Y_{2020} \times Post$ | -0.179*** | -0.167*** | -0.184*** | -0.091*** | -0.089**  | -0.087*** |
|                  | (0.011)   | (0.018)   | (0.020)   | (0.016)   | (0.030)   | (0.027)   |
| **Panel B: Infectious Diseases** |           |           |           |           |           |           |
| $Y_{2020} \times Post$ | -0.501*** | -0.507*** | -0.515*** | -0.516*** | -0.552*** | -0.510*** |
|                  | (0.040)   | (0.040)   | (0.042)   | (0.035)   | (0.047)   | (0.056)   |
| **Panel C: Other Diseases** |           |           |           |           |           |           |
| $Y_{2020} \times Post$ | -0.139*** | -0.124*** | -0.141*** | -0.057*** | -0.051    | -0.053*   |
|                  | (0.007)   | (0.015)   | (0.019)   | (0.018)   | (0.034)   | (0.029)   |

| Observation       | 4,774     |           |           |           |           |           |
| Basic Control     | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         |
| Weather Variables | ✓         | ✓         | ✓         | ✓         | ✓         | ✓         |
| County Fixed Effect | ✓       |           |           |           |           |           |

Note: This table shows the estimated $\beta_{covid}$ (i.e. the coefficient on $Y_{2020} \times Post$) in the equation 1 used poisson model. Sample period is 2014–2020. Basic Control includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). Weather Variables includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e. before the outbreak) for the treatment group (Year 2020). Robust standard errors clustered at the county levels and year week level are reported in parentheses.

* $p < 0.1$** $p < 0.05$*** $p < 0.01$
Table A.2: Robustness Check 2: Unweighted Regressions

| Panel A: Total Visits/Admissions | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|----------------------------------|------|------|------|------|------|------|
| Outpatient Care                  |      |      |      |      |      |      |
| Inpatient Care                   |      |      |      |      |      |      |
| $Y_{2020} \times Post$           | -3,361.90*** | -2,207.25** | -3,484.48*** | -13.62*** | -3.01 | -12.61** |
|                                 | (127.64) | (878.14) | (459.28) | (2.43) | (6.84) | (4.80) |
| Baseline Mean                    | 21,685.89 | 166.85 |      |      |      |      |
| Percent Change                   | -15.50% | -10.18% | -16.07% | -8.17% | -1.80% | -7.56% |
| Panel B: Infectious Diseases     |      |      |      |      |      |      |
| $Y_{2020} \times Post$           | -1,086.15*** | -1,004.11*** | -1,133.38*** | -7.79*** | -7.58*** | -7.64*** |
|                                 | (74.79) | (128.31) | (111.21) | (1.05) | (0.89) | (1.38) |
| Baseline Mean                    | 3,261.51 | 16.46  |      |      |      |      |
| Percent Change                   | -33.30% | -30.79% | -34.75% | -47.34% | -46.06% | -46.42% |
| Panel C: Other Diseases          |      |      |      |      |      |      |
| $Y_{2020} \times Post$           | -2,275.76*** | -1,203.14 | -2,351.10*** | -5.83** | -4.58 | -4.96 |
|                                 | (104.25) | (770.88) | (385.43) | (2.06) | (6.89) | (3.93) |
| Baseline Mean                    | 18,424.38 | 150.39 |      |      |      |      |
| Percent Change                   | -12.35% | -6.53% | -12.76% | -3.88% | -3.04% | -3.30% |

Observation: 4,774

| Basic Control | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Weather Variables | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Fixed County Effect | ✓ | ✓ |

Note: This table shows the estimated $\beta^{covid}$ (i.e. the coefficient on $Y_{2020} \times Post$) in the equation 1. Sample period is 2014–2020. Basic Control includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). Weather Variables includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e. before the outbreak) for the treatment group (Year 2020). Robust standard errors clustered at the year-week and county levels are reported in parentheses.

*p < 0.1*** p < 0.05*** p < 0.01
### Table A.3: Robustness Check 3: Standard Errors Clustered at County Level

| (1) | (2) | (3) | (4) | (5) | (6) |
|-----|-----|-----|-----|-----|-----|
| **Outpatient Care** | **Inpatient Care** | **Outpatient Care** | **Inpatient Care** | **Outpatient Care** | **Inpatient Care** |
| **Panel A: Total Visits/Admissions** | | | | | |
| \(Y_{2020} \times \text{Post} \) | \(-3,720.63^{***}\) | \(-3,445.71^{***}\) | \(-3,827.25^{***}\) | \(-16.32^{***}\) | \(-16.03^{*}\) | \(-15.40^{***}\) |
| (158.22) | (240.76) | (132.47) | (5.51) | (8.07) | (4.91) |
| Baseline Mean | 21,685.89 | 166.85 | | | |
| Percent Change | \(-17.16\%\) | \(-15.89\%\) | \(-17.65\%\) | \(-9.78\%\) | \(-9.61\%\) | \(-9.23\%\) |
| **Panel B: Infectious Diseases** | | | | | |
| \(Y_{2020} \times \text{Post} \) | \(-1,191.01^{***}\) | \(-1,216.48^{***}\) | \(-1,243.02^{***}\) | \(-7.32^{***}\) | \(-7.86^{***}\) | \(-7.21^{***}\) |
| (39.58) | (48.44) | (39.69) | (0.95) | (0.87) | (0.94) |
| Baseline Mean | 3,261.51 | 16.46 | | | |
| Percent Change | \(-36.52\%\) | \(-37.30\%\) | \(-38.11\%\) | \(-44.43\%\) | \(-47.77\%\) | \(-43.79\%\) |
| **Panel C: Other Diseases** | | | | | |
| \(Y_{2020} \times \text{Post} \) | \(-2,529.62^{***}\) | \(-2,229.23^{***}\) | \(-2,584.24^{***}\) | \(-9.01^{**}\) | \(-8.17\) | \(-8.19^{*}\) |
| (142.03) | (226.99) | (119.47) | (5.39) | (7.73) | (4.75) |
| Baseline Mean | 18,424.38 | 150.39 | | | |
| Percent Change | \(-13.73\%\) | \(-12.10\%\) | \(-14.03\%\) | \(-5.99\%\) | \(-5.43\%\) | \(-5.45\%\) |
| **Observation** | | | | | | 4,774 |
| **Basic Control** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Weather Variables** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Fixed County Effect** | ✓ | ✓ |

*Note: This table shows the estimated \(\beta_{\text{covid}}\) (i.e. the coefficient on \(Y_{2020} \times \text{Post}\)) in the equation (1). Sample period is 2014–2020. Basic Control includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). Weather Variables includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e. before the outbreak) for the treatment group (Year 2020). Robust standard errors clustered at the county levels are reported in parentheses.

*\(p < 0.1\) **\(p < 0.05\) ***\(p < 0.01\)**
Table A.4: Robustness Check 4: Standard Errors Clustered at Year-Week Level

|                  | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          |
|------------------|--------------|--------------|--------------|--------------|--------------|--------------|
| **Panel A: Total Visits/Admissions** |              |              |              |              |              |              |
| $Y_{2020} \times \text{Post}$ | $-3,720.63^{***}$ | $-3,445.71^{***}$ | $-3,827.25^{***}$ | $-16.32^{***}$ | $-16.03^{***}$ | $-15.40^{***}$ |
| (95.75)          | (573.91)     | (444.13)     | (3.91)       | (3.58)       | (3.77)       |              |
| Baseline Mean    | 21,685.89    |              |              |              |              |              |
| Percent Change   | $-17.16\%$  | $-15.89\%$  | $-17.65\%$  | $-9.78\%$   | $-9.61\%$   | $-9.23\%$   |
| **Panel B: Infectious Diseases** |              |              |              |              |              |              |
| $Y_{2020} \times \text{Post}$ | $-1,191.01^{***}$ | $-1,216.48^{***}$ | $-1,243.02^{***}$ | $-7.32^{***}$ | $-7.86^{***}$ | $-7.21^{***}$ |
| (114.78)         | (113.13)     | (110.21)     | (0.57)       | (0.67)       | (0.59)       |              |
| Baseline Mean    | 3,261.51     |              |              |              |              |              |
| Percent Change   | $-36.52\%$  | $-37.30\%$  | $-38.11\%$  | $-44.43\%$  | $-47.77\%$  | $-43.79\%$  |
| **Panel C: Other Diseases** |              |              |              |              |              |              |
| $Y_{2020} \times \text{Post}$ | $-2,529.62^{***}$ | $-2,229.23^{***}$ | $-2,584.24^{***}$ | $-9.01^{**}$  | $-8.17^{**}$  | $-8.19^{**}$  |
| (405.44)         | (518.24)     | (377.64)     | (3.57)       | (3.40)       | (3.44)       |              |
| Baseline Mean    | 18,424.38    |              |              |              |              |              |
| Percent Change   | $-13.73\%$  | $-12.10\%$  | $-14.03\%$  | $-5.99\%$   | $-5.43\%$   | $-5.45\%$   |
| Observation      | 4,774        |              |              |              |              |              |
| Basic Control    | ✓            | ✓            | ✓            | ✓            | ✓            | ✓            |
| Weather Variables| ✓            | ✓            |              | ✓            | ✓            | ✓            |
| Fixed County Effect| ✓          |              |              |              |              | ✓            |

Note: This table shows the estimated $\beta_{covid}$ (i.e. the coefficient on $Y_{2020} \times \text{Post}_d$) in the equation 1. Sample period is 2014–2020. Basic Control includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). Weather Variables includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e. before the outbreak) for the treatment group (Year 2020). Robust standard errors clustered at the year-week levels are reported in parentheses.

*p < 0.1 ** p < 0.05 *** p < 0.01
Table A.5: The Effects of the COVID-19 Outbreak on Healthcare Utilization: Influenza-like illness

|                | (1)         | (2)         | (3)         | (4)         | (5)         | (6)         |
|----------------|-------------|-------------|-------------|-------------|-------------|-------------|
| **Outpatient Care** |             |             |             |             |             |             |
| **Inpatient Care**  |             |             |             |             |             |             |
| **Panel A: Influenza-like illness** |             |             |             |             |             |             |
| $Y_{2020} \times Post$ | -265.79*** | -263.19***  | -269.53***  | -5.96***    | -6.33***    | -5.91***    |
|                  | (25.15)     | (26.57)     | (28.61)     | (0.52)      | (0.49)      | (0.85)      |
| Baseline Mean    | 373.04      | 12.01       |             |             |             |             |
| Percent Change   | -71.25%     | -70.55%     | -72.25%     | -49.6%      | -52.69%     | -49.2%      |
| Observation      | 4,774       |             |             |             |             |             |
| Basic Control    | ✓           | ✓           | ✓           | ✓           | ✓           | ✓           |
| Weather Variables| ✓           | ✓           |             | ✓           | ✓           |             |
| County Fixed Effect| ✓          |             |             |             | ✓           |             |

*Note:* This table shows the estimated $\beta_{covid}$ (i.e. the coefficient on $Y_{2020} \times Post$) in the equation 1. Sample period is 2014–2020. Basic Control includes the year fixed effect, the week fixed effect and various holiday dummies (includes New Year Eve, New Year, Chinese New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival). Weather Variables includes weekly average temperatures and precipitation (measured at the county level). Baseline mean is defined as the mean of the first three weeks (i.e. before the outbreak) for the treatment group (Year 2020). Robust standard errors clustered at the year-week and county levels are reported in parentheses.

*p < 0.1**  p < 0.05***  p < 0.01
B Figures

Figure B.1: Weekly Number of New Confirmed COVID-19 Cases in Taiwan

Notes: This figure displays weekly number of new confirmed COVID-19 cases in Taiwan. Data source comes from TCDC.
Figure B.2: Google Search Intensity for COVID-19 Related Keywords: Taiwan and US

Notes: The figures are constructed by using Google Trends data. The daily search volume ranging from 0–100. For Taiwan’s keywords, we use the equivalent term in Chinese for Coronavirus, mask, and sanitizer as the keywords.
Figure B.3: Google Search Intensity for COVID-19 Related Keywords: Washington and Seattle

(a) Coronavirus, Washington

(b) Coronavirus, Seattle

(c) Mask, Washington

(d) Mask, Seattle

(e) Sanitizer, Washington

(f) Sanitizer, Seattle

Notes: The figures are constructed by using Google Trends data. Google Trends only provides a relative measure for daily search volume ranging from 0–100. In order to match the frequency of healthcare data, we aggregate daily data to the weekly level.
Figure B.4: Share of People Wearing a Face Mask When in Public Space

Notes: Data source is from YouGov (Smith, 2020)
Figure B.5: Effects of COVID-19 Outbreak on ILI Mortality

Notes: The treatment group is the year 2020, and the control group is the years 2008 to 2019. The vertical axis denotes the percent change in mortality rate compared to the baseline mean (i.e. outcome in the 2\textsuperscript{nd} week of a year). The horizontal axis denotes weeks from the first COVID-19 case (i.e. the 4\textsuperscript{th} week).