Measuring Voluntary Responses in Healthcare Utilization During and After COVID-19 Pandemic: Evidence from Taiwan

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Abstract

Healthcare has been one of the most affected sectors during the coronavirus disease 2019 (COVID-19) pandemic. The utilization of related services for non-COVID-19 diseases fell dramatically following the point at which the virus broke out; however, little is known about whether this observed decline in healthcare use was due to voluntary behaviors or enforced measures. This paper quantifies the spontaneous change in healthcare utilization during and after the pandemic. We utilize a county-by-week-level dataset from Taiwan's National Health Insurance (NHI) record, covering the entire Taiwanese population, and a difference-in-differences design. Our results indicate that even if there were no human mobility restrictions or supply-side constraints, people voluntarily reduced their demand for healthcare, due to fears of contagion, or COVID-related precautionary behaviors. We find that the number of outpatient visits (inpatient admissions) decreased by 21% (11%) during the pandemic period (February to May 2020). Furthermore, the demand response of healthcare for infectious diseases (e.g., flu) was much greater and more persistent than for non-infectious diseases, thereby suggesting that the substantial decline in accessing healthcare was induced by positive public health externality of prevention measures for COVID-19. Finally, we find that the demand for healthcare services did not get back to the pre-pandemic baseline, even when there were no local coronavirus cases for 253 consecutive days (mid-April to December 2020) in Taiwan.

1 Introduction

COVID-19 has raged through most countries around the world. Although vaccine programs have begun to roll out, as of May 2021, the worldwide vaccinated rate is still less than 11% for at least one dose, and less than 6% for those who are fully vaccinated.¹ The pandemic has changed many aspects of people’s lives and had negative impacts on macroeconomic activities (Atkeson, 2020; 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). Particularly, COVID-19 is a public health crisis, and so healthcare systems have been severely affected during the pandemic. 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 et al., 2020).² However, it is not clear whether this observed decline is due to voluntary behaviors or to other inevitable issues, such as government restrictions on mobility (Chatterji and Li, 2020; Sands et al., 2020; Ziedan et al., 2020) or the availability of health resources (Søreide et al., 2020; Hamel et al., 2020).³

Measuring the voluntary response in healthcare utilization during the pandemic has important policy implications. First, the pandemic significantly strained the capacity of healthcare systems. To free up medical sources for COVID-19 patients, healthcare providers had to restrict or delay the use of services not related to COVID-19. Since such restrictions might also impede the use of

¹Data source: Our World In Data. https://ourworldindata.org/covid-vaccinations?country=OWID_WRL. Date accessed: May. 27th, 2020

²Recent studies indicate that the pandemic and lockdown policies have led to a large decrease in outpatient visits (Baum et al., 2021; Borrelli et al., 2020; Chatterji and Li, 2021; Dewar et al., 2020; Kase et al., 2020; Kutlu et al., 2020; Mehrotra et al., 2020; Patel et al., 2021; Wosik et al., 2021; Ziedan et al., 2020), emergency visits (Giannouchos et al., 2021; Hartnett et al., 2020; Holland et al., 2021; Lange et al., 2020; Lerner et al., 2020), and inpatient admissions (Abbas et al., 2021; Birkmeyer et al., 2020; Gómez-Ramiro et al., 2021; Pelletier et al., 2021). Most studies focus on the US, although a few have been conducted on the UK, Turkey, Spain, and Italy; however, none of them has examined or compared the effects on outpatient and inpatient departments simultaneously. Besides, most of these studies only use data from single medical institutions, single health insurance providers, or data sources with a limited number of hospitals/clinics.

³The Urban Institute Coronavirus Tracking Survey indicates that one-third of adults report encountered an “unmet need for medical care,” due to COVID-19 (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 medical care, even though one-third of them did try to access medical treatment over a 3-month period (Hamel et al., 2020).

some essential medical care and negatively affect people’s health, it raises a question as to what extent the government or healthcare providers have to do so. Previous studies suggest that people change their behaviors voluntarily to reduce the chance of contracting diseases. If the spontaneous response is substantial, the government could achieve a similar outcome by implementing policies with fewer restrictions/costs. Second, compared to policy-induced behavior, voluntary responses could be more persistent. Therefore, understanding voluntary change in healthcare use can help us evaluate the possible impact of disease outbreaks on people’s health behaviors after the pandemic.

This paper fills the gap by examining the effect of the COVID-19 outbreak and pandemic responses on the voluntary demand for non-COVID-19 healthcare. We utilize a difference-in-differences design and a 2014–2020 county-by-week-level dataset from Taiwan’s National Health Insurance (NHI), covering the entire population in Taiwan. Specifically, we examine whether healthcare utilization during the pandemic (2020) varied compared with corresponding weeks in previous years (2014–2019), after controlling for the county-specific trend in demand for healthcare (e.g., county-by-week fixed effects and county-by-year fixed effects).

The case of Taiwan is well-suited for this analysis—for three important reasons. First, as of the end of 2020, Taiwan had only experienced seven deaths and 799 COVID-19 cases, so the pandemic had a very limited impact on healthcare capacity in the country, helping us rule out unmet demand due to supply-side factors. Second, Taiwan did not implement any lockdown or self-isolation policies; the Taiwanese, for their part, carried on with their normal lives alongside relatively looser regulations.⁴ 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 during the whole of 2020. Furthermore, Taiwan had a consecutive 253 days of no local cases from April 15th to the end of 2020.⁵ Basically, Taiwanese people returned to normal life during this period. This experience gives us a unique chance to examine whether the behavioral

⁴For example, crowd control efforts in popular spots and national parks were initiated at the beginning to mid-April, but no bans on domestic travel were put in place.

⁵Since such an achievement was highly unique during 2020, several news outlets reported this record, for example *Time Magazine* (see <https://time.com/5905129/taiwan-coronavirus-record/>)

change in healthcare utilization can persist in a “post-pandemic” period.⁶ Finally, Taiwan’s NHI is a compulsory single-payer system in which everyone has to enroll; thus, 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.

We obtain three key findings from this research. First, our results suggest that on average, the COVID-19 outbreak had larger negative impacts on the utilization of outpatient care (14% decrease) than on inpatient care (4% decrease). In addition, we find that the number of outpatient visits (inpatient admissions) for all diseases decreased by 21% (11%) during the pandemic period (from February to May). Nonetheless, the size of the reduction shrank to 10% for outpatient visits and was null for inpatient admissions in the post-pandemic period (from June to December 2020) when there were no local cases reported.

The decline in the voluntary demand for healthcare after the COVID-19 outbreak is likely the combination of two effects. On the one hand, the fear of contracting COVID-19 in hospitals could have led people to reduce or postpone the use of healthcare services that were not urgent or essential. Such an effect should fade away when the virus disappears from the community. On the other hand, COVID-19 prevention measures, such as wearing face mask, might have had an unintended effect by reducing the transmission of infectious diseases and then decreasing the overall demand for healthcare (i.e., both outpatient and inpatient care). This effect could be large and persistent, since prevention measures for coronavirus indeed mean there is less chance of contracting most infectious diseases, and the Taiwanese still followed these public health measures even when pandemic slowed down.

Second, in order to explore possible mechanisms for our findings, we perform subgroup analyses based on the type of diseases and investigate the dynamic effects of the COVID-19 outbreak.

⁶The COVID-19 pandemic was well controlled in Taiwan during the first half of 2021, with daily cases remaining below 30 till mid-May. On May 15th, 2021, Taiwan experienced a new outbreak of local transmissions, nevertheless daily new confirmed cases remained at around 10 to 25 per million people. Though the pandemic was much more serious than the previous period, Taiwan still had a lower bound compared to other nations. However, we do not include the 2021 period in our analysis.

These subgroup analyses suggest that the COVID-19 outbreak led to a much larger decline in healthcare utilization for infectious diseases than for non-infectious diseases (e.g., outpatient visits: 45% vs. 10% decrease, inpatient admissions: 42% vs. 1% decrease). Based on our results, the demand responses of healthcare for non-infectious diseases were likely driven by the fear of catching coronavirus. Because we find that the COVID-19 outbreak had a negative impact on the utilization of outpatient care (i.e., less essential healthcare) but almost no effect on inpatient care (i.e., more essential healthcare). Moreover, COVID-19 effects faded when no new COVID-19 cases were reported.

For infectious diseases, we believe that the large decline in healthcare utilization was mainly caused by the effect of COVID-19 prevention measure, since the demand for both outpatient and inpatient care in terms of infectious diseases experienced similar drops after the COVID-19 outbreak. Furthermore, we find that the negative demand responses persist throughout the whole of 2020. Consistent with the above evidence, our results indicate that the mortality rate of influenza-like illnesses in 2020 was relatively low compared to previous years, thereby suggesting that precautions taken against COVID-19 might have resulted in unintended health benefits.

Third, our estimates imply that voluntary healthcare demand responses induced by the COVID-19 outbreak could “save” on healthcare expenditure by around 61.4 billion NT\$ (i.e., 2.2 billion US\$), which accounts for 8.6% of the annual healthcare budget .

This paper stands apart from the previous literature in the following ways. First, we contribute to the fast-growing body of literature analyzing the impacts of the COVID-19 pandemic on health-care systems. Several recent studies indicate that there was a large decline in healthcare utilization during the pandemic period in the US ([Ziedan et al., 2020](#); [Birkmeyer et al., 2020](#); [Chatterji and Li, 2020](#); [Mehrotra et al., 2020](#); [Hartnett et al., 2020](#)), UK ([Abbas et al., 2021](#)), Spain ([Gómez-Ramiro et al., 2021](#)), and Italy ([Borrelli et al., 2020](#)).⁷ In addition, our paper provides novel evidence

⁷For example, [Ziedan et al. \(2020\)](#) analyzes how state closure policy affected 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., a 15% decline in outpatient visits) could be explained by states’ closure policies.

by showing that even if there are no government restrictions on human mobility (e.g., lockdowns or stay-at-home orders) and no supply-side constraints (e.g., inadequate healthcare resources for non-COVID-19 patients), people can voluntarily reduce their demand for healthcare services in response to a virus outbreak. We find that the size of this voluntary response was large during the pandemic (e.g., a 21% decline in outpatient visits) and is comparable to the policy-induced effects on healthcare utilization found in [Ziedan et al. \(2020\)](#), which implies that neglect for voluntary responses may overestimate the effects of policy mandates. Moreover, we provide the first evidence on the persistence of COVID-induced change in health behaviors during the post-pandemic period.

Second, the spontaneous response to COVID-19 risk broadly relates to the “prevalence response” in the economic epidemiology literature ([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 were low.⁸

Third, this study is related to the body of theoretical and empirical literature on voluntary avoidance behavior ([Perra et al., 2011](#); [Funk et al., 2010](#); [Rubin et al., 2009](#); [Bayham et al., 2015](#)). For example, several recent studies have found that people’s voluntary response plays an important role in what decisions they make in terms of mobility, social distancing, and mask-wearing during the pandemic ([Gupta et al., 2020](#); [Yan et al., 2021](#); [Chudik et al., 2020](#); [Farboodi et al., 2020](#); [Allcott et al., 2020](#); [Herby, 2021](#)). We contribute to this stream of the literature by quantifying the voluntary avoidance of healthcare utilization during and after the pandemic.

In the Online Appendix [A](#), we provide background information about the COVID-19 pandemic in Taiwan and how its government and residents responded. In sum, the Taiwanese government implemented at least three strategies to prevent the spread of the virus: 1) Early border control

[Birkmeyer et al. \(2020\)](#) examine changes in non-COVID-19 hospital admissions after the COVID-19 outbreak. They find out that hospitals seriously affected by COVID-19 experienced a larger reduction in non-COVID-19 admissions than those with a minimal shock from the outbreak.

⁸As of the end of 2020, the incidence of COVID-19 per million population was 33.55 in Taiwan and 60,723 in the US. Sources: <https://ourworldindata.org/covid-cases>. Date accessed: May. 29th, 2021

and quarantine policies; 2) Distributing and producing face masks; and 3) Disclosing COVID-19 information to the public. In addition, using Google Trends data, we determine that the Taiwanese people responded to the first reported 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 wore face masks at the beginning of the pandemic (i.e., February, 2020). These facts suggest that both the government and citizens reacted to COVID-19 in a rapid and proactive way in the very early stages of the outbreak.

2 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), inspired by [Chang et al. \(2020\)](#) and [Tanaka and Okamoto \(2021\)](#), we use 2020 as the treated year and define the weeks before (and after) the 4th week of the year as the pre-outbreak (post-outbreak) period. To control for the seasonal pattern of healthcare demand unrelated to the COVID-19 outbreak, we use 2014–2019 as untreated years, in order to construct the counterfactual trend of health utilization in 2020.

Table 1 displays summary statistics for the outcome variables and covariates during the pre-outbreak period (i.e., the first three weeks of a year) and the post-outbreak period (i.e., the 4th to 52nd weeks of a year) in the treated year (i.e., 2020) and untreated years (i.e., 2014–2019). We find that compared to the time trend in untreated years, healthcare utilization experienced a substantial decline after the 4th week in 2020, especially for infectious diseases.

We first use a conventional DID design to examine the average effects of the COVID-19 outbreak on healthcare utilization, following which we extend the design to a multiple period DID and an event study design, to investigate further the dynamic trajectory of COVID-19 effects. We provide details on data and empirical specifications in the Methods section (see Section 4).

2.1 Graphical Evidence

Figure 1 displays trends in the utilization of outpatient care and inpatient care. The solid line represents the trend in 2020, and the dashed line denotes the average across 2014–2019 with a 95% confidence interval. 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 in Figure 1 stands for the percentage change in the number of outpatient visits (inpatient admissions) from the baseline weeks, which are the second weeks of each year.

Figure 1a shows the trend in outpatient visits for infectious diseases. As the flu season usually runs from October to April in Taiwan, numbers of visits for infectious diseases tend to be higher until April during 2014–2019 (see the dashed line). In a sharp deviation from the usual seasonal patterns of 2014–2019, the numbers of visits for infectious diseases fell by 30% to 60% after the COVID-19 outbreak, and the declining pattern was still persistent at the end of 2020. For non-infectious diseases, Figure 1b shows that there was a large decline in visits for non-infectious 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. The difference between 2020 and the previous few years is that the average numbers of visits for non-infectious diseases in 2020 did not rebound back to the baseline level, and in fact they declined by around 10% until the middle of the year.

Figure 1c illustrates the evolution of inpatient utilization for infectious diseases. Compared to the baseline weeks, admissions for infectious diseases decreased by 15% to 40% after the 4th week (COVID-19 outbreak) in 2020, which is very different from the trends in 2014–2019. In contrast, Figure 1d suggests inpatient admissions for non-infectious diseases in 2020 only had a negligible decline after the COVID-19 outbreak and largely followed patterns similar to those in 2014–2019.

2.2 COVID-19 Effects on Healthcare Utilization

Table 2 shows the DID estimates (i.e., the coefficient on $Y_{2020} \times Post$ of equation (1) in Section 4.3). The first four columns display our results for outpatient care. We gradually include control variables to test the sensitivity of the results to different specifications. Estimates across the specifications are fairly independent of the introduction of different sets of covariates and fixed effects. Our preferred specification is in Column (4) of Table 2, which includes a full set of covariates. Figure 2a displays the 95% confidence interval (CI) of preferred estimates for outpatient visits by disease type. The estimate in Column (4) of Panel A suggests that compared to the same weeks in 2014–2019, total outpatient visits during the post-outbreak period in 2020 significantly decreased by 14% (CI: –18% to –10%). Furthermore, the estimates in Column (4) of Panels B and C show that infectious disease visits saw a much larger decline (i.e., 45% decrease, CI: –52% to –38%) than non-infectious disease visits (i.e., 10% decrease, CI: –14% to –7%).

Columns (5) to (8) display the DID estimates for inpatient care. Column (8) of Table 2 provides our preferred estimates. Figure 2b presents the corresponding 95% CI by disease type. The estimate in Column (8) of Panel A indicates that the COVID-19 outbreak reduced total inpatient admissions by 4% (CI: –11% to 2%), albeit this estimate is statistically insignificant. The estimates in Column (8) of Panels B and C show the results for infectious disease admissions and other admissions, respectively. Compared to the trend in previous years, the number of infectious disease admissions declined by 42% (CI: –51% to –32%) during the post-outbreak period in 2020 (see Panel B). In contrast, the COVID-19 outbreak had a negligible impact on inpatient admissions for non-infectious diseases (see Panel C).

2.3 COVID-19 Effects During and After the Pandemic

As discussed in the Online Appendix A, the government relaxed disease prevention measures on June 7th 2020, after 56 days of no local COVID-19 cases. Since then, and to the end of 2020, Taiwan entered into a “post-pandemic” period and returned to normal life. To investigate

whether the COVID-19 impact on healthcare utilization persisted when the risk of a getting virus became very low, we implement a multi-period DID by dividing post-outbreak period into 1) During the pandemic period (from February to May); 2) After the pandemic period (from June to December). Table 3 displays the multi-period DID estimates (i.e., the coefficient on $Y_{2020} \times \textit{During}$ and $Y_{2020} \times \textit{After}$ of equation (2) in Section 4.3). Figures 3a and 3b display the 95% confidence interval of the point estimates in Columns (4) and (8) of Table 3 (i.e., our preferred estimates).

The first four columns of Table 3 illustrate the results for outpatient care. Again, we gradually include covariates to examine the robustness of our estimates to various specifications. The DID estimates in all specifications are fairly stable. The estimate in Column (4) of Panel A suggests that compared to the same weeks in 2014–2019, total outpatient visits during the pandemic period in 2020 significantly decreased by 21% (CI: –25% to –17%). In addition, we find that the reduction in outpatient utilization persisted after the pandemic period, but the estimate shrank to a 10% decline (CI: –13% to –6%). The estimates in Panel B indicate that infectious diseases visits experienced a large decline in both the pandemic period (53% decrease, CI: –63% to –43%) and the post-pandemic period (39% decrease, CI: –45% to –35%). However, we find that outpatient visits for non-infectious diseases saw a 17% drop (CI: –21% to –13%) during the pandemic period and rebounded to only a 6% reduction (CI: –10% to –2%) after the pandemic period (see Panel C).

The last four columns of Table 3 show the results for inpatient care. Column (8) of Table 3 is our preferred specification. We find that the COVID-19 outbreak did indeed significantly reduce total inpatient admissions by 11% (CI: –17% to –5%) in the pandemic period. In contrast, the COVID-19 impact disappeared during the post-pandemic period when Taiwan had no local COVID-19 cases (point estimate is zero, CI: –7% to 7%). Similar results can be found in Panel C for inpatient admissions for non-infectious diseases. Interestingly, we find that the decline in inpatient utilization for infectious diseases continued during both the pandemic period (47% decrease, CI: –59% to –34%) and the post-pandemic period (38% decrease, CI: –47% to –29%).

2.4 Dynamic Effects of COVID-19 on Healthcare Utilization

To examine and understand the complete trajectory of the dynamic effects of COVID-19, we further employ an event-study analysis (see Section 4.4 for details). Figure 4 highlights the estimated β_d in equation (3), which measures the dynamic effect of the COVID-19 outbreak on healthcare utilization, and the corresponding 95% confidence intervals. The horizontal axis denotes the number of weeks from the COVID-19 outbreak (i.e., the 4th week in a year). The top (bottom) panel of Figure 4 displays the results for outpatient (inpatient) care.

Three key insights emerge from the figures. First, 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 treated year (i.e., 2020) and the untreated years (i.e., 2014–2019) were in parallel before the COVID-19 outbreak. Therefore, the common trend assumption of our DID design is valid.

Second, Figure 4a indicates that the size of the reduction in visits for infectious diseases is very large. The COVID-19 outbreak reduced the utilization of outpatient care for infectious diseases by about 60% within the first four weeks of the pandemic, and these effects then persisted, thereby suggesting that infectious disease visits still declined by at least 30% at the end of the sample period. For visits in relation to non-infectious diseases, Figure 4b suggests that the reduction in outpatient use is relatively smaller. The number of visits for non-infectious diseases declined by 20% in the 4th week after the first case was reported and shrank to zero in late June (i.e., the 23rd week after first COVID-19 case), because there were no local COVID-19 cases in Taiwan for around two months.

Third, Figure 4c 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-pandemic level until the end of 2020. Figure 4d indicates that inpatient admissions for

non-infectious diseases significantly declined by around 15% 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 non-infectious 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).

2.5 Placebo Test and Robustness Checks

In this section, we first implement a series of placebo tests by excluding observations in 2020 and only using the 2014–2019 sample. Following previous studies (Tanaka and Okamoto, 2021; Leslie and Wilson, 2020; Heft-Neal et al., 2020), we randomly select one year as the pseudo “treated year” in each county and estimate equation (1). We repeat the above procedures 1,000 times to obtain the distribution of placebo estimates. Figure 5 compares our real estimate with these placebo estimates. Our results suggest that for the outpatient care of all diseases and inpatient care of infectious diseases, the real estimates are way below the placebo ones (see Figure 5a, 5c, 5d, and 5e). In sum, this placebo test indicates that the significant estimates in Table 2 should be treated as causal and are not just findings made by chance.

We perform the same placebo tests for our multi-period DID design (equation (2)) and event-study analysis (equation (3)). Figure 6 displays the results for equation (2). The red (blue) dashed line denotes the real estimates for COVID-19 effects during (and after) the pandemic period. The placebo test verifies that all significant estimates in Table 3 are not the result of randomness. Figure 7 illustrates the results for equation (3). The red lines show real estimates, and the gray lines denote 1,000 placebo ones. Again, the falsification test confirms that significant estimates in the event-study analysis are unlikely to be chance findings.

Next, we conduct several robustness checks, using various specifications. First, we calculate standard errors based on different clustering levels, in order to examine the robustness of statistical inference. In our main specification, we cluster the standard error at both the year-week and the

county levels. We also conduct statistical hypothesis tests using standard errors clustered on the county or year-week levels, respectively (see Table B.1 and Table B.2 of the Online Appendix B). We find that the statistical significance of the estimates is robust to the standard errors clustered at different levels. Second, Table B.3 and B.4 of the Online Appendix B show the estimates based on regression (equation (1) and (2)) without weighting by county population size. We find that our estimates are robust to this change.

3 Discussion

3.1 Interpretation of the Results

So far, we have found that the COVID-19 outbreak was 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 non-infectious diseases. Further, negative impacts peaked during the pandemic period, and then began to rebound when there were no local cases (after 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, namely the fear effect and the prevention effect. 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, COVID-19 prevention measures, such as wearing a face mask, hand-washing, and social distancing, might have had an unintended effect by reducing the transmission of infectious diseases other than COVID-19 (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 health-care utilization for infectious diseases and non-infectious diseases. Furthermore, the negative impact of the COVID-19 outbreak was most severe during the pandemic period and faded out when there was very little risk of the local spread of COVID-19 in Taiwan. Such differences 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 that the COVID-19 outbreak would have had less of a negative impact on the utilization of inpatient care (i.e., more essential healthcare) than of outpatient care (i.e., less essential healthcare). In addition, the demand response to the fear of contracting COVID-19 might have disappeared when the risk of catching the virus was low.

Our results indicate that the demand response of healthcare for non-infectious diseases could have been induced by the fear effect of contracting COVID-19. For non-infectious diseases, the COVID-19 outbreak led to a 10% reduction in outpatient visits but almost no impact on inpatient admissions (i.e., insignificant 1% decrease). Furthermore, we find that the negative effect of the COVID-19 outbreak on the utilization of both outpatient care and inpatient care for non-infectious diseases faded out when no new local COVID-19 cases were reported in Taiwan. Interestingly, the event study analysis indicates that the demand response of inpatient care vanished earlier than for outpatient care (i.e., the 14th week vs. the 23rd week after the first COVID-19 case).

On the other hand, if the reduction in healthcare utilization was mainly driven by the effect of COVID-19 preventive measures, we should expect that the negative effect of the COVID-19 outbreak would have had a similar impact on both outpatient and inpatient care. In addition, the negative effect should be sizable and persistent, because these measures basically helped stop the spread of infectious diseases, and Taiwanese people still maintain these healthy habits. For example, Figure C.2 of the Online Appendix C shows that the proportion of people who wear a

face mask in public spaces remained at over 80% throughout the whole of 2020.

Our results indicate that the prevention effect of COVID-19 encouraged a reduction in demand for infectious disease healthcare. First, we find that the COVID-19 outbreak led to a large decline in both outpatient visits and inpatient admissions for infectious diseases (i.e., a 45% and a 42% decrease, respectively). Second, our results suggest that the negative effect induced by the COVID-19 outbreak on healthcare utilization for infectious diseases was quite persistent, even during the period when Taiwan had no local COVID-19 case. Finally, among infectious diseases, influenza-like illness (ILI) shares 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 led to a decline in healthcare use for infectious diseases, we should also find corresponding evidence on improvements in health status, such as a decline in ILI mortality.

Figure C.3 of the Online Appendix C 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 second 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 95% confidence interval. Again, the vertical line in the graph denotes the 4th week of a year. Our results suggest that the trend for the ILI-related mortality rate in 2020 is an outlier 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 30% during and after the pandemic period. This result is consistent with the finding in recent literature on unintended health benefits of non-pharmaceutical interventions against COVID-19 (Qi et al., 2021).

3.2 Implications for the Observed Decline in Healthcare Utilization

Our results indicate that outpatient visits and inpatient admissions fell by 21% and 11%, respectively, during the pandemic period. For infectious diseases, the declines in outpatient visits and inpatient admissions were even larger (i.e. more than 40% decrease). Compared to estimates

in recent studies, we find that the voluntary response is substantial. For example, [Birkmeyer et al. \(2020\)](#) found that hospital admissions for non-COVID-19 diseases decreased by more than 20% from February to April 2020 in the US. In addition, their results suggest that admissions for infectious diseases, such as urinary tract infection and pneumonia, fell by 40% to 50%.

Given the low risk of contracting COVID-19 in Taiwan, we believe our estimates could serve as a “lower bound” for voluntary healthcare utilization responses in other countries. This implies that we may treat voluntary behavior as a major reason for the observed decline in healthcare utilization. Furthermore, our results indicate that the demand for healthcare services did not get back to the pre-pandemic baseline, even after the pandemic died away in Taiwan, thereby suggesting that the COVID-19 outbreak might have had (and be having) a long-term impact on people’s health behaviors.

3.3 Implications for 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 per inpatient admission are around 1,387 NT\$ (i.e., 49.5 US\$) and 63,249 NT\$ (i.e., 2,258.8 US\$), respectively. Based on the above information, our DID estimates suggest that the COVID-19 outbreak could have “saved” the NHI around 61.4 billion NT\$ (i.e., 2.2 billion US\$), which accounts for 8.6% of the annual NHI budget.⁹

⁹We use estimates in column (4) and (8) in Panel A of Table 3 and number of total outpatient visits (inpatient admissions) in pre-outbreak period to obtain the change in healthcare expenditure induced by COVID-19 pandemic (around 61.4 billion NT\$). Compared to the NHI annual budget in 2019, which was 715.3 billion NT\$, our result suggests that COVID-19 outbreak reduced annual healthcare budget by 8.6%.

4 Methods

4.1 Data

Our healthcare utilization data originate from the Taiwan National Infectious Disease Statistics System, accessed via the Taiwan Center for Disease Control’s (TCDC) Open Data Portal.¹⁰ This database holds NHI claim data, so it covers almost the entire population’s healthcare utilization. In order to investigate the outbreak of infectious diseases in a timely manner, the TCDC provides the public with weekly data on the numbers of outpatient visits and inpatient admissions by county, age group, and category of 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.

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.¹¹ In our estimated sample, we also include time-varying variables, 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 for each county.¹²

4.2 Sample

The estimated sample is at the weekly-county level. The sample period is from 2014 to 2020, and we use data from the first to the 52nd week.¹³ Thus, the estimated sample includes 22 counties $\times$ 52 weeks $\times$ 7 years (2014 to 2020), leading to a sample size of 8,008. Furthermore, in order

¹⁰<https://data.cdc.gov.tw/>

¹¹<https://www.ris.gov.tw/app/portal/346>

¹²<https://e-service.cwb.gov.tw/HistoryDataQuery/index.jsp>

¹³Some years have a 53rd week, but we do not include that period.

to examine the mechanisms behind COVID-19 effects, we categorize diseases into infectious (e.g., influenza-like illness and diarrhea) and non-infectious.¹⁴

4.3 Difference-in-Differences Design

As outpatient visits (inpatient admissions) is a count data and is positively skewed, we use the Poisson model to estimate the regression. We specify the DID design as the following regression:

$$\ln\left(\frac{H_{idt}}{E_{idt}}\right) = \alpha + \gamma_0 Y_{2020} \times Post_d + \lambda_i + \eta_d + \theta_t + \lambda_i \times \eta_d + \lambda_i \times \theta_t + X_{idt}\psi + \varepsilon_{idt} \quad (1)$$

Our estimation is implemented at the weekly-county level. H_{idt} represents the outcomes of interest, namely, numbers of outpatient visits (inpatient admissions) in county i in week d of year t . E_{idt} is the exposure variable, which is the number of people in county i in week d of year t . We focus on three measures of weekly outpatient visits (inpatient admissions) volume: 1) Total visits/admissions; 2) Visits/admissions for infectious diseases; and 3) Visits/admissions for non-infectious diseases.

¹⁴According to Taiwan National Infectious Disease Statistics System, infectious diseases include Influenza-like illness, Diarrhea, Enterovirus, and Conjunctivitis etc. The corresponding ICD 9 code is the following: 008.67, 047, 047.0, 047.1, 048, 074, 074.0, 074.1, 074.2, 074.20, 074.21, 074.22, 074.23, 074.3, 074.8, 079.1, 079.2, 074.0, 074.3, 077, 077.0, 077.1, 077.2, 077.3, 077.4, 077.8, 077.9, 370.4, 370.40, 372, 372.0, 372.00, 372.71, 372.72, 003.22, 010, 010.0, 010.00, 010.01, 010.02, 010.03, 010.04, 010.05, 010.06, 010.1, 010.10, 010.11, 010.12, 010.13, 010.14, 010.15, 010.16, 010.8, 010.80, 010.81, 010.82, 010.83, 010.84, 010.85, 010.86, 010.9, 010.90, 010.91, 010.92, 010.93, 010.94, 010.95, 010.96, 011, 011.0, 011.00, 011.01, 011.02, 011.03, 011.04, 011.05, 011.06, 011.1, 011.10, 011.11, 011.12, 011.13, 011.14, 011.15, 011.16, 011.2, 011.20, 011.21, 011.22, 011.23, 011.24, 011.25, 011.26, 011.3, 011.30, 011.31, 011.32, 011.33, 011.34, 011.35, 011.36, 011.4, 011.40, 011.41, 011.42, 011.43, 011.44, 011.45, 011.46, 011.5, 011.50, 011.51, 011.52, 011.53, 011.54, 011.55, 011.56, 011.6, 011.60, 011.61, 011.62, 011.63, 011.64, 011.65, 011.66, 011.7, 011.70, 011.71, 011.72, 011.73, 011.74, 011.75, 011.76, 011.8, 011.80, 011.81, 011.82, 011.83, 011.84, 011.85, 011.86, 011.9, 011.90, 011.91, 011.92, 011.93, 011.94, 011.95, 011.96, 020, 020.3, 020.4, 020.5, 020.9, 021.2, 022, 022.1, 024, 025, 032, 032.0, 032.1, 032.2, 032.3, 032.89, 033, 033.0, 033.1, 033.8, 033.9, 034, 034.0, 052.1, 055.1, 073, 073.0, 074.1, 079, 079.8, 079.81, 079.88, 079.89, 079.9, 079.98, 079.99, 083.0, 112.4, 114.0, 114.9, 115, 115.0, 115.00, 115.05, 115.15, 115.9, 115.90, 115.95, 130.4, 136.3, 460, 462, 463, 464, 464.0, 464.1, 464.10, 464.11, 464.2, 464.20, 464.21, 464.3, 464.30, 464.31, 464.4, 465, 465.0, 465.8, 465.9, 466, 466.0, 466.1, 466.11, 466.19, 480, 480.0, 480.1, 480.2, 480.8, 480.9, 481, 482, 482.0, 482.1, 482.2, 482.3, 482.30, 482.31, 482.32, 482.39, 482.4, 482.40, 482.41, 482.49, 482.8, 482.81, 482.82, 482.83, 482.84, 482.89, 482.9, 483, 483.0, 483.1, 483.8, 484, 484.1, 484.3, 484.5, 484.6, 484.7, 484.8, 485, 486, 487, 487.0, 487.1, 490, 491, 491.0, 491.1, 491.20, 491.21, 491.8, 491.9, 507, 507.0, 507.1, 507.8, 511, 511.0, 511.1, 511.8, 511.9, 513, 513.0, 513.1, 518, 518.0, 518.4, 518.8, 518.81, 518.82, 518.84, 518.89, 519.2, 784.1, 786.0, 786.00, 786.05, 786.06, 786.07, 786.09, 786.1, 786.2, 786.52, 795.31, V01.81, 001, 001.0, 001.1, 001.9, 002, 002.0, 002.1, 002.2, 002.3, 002.9, 003, 003.0, 003.1, 003.2, 003.20, 003.21, 003.22, 003.23, 003.24, 003.29, 003.8, 003.9, 004, 004.0, 004.1, 004.2, 004.3, 004.8, 004.9, 005.0, 005.1, 005.2, 005.3, 005.4, 005.8, 005.81, 005.89, 005.9, 006, 006.0, 006.2, 006.9, 007, 007.0, 007.1, 007.2, 007.3, 007.4, 007.5, 007.8, 007.9, 008, 008.0, 008.00, 008.01, 008.02, 008.03, 008.04, 008.09, 008.1, 008.2, 008.3, 008.4, 008.41, 008.42, 008.43, 008.44, 008.45, 008.46, 008.47, 008.49, 008.5, 008.6, 008.61, 008.62, 008.63, 008.64, 008.65, 008.66, 008.67, 008.69, 008.8, 009, 009.0, 009.1, 009.2, 009.3, 558, 558.9, 787.91, 988

Y_{2020} is a dummy for the treated year that takes one if the observation is in 2020, and zero otherwise. $Post_d$ is a dummy indicating the post-outbreak period (after the 4th week of a year). We include the county fixed effect λ_i to control for any time-invariant confounding factors at the county level. The week-of-the-year fixed effect η_d controls for seasonal patterns in healthcare utilization at the national level within a year. We also include the year fixed effect θ_t to control for the general trend in healthcare utilization over time. To account for any county-specific seasonal patterns or health shocks, we also include the county-by-week fixed effect ($\lambda_i \times \eta_d$) and the county-by-year fixed effect ($\lambda_i \times \theta_t$). X_{idt} refers to a set of covariates, including various holiday dummies (e.g., the Lunar New Year week), average weekly temperature, and average weekly rainfall. In order to account for possible within-group correlations of errors, we use the multiway clustering approach proposed by [Cameron et al. \(2012\)](#) to calculate standard errors clustered at both the year-week and the county levels in all regressions. Finally, all regressions are weighted by the monthly population size of a county. In [Section 2.5](#), we conduct robustness checks on the estimates by utilizing different specifications and computing the standard errors at different cluster levels.

The key variable used for identification in regression [\(1\)](#) is an interaction term between an indicator for the treated year Y_{2020} and a dummy for the post-outbreak period $Post_d$. The coefficients of interest are γ_0 , measuring the difference in healthcare utilization before and after the COVID-19 outbreak in 2020 (i.e., the treated year), relative to the difference in the corresponding periods for 2014–2019 (i.e., the untreated years). γ_0 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 treated and the untreated years. We examine this assumption by using the DID event study design and a set of placebo tests.

In 2020, Taiwan had no local COVID-19 cases from April 15th to the end of 2020 (i.e., around 250 days), so the government relaxed preventive measures for COVID-19 on June 7th and suggested that people could return to a normal life. Therefore, we divide the post-outbreak period into 1) during the pandemic period and 2) after the pandemic period, and estimate the following Poisson

regression (i.e., a multi-period DID design):

$$\ln\left(\frac{H_{idt}}{E_{idt}}\right) = \alpha + \gamma_1 Y_{2020} \times \textit{During}_d + \gamma_2 Y_{2020} \times \textit{After}_d + \lambda_i + \eta_d + \theta_t + \lambda_i \times \eta_d + \lambda_i \times \theta_t + X_{idt}\psi + \varepsilon_{idt} \quad (2)$$

$\textit{During}_d$ denotes the dummy variable, which takes a value of 1 during the 4th to the 23rd weeks (during the pandemic period). $\textit{After}_d$ takes the value 1 during 24th to the 52nd weeks (after the pandemic period). The coefficients of interest are γ_1 (γ_2), which measure changes in healthcare utilization during the pandemic period (after the pandemic period) compared to the pre-outbreak period (the first three weeks of a year) in 2020, relative to the corresponding weeks in the untreated years. If the COVID-19 effects faded out when there were no local cases, the γ_2 should shrink to zero.

4.4 Event Study Design

In order to examine common trend assumption and outline the full dynamic trajectory of the COVID-19 effects, we implement an event study design by interacting the treated year dummy Y_{2020} with lead and lag time dummies W_d .

$$\ln\left(\frac{H_{idt}}{E_{idt}}\right) = \gamma_0 + \sum_d \beta_d Y_{2020} \times W_d + \lambda_i + \eta_d + \theta_t + \lambda_i \times \eta_d + \lambda_i \times \theta_t + X_{idt}\psi + \varepsilon_{idt} \quad (3)$$

We use W_d , where $d = -3, -1, 0, 1, 2, 3, \dots, 25, 26, 48$, 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 (3) are a set of week dummies W_d interacted with the treated year dummy Y_{2020} . The coefficients of interest are β_d , measuring the difference in healthcare utilization between week d and the baseline week for 2020 (i.e., the treated

year), relative to the difference for 2014–2019 (i.e., the untreated years). β_d can represent the dynamic effect of the COVID-19 outbreak on healthcare utilization.

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Tables

Table 1: Summary Statistics for the Treated and Untreated Years

	Treated Year 2020		Untreated Years 2014–2019	
	Pre-outbreak	Post-outbreak	Pre-outbreak	Post-outbreak
Number of total outpatient visits (per 100,000 population)	21,685.89 (5,458.42)	18,713.31 (4,903.73)	20,915.68 (5,644.64)	20,269.15 (5,649.48)
Number of outpatient visits for infectious diseases (per 100,000 population)	3261.51 (687.38)	1850.65 (593.38)	3259.82 (725.32)	2729.50 (726.87)
Number of outpatient visits for non-infectious diseases (per 100,000 population)	18,424.38 (5,047.43)	16,862.66 (4,649.73)	17,655.86 (5,202.65)	17,539.66 (5,235.06)
Number of total inpatient admissions (per 100,000 population)	166.85 (87.61)	168.51 (88.11)	148.20 (85.92)	158.38 (86.29)
Number of inpatient admissions for infectious diseases (per 100,000 population)	16.46 (8.75)	11.04 (6.01)	13.92 (8.87)	15.02 (8.73)
Number of inpatient admissions for non-infectious diseases (per 100,000 population)	150.39 (83.49)	157.46 (84.54)	134.28 (80.03)	143.35 (80.80)
Number of influenza like illness mortality (per 100,000 population)	1.93 (0.07)	1.70 (0.03)	1.54 (0.06)	1.44 (0.01)
Population	1,072,904 (1,110,366)	1,071,852 (1,102,265)	1,068,3167 (1,091,071)	1,068,950 (1,091,290)
Temperature (°C)	17.12 (2.12)	22.95 (4.68)	16.05 (2.69)	22.65 (4.85)
Precipitation (mm)	7.48 (10.98)	4.47 (7.13)	3.34 (5.93)	5.83 (9.59)
Observations	66	1,078	396	6,468

Note: Healthcare utilization data comes 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 (MOI), 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-week level. Standard deviations are in parentheses.

Table 2: Effects of COVID-19 Outbreak on Non-COVID-19 Health Utilization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outpatient Care				Inpatient Care			
Panel A: Total Visits/Admissions								
$Y_{2020} \times Post$	-0.14*** (0.01)	-0.14*** (0.01)	-0.14*** (0.02)	-0.14*** (0.02)	-0.05*** (0.01)	-0.05*** (0.02)	-0.05 (0.03)	-0.04 (0.03)
Panel B: Infectious Diseases								
$Y_{2020} \times Post$	-0.44*** (0.03)	-0.45*** (0.03)	-0.45*** (0.03)	-0.45*** (0.03)	-0.43*** (0.01)	-0.47*** (0.04)	-0.42*** (0.05)	-0.42*** (0.05)
Panel C: Non-infectious diseases								
$Y_{2020} \times Post$	-0.10*** (0.01)	-0.09*** (0.01)	-0.10*** (0.02)	-0.10*** (0.02)	-0.02*** (0.00)	-0.02 (0.02)	-0.02 (0.03)	-0.01 (0.04)
Observation	8,008							
Basic control	✓	✓	✓	✓	✓	✓	✓	✓
Weather variables		✓	✓	✓		✓	✓	✓
County fixed effect			✓	✓			✓	✓
County-by-year fixed effect				✓				✓
County-by-week fixed effect				✓				✓

Note: This table shows the estimated γ_0 (i.e. the coefficient on $Y_{2020} \times Post_d$) in the equation (1) used poisson model (and use county-level population as exposure variable). 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, Lunar New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival, Moon Festival, and National Day). *Weather Variables* includes weekly average temperatures and precipitation (measured at the county level). 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: Effects of COVID-19 Outbreak on Health Utilization (by Pandemic Periods)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outpatient Care				Inpatient Care			
Panel A: Total Visits/Admissions								
$Y_{2020} \times \textit{During}$	-0.21*** (0.01)	-0.20*** (0.01)	-0.21*** (0.02)	-0.21*** (0.02)	-0.12*** (0.01)	-0.11*** (0.03)	-0.12*** (0.03)	-0.11*** (0.03)
$Y_{2020} \times \textit{After}$	-0.09*** (0.01)	-0.09*** (0.01)	-0.10*** (0.02)	-0.10*** (0.02)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.03)	0.00 (0.03)
Panel B: Infectious Diseases								
$Y_{2020} \times \textit{During}$	-0.52*** (0.05)	-0.53*** (0.05)	-0.53*** (0.05)	-0.53*** (0.05)	-0.48*** (0.03)	-0.52*** (0.06)	-0.47*** (0.07)	-0.47*** (0.07)
$Y_{2020} \times \textit{After}$	-0.37*** (0.02)	-0.38*** (0.02)	-0.38*** (0.03)	-0.39*** (0.03)	-0.39*** (0.02)	-0.44*** (0.03)	-0.39*** (0.05)	-0.38*** (0.05)
Panel C: non-infectious diseases								
$Y_{2020} \times \textit{During}$	-0.17*** (0.01)	-0.16*** (0.01)	-0.17*** (0.02)	-0.17*** (0.02)	-0.09*** (0.01)	-0.08** (0.03)	-0.09** (0.03)	-0.08** (0.04)
$Y_{2020} \times \textit{After}$	-0.06*** (0.01)	-0.05*** (0.00)	-0.06*** (0.02)	-0.06*** (0.02)	0.02*** (0.00)	0.02 (0.02)	0.02 (0.03)	0.03 (0.04)
Observation	8,008							
Basic control	✓	✓	✓	✓	✓	✓	✓	✓
Weather variables		✓	✓	✓		✓	✓	✓
County fixed effect			✓	✓			✓	✓
County-by-year fixed effect				✓				✓
County-by-week fixed effect				✓				✓

Note: This table shows the estimated γ_1 (i.e. the coefficient on $Y_{2020} \times \textit{During}_d$) and γ_2 (i.e. the coefficient on $Y_{2020} \times \textit{After}_d$) in the equation (2) used poisson model (and use county-level population as exposure variable). 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, Lunar New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival, Moon Festival, and National Day). *Weather Variables* includes weekly average temperatures and precipitation (measured at the county level). 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: Percentage Change in Outpatient Visits/Inpatient Admissions per 100,000 People

(a) Outpatient Visits, Infectious Diseases

(b) Outpatient Visits, Non-infectious Diseases

(c) Inpatient Admissions, Infectious Diseases

(d) Inpatient Admissions, Non-infectious Diseases

Notes: Sample period is 2014–2020. 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 this figure stands for the percentage change in the number of outpatient visits (inpatient admissions) from the baseline. We use the number of outpatient visits (inpatient admissions) in the second weeks of each year as the baseline.

Figure 2: Effects of COVID-19 Outbreak on Non-COVID-19 Health Utilization

(a) Outpatient Visits

(b) Inpatient Admissions

Notes: Sample period is 2014–2020. The vertical axis displays the estimated γ_0 (i.e. the coefficient on $Y_{2020} \times Post_d$) in the equation (1) and the corresponding 95% confidence intervals.

Figure 3: Effects of COVID-19 Outbreak on Non-COVID-19 Health Utilization During and After the Pandemic Period

(a) Outpatient Visits

(b) Inpatient Admissions

Notes: Sample period is 2014–2020. The vertical axis displays the estimated γ_1 (i.e. the coefficient on $Y_{2020} \times During_d$) and γ_2 (i.e. the coefficient on $Y_{2020} \times After_d$) in the equation (2) and the corresponding 95% confidence intervals.

Figure 4: Dynamic Effects of COVID-19 Outbreak on Non-COVID-19 Health Utilization

(a) Outpatient Visits: Infectious Diseases

(b) Outpatient Visits: Non-infectious Diseases

(c) Inpatient Admissions: Infectious Diseases

(d) Inpatient Admissions: Non-infectious Diseases

Notes: Sample period is 2014–2020. The vertical axis displays the estimated β_d in the equation (3) and the corresponding 95% confidence intervals. The horizontal axis denotes weeks from the 4th week of a year.

Figure 5: Placebo Test: DID Design

(a) Outpatient Visits, Total Diseases

(b) Inpatient Admissions, Total Diseases

(c) Outpatient Visits, Infectious Diseases

(d) Inpatient Admissions, Infectious Diseases

(e) Outpatient Visits, Non-infectious Diseases

(f) Inpatient Admissions, Non-infectious Diseases

Notes: The sample period for the placebo test is 2014–2019. The horizontal axis denotes the estimates of γ_0 (i.e. the coefficient on $Y_{2020} \times Post_d$) in the equation (1). The vertical axis displays the relative frequency of the estimates. The gray bars denote the placebo estimates, and the red dashed lines denote the real ones.

Figure 6: Placebo Test: Multi-Period DID Design

(a) Outpatient Visits, Total Diseases

(b) Inpatient Admissions, Total Diseases

(c) Outpatient Visits, Infectious Diseases

(d) Inpatient Admissions, Infectious Diseases

(e) Outpatient Visits, Non-infectious Diseases

(f) Inpatient Admissions, Non-infectious Diseases

Notes: The sample period for the placebo test is 2014–2019. The horizontal axis denotes the estimates. The vertical axis displays the relative frequency of the estimates. The light red bars denote the placebo estimates for γ_1 (i.e. the coefficient on $Y_{2020} \times During_d$), and the red dashed lines denote the real estimate. The light blue bars denote the placebo estimates for γ_2 (i.e. the coefficient on $Y_{2020} \times After_d$) in the equation (2), and the blue dashed lines denote the real estimate.

Figure 7: Placebo Test: Event-study Design

(a) Outpatient Visits, Total Diseases

(b) Inpatient Admissions, Total Diseases

(c) Outpatient Visits, Infectious Diseases

(d) Inpatient Admissions, Infectious Diseases

(e) Outpatient Visits, Non-infectious Diseases

(f) Inpatient Admissions, Non-infectious Diseases

Notes: The sample period for the placebo test is 2014–2019. The vertical axis displays the estimated β_d in the equation (3). The gray lines denote the placebo estimates, and the red dots and blue dashed lines denote the real estimates and the corresponding 95% confidence intervals.

Online Appendix

Section A	Taiwan's Response to the COVID-19 Pandemic
Section B	Additional Tables
Section C	Additional Figures

A Taiwan's Response to the COVID-19 Pandemic

Taiwan had been praised by international medias as a success story of COVID-19 prevention.¹⁵ As of 9th January 2021, Lowy Institute ranked Taiwan as the top three countries with the best performance on COVID-19 pandemic management.¹⁶ Specifically, upon December 31st, 2020, Taiwan had recorded only seven deaths and 799 confirmed cases—671 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 had occurred in Taiwan in 2020. Fewer than 10% of confirmed cases are local ones, and there have been no new confirmed local cases from April 14th to December 22nd. Figure C.1 in the Online Appendix displays the number of new confirmed cases for each week of 2020.

Basically, COVID-19 pandemic had very limited impacts on people's daily life in Taiwan during 2020. On March 25th, the government announced a guidance suggesting to cancel public gatherings with more than 100 people indoors or 500 people outdoors.¹⁷ However, no any lockdown policy, stay-at-home order, or domestic travel ban had been initiated. The biggest turning point was on June 7th. As a consecutive 8 weeks without any local case, the government announced to relax all disease-prevention measures and suggest people can get back to normal life. 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.

¹⁵Including Reuters, New York Time, CNN and Economist (<https://www.reuters.com/article/uk-gay-pride-taiwan-idUKKBN27GOCM>, <https://www.reuters.com/article/us-health-coronavirus-taiwan-idUKKBN27YOR7>, <https://www.nytimes.com/2021/03/13/world/asia/taiwan-covid.html>, <https://www.nytimes.com/2021/03/13/world/taiwan-a-covid-19-outlier-is-selling-something-scarce-life-without-fear-of-the-virus.html>, <https://www.cnn.com/2020/10/29/asia/taiwan-covid-19-intl-hnk>, <https://www.cnn.com/2020/04/04/asia/taiwan-coronavirus-response-who-intl-hnk/index.html>, <https://www.economist.com/asia/2020/12/02/covid-19-has-ravaged-economies-all-over-the-world-but-not-taiwans>. Date Accessed: May 26th, 2021)

¹⁶The first place is New Zealand, and the second place is Vietnam. Totally 116 countries were evaluated. <https://interactives.lowyinstitute.org/features/covid-performance>. Date Accessed: May 26th, 2021.

¹⁷The government also suspended some of the sex-related leisure and entertainment venues from April 9th.

A.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 overseas had to take 14 days’ quarantine.¹⁸

A.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, 2020) 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,¹⁹ but currently, Taiwan is able to produce more than 15 million per day.²⁰ Moreover, starting from February 6th, 2020, 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.

A.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, 2020, the Central Epidemic Command Center (CECC) was initiated. When the first confirmed case was corroborated on January 22nd, the CECC held

¹⁸The border control policy for the foreigners had been relaxed from June 29th. But foreigners entry from other countries need to provide COVID-19 testing with negative results.

¹⁹https://www.moea.gov.tw/MNS/populace/news/News.aspx?kind=1&menu_id=40&news_id=88545, Date accessed: Sep. 5th, 2020

²⁰https://www.moea.gov.tw/MNS/populace/news/News.aspx?kind=9&menu_id=22333&news_id=89290, Date accessed: Sep. 5th, 2020

press conferences every day to report on the epidemic and to offer self-protection information to citizens.²¹

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.²² 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 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.²³

A.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 sanitizer.²⁴ 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 A.1a suggests that the search intensity of the keywords “Coronavirus” nearly reached 250 in the week of the first confirmed case announcement.²⁵ 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

²¹The frequency of these briefings was reduced to once a week from June 8th, 2020, following a consecutive 8 weeks of no local confirmed cases.

²²https://nidss.cdc.gov.tw/ch/NIDSS_DiseaseMap.aspx?dc=1&dt=5&disease=19CoV

²³More detailed review on Taiwan’s pandemic responses can be found in Wang (2020).

²⁴Google 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: <https://trends.google.com.tw/>.

²⁵We use the equivalent term in Chinese for Coronavirus as the keywords.

of the first local COVID-19 case (See Figure A.1c and A.1e).²⁶ Due to the painful experience of the 2003 outbreak of SARS (Bennett et al., 2015), both the Taiwanese government and its people responded to the first COVID-19 case very quickly indeed.²⁷

Not every country responded to the first COVID-19 case in such a way, with the United States being a counterexample. Consistent with Bento et al. (2020), Figures A.1b, A.1d and A.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 21st, 2020. However, in contrast to Taiwan, the peak of the relative search volume for COVID-19 and PPE-related key words happened on the 7th week (i.e. March 8th to 14th) after the first confirmed case, because the US government verified this case was COVID-19 on March 1st. In addition, the search intensity for face masks (see Figure A.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).²⁸ Figure A.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 A.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,²⁹ 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 C.2 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

²⁶We use the equivalent term in Chinese for mask and sanitizer as the keywords.

²⁷SARS severely hurt Taiwan in 2003, with a total of 668 reported cases and 181 death cases (Chen et al., 2005).

²⁸<https://www.livescience.com/cdc-recommends-face-masks-coronavirus.html>, Date accessed: Aug. 20th, 2020

²⁹<https://news.sina.com.tw/article/20200509/35111198.html>, Date accessed: Aug. 10th, 2020

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.

Figure A.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 A.2: 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. 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 A.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.

B Additional Tables

Table B.1: Effects of COVID-19 Outbreak on Non-COVID-19 Health Utilization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outpatient Care				Inpatient Care			
Panel A: Total Visits/Admissions								
$Y_{2020} \times Post$	-0.14***	-0.14***	-0.14***	-0.14***	-0.05***	-0.05***	-0.05	-0.04
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[0.04]	[0.03]	[0.03]
Cluster at YearWeek Level	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}
Panel B: Infectious Diseases								
$Y_{2020} \times Post$	-0.44***	-0.45***	-0.45***	-0.45***	-0.43***	-0.47***	-0.42***	-0.42***
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.04]	[0.06]	[0.04]	[0.04]
Cluster at YearWeek Level	{0.04}	{0.04}	{0.04}	{0.04}	{0.04}	{0.05}	{0.04}	{0.04}
Panel C: non-infectious diseases								
$Y_{2020} \times Post$	-0.10***	-0.09***	-0.10***	-0.10***	-0.02***	-0.02	-0.02	-0.01
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.04]	[0.04]	[0.03]	[0.03]
Cluster at YearWeek Level	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}
Observation	8,008							
Basic control	✓	✓	✓	✓	✓	✓	✓	✓
Weather variables		✓	✓	✓		✓	✓	✓
County fixed effect			✓	✓			✓	✓
County-by-year fixed effect				✓				✓
County-by-week fixed effect				✓				✓

Note: This table shows the estimated γ_0 (i.e. the coefficient on $Y_{2020} \times Post_d$) in the equation (1) used poisson model (and use county-level population as exposure variable). 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, Lunar New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival, Moon Festival, and National Day). *Weather Variables* includes weekly average temperatures and precipitation (measured at the county level). Robust standard errors clustered at the county level are reported in squared brackets. Robust standard errors clustered at the year-week level are reported in curly brackets.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table B.2: Effects of COVID-19 Outbreak on Health Utilization (by Pandemic Periods)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outpatient Care				Inpatient Care			
Panel A: Total Visits/Admissions								
$Y_{2020} \times \textit{During}$	-0.21***	-0.20***	-0.21***	-0.21***	-0.12***	-0.11***	-0.12***	-0.11***
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[0.04]	[0.03]	[0.03]
Cluster at YearWeek Level	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.03}	{0.02}	{0.02}
$Y_{2020} \times \textit{After}$	-0.09***	-0.09***	-0.10***	-0.10***	-0.01	-0.02	-0.01	0.00
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[0.03]	[0.03]	[0.03]
Cluster at YearWeek Level	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}
Panel B: Infectious Diseases								
$Y_{2020} \times \textit{During}$	-0.52***	-0.53***	-0.53***	-0.53***	-0.48***	-0.52***	-0.47***	-0.47***
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.05]	[0.07]	[0.06]	[0.05]
Cluster at YearWeek Level	{0.05}	{0.05}	{0.05}	{0.05}	{0.05}	{0.06}	{0.05}	{0.05}
$Y_{2020} \times \textit{After}$	-0.37***	-0.38***	-0.38***	-0.39***	-0.39***	-0.44***	-0.39***	-0.38***
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.04]	[0.05]	[0.04]	[0.03]
Cluster at YearWeek Level	{0.03}	{0.03}	{0.03}	{0.03}	{0.04}	{0.05}	{0.04}	{0.04}
Panel C: non-infectious diseases								
$Y_{2020} \times \textit{During}$	-0.17***	-0.16***	-0.17***	-0.17***	-0.09***	-0.08**	-0.09**	-0.08**
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[0.05]	[0.03]	[0.03]
Cluster at YearWeek Level	{0.02}	{0.03}	{0.02}	{0.02}	{0.02}	{0.03}	{0.02}	{0.02}
$Y_{2020} \times \textit{After}$	-0.06***	-0.05***	-0.06***	-0.06***	0.02***	0.02	0.02	0.03
Cluster at County Level	[0.01]	[0.01]	[0.01]	[0.01]	[0.04]	[0.04]	[0.03]	[0.04]
Cluster at YearWeek Level	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}	{0.02}
<hr/>								
Observation	8,008							
Basic control	✓	✓	✓	✓	✓	✓	✓	✓
Weather variables		✓	✓	✓		✓	✓	✓
County fixed effect			✓	✓			✓	✓
County-by-year fixed effect				✓				✓
County-by-week fixed effect				✓				✓

Note: This table shows the estimated γ_1 (i.e. the coefficient on $Y_{2020} \times \textit{During}_d$) and γ_2 (i.e. the coefficient on $Y_{2020} \times \textit{After}_d$) in the equation (2) used poisson model (and use county-level population as exposure variable). 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, Lunar New Year, Peace Memorial Day, Qing-Ming Festival, Labor's Day, and Dragon Boat Festival, Moon Festival, and National Day). *Weather Variables* includes weekly average temperatures and precipitation (measured at the county level). Robust standard errors clustered at the county level are reported in squared brackets. Robust standard errors clustered at the year-week level are reported in curly brackets.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table B.3: Robustness Check: Unweighted Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outpatient Care				Inpatient Care			
Panel A: Total Visits/Admissions								
$Y_{2020} \times Post$	-0.14*** (0.01)	-0.13*** (0.02)	-0.14*** (0.02)	-0.14*** (0.02)	-0.05*** (0.00)	-0.05*** (0.02)	-0.05 (0.03)	-0.04 (0.03)
Panel B: Infectious Diseases								
$Y_{2020} \times Post$	-0.42*** (0.03)	-0.43*** (0.03)	-0.44*** (0.04)	-0.44*** (0.04)	-0.43*** (0.01)	-0.46*** (0.03)	-0.42*** (0.05)	-0.42*** (0.05)
Panel C: non-infectious diseases								
$Y_{2020} \times Post$	-0.10*** (0.00)	-0.09*** (0.01)	-0.10*** (0.02)	-0.10*** (0.02)	-0.02*** (0.00)	-0.02 (0.02)	-0.02 (0.03)	-0.01 (0.03)
Observation	8,008							
Basic control	✓	✓	✓	✓	✓	✓	✓	✓
Weather variables		✓	✓	✓		✓	✓	✓
County fixed effect			✓	✓			✓	✓
County-by-year fixed effect				✓				✓
County-by-week fixed effect				✓				✓

Note: This table shows the estimated γ_0 (i.e. the coefficient on $Y_{2020} \times Post_d$) in the equation (1) used poisson model (and use county-level population as exposure variable). 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, Lunar New Year, Peace Memorial Day, Qing-Ming Festival, Labor’s Day, and Dragon Boat Festival, Moon Festival, and National Day). *Weather Variables* includes weekly average temperatures and precipitation (measured at the county level). 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 B.4: Robustness Check: Unweighted Regressions (by Pandemic Periods)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outpatient Care				Inpatient Care			
Panel A: Total Visits/Admissions								
$Y_{2020} \times \textit{During}$	-0.21*** (0.01)	-0.19*** (0.02)	-0.21*** (0.02)	-0.21*** (0.02)	-0.12*** (0.00)	-0.11*** (0.02)	-0.12*** (0.03)	-0.11*** (0.03)
$Y_{2020} \times \textit{After}$	-0.09*** (0.01)	-0.08*** (0.01)	-0.09*** (0.02)	-0.09*** (0.02)	-0.01*** (0.00)	-0.01 (0.01)	-0.01 (0.03)	-0.00 (0.03)
Panel B: Infectious Diseases								
$Y_{2020} \times \textit{During}$	-0.51*** (0.05)	-0.52*** (0.05)	-0.53*** (0.05)	-0.53*** (0.05)	-0.50*** (0.03)	-0.52*** (0.04)	-0.49*** (0.06)	-0.48*** (0.06)
$Y_{2020} \times \textit{After}$	-0.35*** (0.03)	-0.36*** (0.03)	-0.37*** (0.03)	-0.37*** (0.03)	-0.38*** (0.02)	-0.42*** (0.03)	-0.38*** (0.05)	-0.38*** (0.05)
Panel C: non-infectious diseases								
$Y_{2020} \times \textit{During}$	-0.16*** (0.01)	-0.15*** (0.02)	-0.16*** (0.02)	-0.16*** (0.02)	-0.09*** (0.00)	-0.08*** (0.03)	-0.08*** (0.03)	-0.08*** (0.03)
$Y_{2020} \times \textit{After}$	-0.06*** (0.01)	-0.05*** (0.01)	-0.06*** (0.02)	-0.06*** (0.02)	0.02*** (0.00)	0.02 (0.02)	0.02 (0.03)	0.02 (0.03)
Observation	8,008							
Basic control	✓	✓	✓	✓	✓	✓	✓	✓
Weather variables		✓	✓	✓		✓	✓	✓
County fixed effect			✓	✓			✓	✓
County-by-year fixed effect				✓				✓
County-by-week fixed effect				✓				✓

Note: This table shows the estimated γ_1 (i.e. the coefficient on $Y_{2020} \times \textit{During}_d$) and γ_2 (i.e. the coefficient on $Y_{2020} \times \textit{After}_d$) in the equation (2) used poisson model (and use county-level population as exposure variable). 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, Lunar New Year, Peace Memorial Day, Qing-Ming Festival, Labor's Day, and Dragon Boat Festival, Moon Festival, and National Day). *Weather Variables* includes weekly average temperatures and precipitation (measured at the county level). Robust standard errors clustered at the year-week and county levels are reported in parentheses.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

C Additional Figures

Figure C.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 C.2: Share of People Wearing a Face Mask When in Public Space

Notes: Data source is from YouGov ([Smith, 2020](#))

Figure C.3: Effects of COVID-19 Outbreak on ILI Mortality

Notes: The treated year is the year 2020, and the untreated years are the years 2008 to 2019. The vertical axis denotes the percentage change in mortality rate compared to the baseline mean (i.e. outcome in the second week of a year). The horizontal axis denotes weeks from the first COVID-19 case (i.e. the 4th week of a year).