Do Masks Protect Children? Evidence from Florida's Mask Mandate Ban Using Large-Scale School Transmission Data

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Abstract

Our study examines the causal impact of mask mandates on COVID-19 transmission in elementary and middle schools using a natural experiment in Florida. While randomized controlled trials (RCTs) have been the gold standard for causal investigation, they face challenges such as lower compliance rates and typically focus only on the direct impact on mask wearers, overlooking the potential benefits of transmission reduction. Our natural experiment overcomes these issues, providing a broader view of mask mandates' effects. The results show a 20.6% increase in COVID-19 cases when mask mandates are banned. We also explore the moderating effects of school size, search volume for "mask," and racial and poverty groups on the impact of the mask ban. Our study underscores the critical role of mask mandates and showcases the potential of utilizing publicly accessible data to generate insights on significant societal issues – a principle at the core of crowd-based platforms.

Keywords: COVID-19, mask mandate, mask ban, policy evaluation, counterfactual analysis

1. Introduction

The effectiveness of masks in preventing the spread of the virus plays a vital role in making public policies. According to the CDC's suggestion, using masks could limit respiratory droplets and slow the transmission of COVID-19 (Gostin et al. 2020), and many states enacted their mask mandates in 2020 (Markowitz 2023). Although previous studies show that wearing a mask is an effective way of fighting against COVID-19 (Chernozhukov et al. 2021; Howard et al. 2021), there are ongoing debates regarding the effectiveness of mask mandates in school settings.

On the one hand, wearing masks can reduce the spread of COVID-19 and protect students and staff from getting infected. It creates a safer environment for students and teachers, which can help schools remain open and prevent disruptions to learning (Balzer 2022). On the other hand, research has indicated that children are less susceptible to COVID-19 than the flu, with a survival rate of approximately 99.99% (Sood and Bhattacharya 2022). There is limited evidence to support the effectiveness of mask mandates in reducing the spread of COVID-19 for young children. In addition, the potential long-term impact of wearing masks on children might be significant. For example, wearing masks can cause psychological stress and interfere with their learning, as it impedes communication when the teachers' and students' lower faces are covered (Sood and Bhattacharya 2022). Therefore, the impact of mask mandate policies in school areas should be carefully assessed. Our research aims to address this practical challenge and evaluate the effectiveness of mask mandate policies in schools.

As the pandemic gradually improves, most schools are resuming their operations for the academic year of 2021-2022. Simultaneously, various states have revised their epidemic prevention policies, including the school mask requirement policy (Markowitz 2023). For instance, Governor Ron DeSantis in Florida implemented the "Mask Mandate Ban" policy on May 3, 2021. This policy means that school districts in Florida are no longer allowed to mandate mask-wearing for K-12 students. Instead, parents are responsible for deciding whether their children should wear masks or not. However, it is worth noting that the school districts in Florida have the choice to follow this policy or not (Mckay 2021). For example, Broward and Alachua counties continue to require students to wear masks in schools (Santiago and Weisfeldt 2021).

The debate over mandatory mask-wearing in schools remains controversial in the United States. While some parents favor requiring masks for all students, others refuse to send their children to school with any face covering (Brenan 2021). However, multiple studies have shown the minimal impact of

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wearing masks among children. For instance, Chandra and Høeg (2022) find no significant relationship between mask mandates in schools and pediatric COVID-19 cases after weeks of implementation. Moreover, Evans (2022) doubts the effectiveness of mask mandates in schools, citing a government study in England that failed to demonstrate a statistically significant impact on wearing masks in schools. Bloomberg has also reported that most studies focused on "universal masking" are inconclusive (Flam 2022). One controlled study even shows only a 1% difference in symptomatic infections between people who consistently used masks and those who did not (Abaluck et al. 2021).

Despite that, most studies have focused on the period from March 2020 to early 2021, the very first stage of the pandemic. Many other policies and instructions are announced, including stay-at-home orders during this period (Wang 2022; Bonardi et al. 2023; Liu et al. 2023). This would significantly alter individuals' daily behaviors, making it difficult to determine the pure causal link between the mask mandate regulation and COVID-19 transmission spread since multiple factors would interact with each other. Hence, our research finds evidence of an exogenous shock and utilizes a natural experiment to address this issue. The fact that natural experiments look for chance occurrences that would randomly place students in the treatment group can help minimize biases resulting from observational data (Jena and Worsham 2020; Balawi et al. 2023). Using a natural experiment, we can better understand the causal effects of the mask ban policy.

There is a vast policy debate on the impact of the mask mandate policy (Leonhardt 2022). The literature has not provided sufficient evidence to draw a firm conclusion about the relationship between COVID-19 transmission in schools and the mask mandate policy. One reason is that the prior studies have mainly focused on the mask requirement policy on the COVID-19 transmission between March 2020 and early 2021 (Chernozhukov et al. 2021; Karaivanov et al. 2021). Most of the stores, however, were compelled to close at the time, and individuals, including students, were obliged to stay at home rather than travel or attend social activities. As a result, it is difficult to assess the effectiveness of the mask mandate policy, especially when some studies show no connection between the policy and COVID-19 transmission (Chandra and Høeg 2022).

More importantly, the prior literature presents tension regarding the effectiveness of mask-wearing. While numerous observational studies consistently demonstrate the significant reduction in transmission of respiratory viruses through mask-wearing (e.g., Chernozhukov et al. 2021; Howard et al. 2021), some previous randomized controlled trials report mixed or limited findings in preventing influenza-like illnesses (e.g., Jefferson et al., 2023). Although randomized controlled trials are traditionally considered the gold standard for establishing causation, our natural experiment approach offers two distinct advantages specific to our context.

First, many randomized controlled trials encounter challenges with lower compliance rates of mask-wearing, particularly among children in the treatment group (Jefferson et al. 2023). Ensuring proper adherence to mask usage is crucial for the validity of randomized controlled trials (Fischhoff et al., 2023), but in reality, a relatively low number of participants in the treatment group adhere to mask-wearing guidelines (Jefferson et al., 2023). Second, most randomized controlled trials focus solely on assessing the effects of mask-wearing on the wearers themselves, thereby capturing only a partial view of the impact. However, an important consideration is how masks can potentially reduce virus transmission to others if the wearer is already infected, which can be more challenging to ascertain (Soares-Weiser et al., 2020). In other words, solely conducting a granular individual-level analysis may not always be the most effective approach and may overlook potential spillover effects at the individual level. Our natural experiment at the school level allows us to examine both these impacts, providing a comprehensive understanding of mask-wearing effects. Therefore, while randomized controlled trials are valuable in addressing unobserved confounders, carefully designed observational studies can be equally important, if not superior, in certain cases. Using a natural experiment approach, we can overcome compliance limitations and assess the broader effects of mask-wearing on transmission, benefiting our understanding of its effectiveness.

Furthermore, there is evidence suggesting that using masks, especially for disabled students, may hurt their ability to learn and communicate effectively in the classroom (Khandelwal and Apodaca 2022). In this case, evaluating the importance of continuing the implementation of the mask mandate policy in schools is necessary. Thus, we pose our first research question: *What is the causal impact of the mask mandate policy on COVID-19 transmission in elementary and middle schools?*

Our research uses data from Florida public schools from March 2021 to October 2021, during which restaurants gradually opened but had small serving sizes and K-12 students returned to face–to–face instruction (Markowitz 2023). Additionally, Florida announced a regulation known as the "Mask

Mandate Ban" to all school districts during this time (Mckay 2021). However, each school district is free to choose whether to implement this policy or not. The ban on mask mandates in Florida represents an abrupt and unexpected change in the policy environment, creating a unique natural experiment that allows for a rigorous comparison of schools with and without mask mandates.

This sudden policy change provides an opportunity to evaluate the causal effect of masks on COVID-19 transmission in schools without the confounding influence of pre-existing differences in mask-wearing behavior or compliance. Although school district-level compliance with the ban may vary due to contextual factors such as COVID-19 prevalence or vaccination rates, schools cannot choose whether to implement mask mandates. They are bound by their school district's decision on the ban, even if they may be experiencing severe issues with COVID-19 cases. Thus, the policy acts as an exogenous shock that affects schools' ability to implement mask mandates, regardless of their local conditions.

Furthermore, in our analysis, we use a set of causal identification methods, including counterfactual analysis (Abadie et al. 2010; Athey et al. 2021), to handle the potential violation of the parallel trend assumption, accounting for the fact that treated schools may not be randomly chosen due to different COVID-19 scenarios influencing school district decisions. For instance, we use the synthetic control method proposed by Abadie et al. (2010) to create a weighted combination of control schools that closely resemble the treated school in terms of pretreatment COVID-19 transmission. This method allows us to generate a counterfactual prediction for the treated school by using the outcome variable of the synthetic control school. We find that the number of students that tested positive for COVID-19 increases by 20.6% when the mask mandate policy is banned, suggesting that there is a significant advantage to enforcing mask mandates.

Different schools have varying student demographics, including racial composition and family situations, which can impact their attitudes toward mask requirements and susceptibility to COVID-19, such as death and hospitalization rates (Buckman et al. 2023). Additionally, poverty levels can affect living habits, further increasing the likelihood of infection (Pereira and Oliveira 2020). While low-income families often lack resources for protective equipment and safe food, and live in crowded conditions, leading to a higher risk of infection (Devakumar et al. 2020), wealthy individuals may face increased risk due to their more extensive social networks and frequent travel opportunities. Therefore, evaluating the impact of the mask ban on different racial and poverty groups is essential. To address this issue, our second research question is: *How do racial and poverty groups influence the impact of the mask ban in elementary and middle schools?*

We use the proportion of economically disadvantaged students and the percentage of minority (African American/Hispanic) students in a school as moderators in our analysis. We find that schools with a higher percentage of economically disadvantaged or minority students will experience a lower increase in the spread of the disease than other schools. For economically disadvantaged students, one possible explanation is that they may have been more vulnerable to contracting COVID-19 during the early stages of the pandemic due to their challenging living conditions. As a result, even with the implementation of mask mandate bans, the impact on these populations may have been limited. For minorities, the reason is that Black or Latino individuals have higher probability of wearing masks compared to white individuals (Hearne and Niño, 2021). Therefore, even if schools were to enforce a ban on mask mandates, parents from minority communities would probably continue to prioritize mask-wearing for their children. As a result, schools with a larger representation of minority students would be less affected by the policy prohibiting mask mandates. Our findings suggest that poverty level and racial composition can play crucial roles in determining the effectiveness of mask mandates, and policymakers should consider this factor when making decisions about mask mandates for schools.

The COVID-19 pandemic has underscored the importance of social media as a vital tool for generating, disseminating, and consuming information (Tsao et al. 2021; Vaast and Pinsonneault 2022; Park et al. 2023). People use it to search for information about COVID-19, including the number of cases and how to protect themselves. One indicator of people's concern about the virus is the search volume for face masks. Higher search volumes suggest that people are more cautious and take more precautions to protect themselves (D'Arcy and Basoglu 2022). However, it is essential to note that not all information found online supports wearing masks in schools. Some pages may suggest that wearing a mask has disadvantages for children, which could decrease their willingness to wear one. Thus, our third research question is: *How does search volume affect the impact of mask ban policies in elementary and middle schools?* To address this question, we aggregate the number of times the term "mask" is searched in each school over a specific period. Our findings indicate that schools with higher search volumes for "mask" tend to have lower COVID-19 transmission rates after the ban on mask mandates, compared to schools with lower search volumes for "mask." One potential reason for this discovery could be that individuals more focused on the concept of "mask" may be intentionally seeking out information regarding the advantages of utilizing them. Note that the mask mandate ban allows children to continue wearing masks if their parents choose to, and parents who intentionally seek out mask information might be more likely to do so. Therefore, the impact of the mask mandate ban is smaller for schools with higher search volumes for "mask."

Finally, it has been shown that the size of gatherings can significantly impact the transmission rates of COVID-19. More confined environments with larger gatherings tend to have higher incidence rates of transmission (Liu et al. 2022). Similarly, larger school sizes, which tend to be more crowded, can also impact the transmission of COVID-19. Therefore, our fourth research question is: *How does school size influence the impact of mask ban policies in elementary and middle schools?* For this research question, we propose to use the total number of enrolled students (in thousands) as a proxy variable for school size. We find that schools with larger enrollments will experience higher COVID-19 transmission rates compared to schools with smaller enrollments after implementing the mask mandate ban policy.

To the best of our knowledge, our study is the first empirical research that uses natural experiments to examine the causal relationship between the mask mandate policy and COVID-19 transmission in school. More importantly, we find that the mask mandate is crucial for protecting students in schools, and more specifically, the COVID-19 transmission rate is different in different types of schools, which can help school districts easier to make decisions for their students.

2. Data Description

Our data is collected from publicly released data on COVID-19 cases in public schools in Florida.[1] The requirement for public school students to wear masks varied among school districts in Florida. Beginning in late 2021, the Governor of Florida issued an executive order requiring Florida public schools not to mandate that students wear masks (Mckay 2021). Subsequently, some counties rescinded the mandatory mask policy, while others still insisted that public school students wear masks (Santiago and Weisfeldt 2021). In this study, we use the changes in the mask mandate policy to examine the impact of mandatory mask-wearing on COVID-19 transmission among school children.

We collected a school-level COVID-19 case dataset from March to October 2021 for our empirical analysis. Most of the counties in Florida release the COVID-19 case information of each public school on their websites. Therefore, we can collect and aggregate each school's data to obtain a dedicated dataset. Our dataset mainly includes information on how many students were infected with the coronavirus in each school in a specific week. Our dataset contains 1,530 elementary, middle, and high schools from 32 counties in Florida. The data covers a total of 19 weeks, including 8 weeks in the Spring 2021 semester and 11 weeks in the Fall 2021 semester. In addition, we supplemented our dataset with school-level information,[2] including the percentage of minority students, the percentage of students in need of financial aid, and the total number of enrolled students. We also collected temperature information, air quality data, unemployment rate, and COVID-19 vaccination data at the county level. The definitions and summary statistics of key variables are presented in Table 1.

Table 1. Definitions and Summary Statistics

Variable	Definition	Mean	Std.	Min	Max
PositiveNum	The number of students who tested positive in a school in a week	2.52	9.78	0	672
MaskBan	A dummy variable indicating whether a school lifts the mask mandate in a week (1 indicates that the mask mandate is lifted)	0.20	0.40	0	1
AveHighTemp	The average of the highest local temperature recorded each day in a week	86.17	4.25	71.86	94.00
AveLowTemp	The average of the lowest local temperature recorded each day in a week	70.05	7.21	20.57	81.43
AveAQI	The average local air quality index each day in a week	34.59	7.86	12.71	60.36
UnemployRate	The local unemployment rate in percentage	4.74	0.91	2.40	8.20
VaccRate	The percentage of people vaccinated with at least one dose of COVID-19 vaccines in a county	54.49	17.44	14.35	90.59
Size	The number of enrolled students (in thousands) in a school	0.91	0.59	0.05	4.80
Minority	The proportion of Black or Hispanic students in a school	0.66	0.25	0.05	1.00
EconDisadv	The proportion of students who are economically disadvantaged in a school[3]	0.60	0.22	0.03	0.99
SearchVolume	The search volume (indicated by Google Trends) for the term "mask" in the city where a school is located in a week	2.16	3.92	0.00	61.86

[1] We collected data on COVID-19 cases from each county's COVID-19 dashboard website (e.g., Alachua County: https://www.sbac.edu/Page/30007).
[2] We collected school information from U.S. News & World Report.

[3] An economically-disadvantaged student is a student whose household income is determined to be low income according to the latest available data from the U.S. Department of Commerce.

In our study, treated units are public schools in counties that have ever blocked the mask mandate policy. Public schools in the same county (school district) follow the same mask policy over time. Figure 1 illustrates the treatment variation plot that presents the dynamics of the ban on mask mandates across counties and time in the data. From Figure 1, we can see that there are 6 counties that have never rescinded mask mandates within the observation window. The missing values in the figure are because schools in those counties had not started the new semester yet during those time periods. In addition, we do not incorporate the data of schools from Charlotte County because it did not disclose separate data on the COVID-19 cases of students. The average number of schools in each county is 47.8.

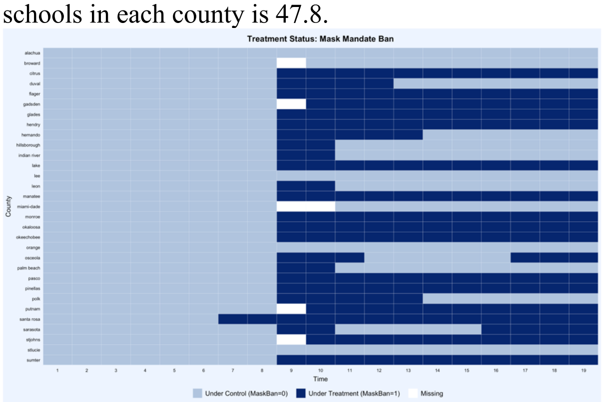

Figure 1. Treatment Status: Mask Mandate Ban

3. Empirical Analysis

3.1. Main Results

To examine the relationship between mask mandate policy and COVID-19 transmission in elementary and middle schools, we start with the following difference-in-differences (DID) regression specification to implement the natural experimental design (Qiu and Kumar 2017; Wang et al. 2022):

$$\log(\text{PositiveNum}_{i,t}) = s_i + w_t + \beta_0 + \beta_1 \text{MaskBan}_{i,t-1} + \beta_2 \text{Controls} + \varepsilon_{i,t}, \quad (1)$$

where the dependent variable $log(PositiveNum_{i,t})$ denotes the logarithm number of students who tested positive for COVID-19 in school i in time period t. s_i is the unobserved school fixed effect, w_t is the weekly time fixed effect, and $MaskBan_{i,t-1}$ is a dummy variable indicating whether school i lifted its mask mandate in time period t - 1 (1 indicates that the mask mandate was lifted). Controls include *AveHighTemp* (the average of the highest local temperature recorded each day in a week), *AveLowTemp* (the average of the lowest local temperature recorded each day in a week), *AveAQI* (the average of local air quality index[4] each day in a week), *UnemployRate* (the local unemployment rate[5]), and *VaccRate* (the percentage of people vaccinated with at least one dose of the COVID-19 vaccine).

The fixed effect regression result is presented in column 1 of Table 2. $MaskBan_{it}$ is the key variable of our interest. We find that the coefficient on $MaskBan_{it}$ is significantly positive: The ban of mask mandate policy increases the transmission by 20.7% in terms of the number of students who tested positive for COVID-19, which indicates a significant benefit of imposing mask mandates. To further confirm the effect of mask mandates on COVID-19 transmission, we also use an alternative dependent variable, $PositiveRate_{it}$, which is calculated by dividing the number of students who tested positive in week *t* by the total number of enrolled students in school *i*. The larger this ratio variable, the more serious the spread of the coronavirus disease. The estimation result is consistent with the prior findings and is shown in column 2 of Table 2. The ban on mask mandates increases the ratio variable by 0.3%. Note that it is economically significant since the mean of $PositiveRate_{it}$ is 0.2% during mask mandate periods. The results show that our findings are robust to the selection of dependent variables by using alternative measures of virus transmission.

Table 2. The Impact of Mask Ban on COVID-19 Transmission in Elementary, Middle, and High Schools

Variables	(1) log(PositiveNum)	(2) PositiveRate
MaskBan	0.207***	0.003***
	(0.025)	(0.000)
AveHighTemp	0.032***	0.000***
	(0.004)	(0.000)
AveLowTemp	0.003*	0.000***
	(0.002)	(0.000)
AveAQI	-0.009***	-0.000
	(0.001)	(0.000)
UnemployRate	-0.204***	-0.001***
	(0.023)	(0.000)
VaccRate	-0.028***	-0.000***
	(0.002)	(0.000)
School FE	Yes	Yes
Weekly FE	Yes	Yes
Observations	25,660	25,660

Note: ***p < 0.01; **p < 0.05; *p< 0.1; Robust standard errors clustered at the school level are in parentheses.

[4] Florida Department of Environmental Protection: https://floridadep.gov/air/air-monitoring/content/floridas-air-quality, accessed on April 4, 2022.

[5] U.S. Bureau of Labor Statistics: https://www.bls.gov/lau/home.htm, accessed on April 4, 2022.

It is worth noting that our DID analysis relies on the "parallel paths" assumption that the average outcomes of the control and counterfactual treatment groups (in the absence of treatments) should follow parallel trends (Cheng et al. 2020). However, the "parallel paths" assumption may not be satisfied because the treated schools were not randomly chosen. For example, after the mask ban regulation was announced, some counties would not abide by it if they already had significant COVID-19 transmission. Furthermore, school sizes, funding, or even the percentage of the minority would also affect counties' decisions on whether they follow the mask ban policy. For example, Governor Ron DeSantis of Florida announced that school districts in the state that do not follow the mask ban mandate policy would lose funding from the government (Luscombe 2022). As a result, school districts with lower budget and fewer resources may be more likely to comply with the mandate. To alleviate such endogeneity concerns, we perform a counterfactual analysis for robustness checks in the following section.

3.2. Robustness Checks: Counterfactual Analysis

3.2.1. Counterfactual Estimators. An ideal causal identification design for inferring the relationship between mask policy and transmission rate is to compare the mask mandate ban on a school with the absence of such a ban on the *same* school at the *same* point in time (Tafti and Shmueli 2020; Pan and Qiu 2022). However, we can never observe both of the outcomes. The best way is to generate a credible counterfactual outcome for each treated school.

In this section, we use two popular methods to estimate the unobservable counterfactual for robustness checks. First, we follow the idea of synthetic control proposed by Abadie et al. (2010) to synthetic a weighted combination of control schools that are similar in terms of the pretreatment COVID-19 transmission to the corresponding treated school. Then we can take the outcome variable of the synthetic control school as the counterfactual prediction for the treated school. The synthetic control method is gaining increasing popularity in various social science research contexts with quasi-experimental designs (Bischof and Wagner 2019; Gaughan et al. 2019; Puranam et al. 2021). There are multiple treated units in our context, so we use the generalized synthetic control method (GSCM) (Xu 2017) to apply the idea of synthetic control to multiple treated schools. The benefit of using GSCM is that it captures the trend of the outcome variable and can account for the effects of both unobservable and observable confounders changing over time. Besides, the GSCM allows for heterogeneous treatment effects across units, which is in perfect accord with our context, where the impact of the mask mandate ban is heterogeneous across schools. Thus, we can address the endogeneity concerns by combining the GSCM with a DID design.

Second, we use a machine learning-based econometric approach, the matrix completion method (MCM) proposed by Athey et al. (2021), to obtain a counterfactual estimation and further explore the robustness of our findings. The MCM relaxes the parallel paths assumption and allows for heterogeneous unobserved trends. Like the GSCM, the MCM also accounts for unobserved time-varying factors and thus can mitigate endogeneity concerns. However, the MCM uses a different method of estimation, predicting the counterfactual outcomes based on matrix factorization for the treatment group. The technique has been inspired by machine learning literature. It interprets the problem of counterfactual prediction as a problem of completing an $N \times T$ matrix with missing elements, where N represents the number of units, and T denotes the number of time periods. The MCM is shown to produce credible results when the matrix is unbalanced (either when T is small or larger relative to N) (Athey et al. 2021). In our case, we have a large dataset where the number of schools is much larger than the number of periods ($N \gg T$), so the MCM would fit our context well. In addition, MCM can accommodate treatment reversals, which is the case in our context.

The estimation results are reported in Table 3 (columns 1 and 2 for GSCM and columns 3 and 4 for MCM). We can see that the results are consistent with the main findings, which suggests that our conclusions are robust when using counterfactual estimation for causal identification.

Table 3. Robustness Checks: GSCM and MCM

Variables	Generalized Synthetic Control Method		Matrix Completion Method	
	(1) log(PositiveNum)	(2) PositiveRate	(3) log(PositiveNum)	(4) PositiveRate
MaskBan	0.229^{***}	0.004^{***}	0.225^{***}	0.004^{***}
	(0.031)	(0.001)	(0.023)	(0.001)
AveHighTemp	0.009^{***}	-0.000	0.009^{***}	-0.000
	(0.003)	(0.000)	(0.003)	(0.000)
AveLowTemp	0.004^{***}	-0.000	0.003^{**}	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)
AveAQI	-0.007^{***}	-0.000^{**}	-0.005^{***}	-0.000^{***}
	(0.001)	(0.000)	(0.001)	(0.000)
UnemployRate	-0.177^{***}	-0.000	-0.181^{***}	-0.000
	(0.016)	(0.000)	(0.016)	(0.000)
VaccRate	-0.025^{***}	-0.000^{***}	-0.025^{***}	-0.000^{***}
	(0.002)	(0.000)	(0.002)	(0.000)
School FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Observations	25,660	25,660	25,660	25,660

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Robust standard errors clustered at the school level are in parentheses.

3.2.2. Diagnostic Tests for Counterfactual Estimators. In this section, we conduct diagnostic tests proposed by Hartman and Hidalgo (2018) and Liu et al. (2023) to validate the absence of time-varying confounders in our estimation and confirm the parallel trend assumption. First, we plot the dynamic treatment effect (Heckman et al. 2016) based on the two counterfactual estimations (GSCM and MCM). The plots can intuitively show the temporal heterogeneity of the treatment effects. Figure 2 displays the dynamic treatment estimates with 95% confidence intervals on $\log(PositiveNum_{i,t})$ based on GSCM and MCM, respectively. The coefficients in the pretreatment periods largely bounce around zero in both figures, indicating that the issue of pretreatment trends is not severe. In addition, we can see that the coefficients in the posttreatment periods are significantly above zero (in most of the cases) in Figure 2, which suggests that the ban of mask mandate policy does significantly increase the COVID-19 transmission among the student population in Florida.

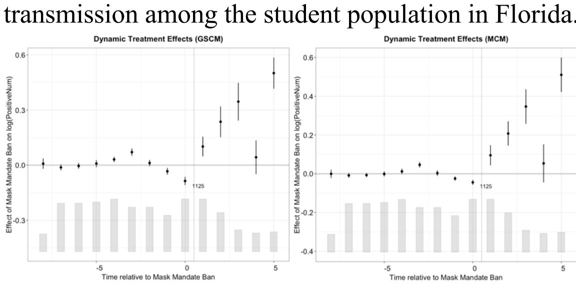

Figure 2. The Dynamic Treatment Effects of Mask Ban on COVID-19 Transmission

Second, following prior literature (Hartman and Hidalgo 2018), we employ the equivalence test to examine the presence of a pretreatment trend. For example, schools with fewer COVID-19 cases before may be more likely to follow the mask mandate policy. The test is passed if the residual average for any pretreatment period is within the equivalence range (Liu et al. 2023). Figure 3 displays the equivalence test results based on GCSM and MCM. The equivalence range is the red dashed line. We can see that the residual averages with 90% confidence intervals are within the equivalence ranges. Therefore, we can reject the null hypothesis of inequivalence and reckon that no significant pretreatment trends exist of the coefficients. The result also suggests that a sufficient set of confounders has been controlled to address the endogeneity concerns by constructing the control group using GSCM and MCM. Note that we also use the alternative dependent variable, $PositiveRate_{it}$, as a robustness check for the diagnostic tests and obtain very similar results. To sum up, the results of diagnostic tests show that the estimation results of our counterfactual analysis are reliable and provide additional support for our findings.

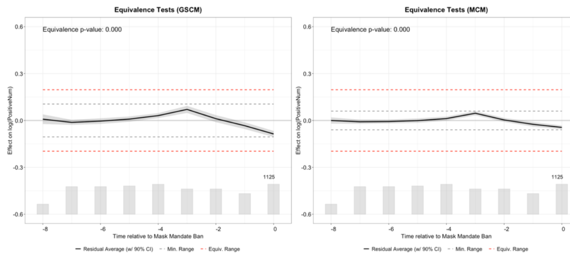

Figure 3. Testing for No Pre-Trends

3.3. Moderating Factors

In this section, we investigate moderating factors' effects on the impact of the ban on mask mandates. We estimate the following regression specification:

$$\log(\mathrm{PositiveNum}_{it}) = s_i + w_t + \beta_0 + \beta_1 \mathrm{MaskBan}_{it} + \beta_2(\mathrm{MaskBan}_{it} \times \mathrm{Moderator}_i) + \beta_3 \mathrm{Controls} + \varepsilon_{it}\,, \quad (2)$$

where $Moderator_i$ represents the proposed moderating factor. First, we examine the moderating role of the proportion of economically disadvantaged students in schools. We use *EconDisadv$_i$*, which represents the proportion of students who are economically disadvantaged in a school. The estimation result in column 1 of Table 4 indicates a significant negative result for the interaction term (*MaskBan$_{it}$* × *EconDisadv$_i$*), suggesting that the detrimental impact of the mask mandate ban is smaller for schools with higher percentages of economically disadvantaged students. One possible explanation for the situation is that economically disadvantaged people lack enough COVID-19 protection compared to others. For example, individuals living in poverty are more likely to reside in crowded households, which can contribute to a higher rate of infection transmission (Devakumar et al. 2020). Therefore, economically disadvantaged students may already get an infection with COVID-19 before the mask ban mandate was implemented. Hence, after the mask mandates ban policy, schools with a higher proportion of economically disadvantaged students would have lower COVID-19 transmission.

Additionally, we also examine the relationship between masks and the minority size in the schools. We use *Minority$_i$*, which reflects the percentage of Hispanic and black students in a school. According to the estimation results in column 2 of Table 4, there is a significantly detrimental coefficient for the interaction term (*MaskBan$_{it}$* × *Minority$_i$*), showing that the negative impact of the mask mandate ban is smaller for schools with larger percentages of minority students. One possible explanation for this situation is that white individuals are less likely to wear masks than black or Latino individuals (Hearne and Niño, 2021). Consequently, even if a ban on mask mandates is implemented in schools, parents belonging to minority communities would likely still insist that their children wear masks. As a result, schools with a higher proportion of minority students would experience a lesser impact from the policy prohibiting mask mandates.

Table 4. The Moderating Effects on the Impact of Mask Ban

Variables	(1) log(PositiveNum)	(2) log(PositiveNum)	(3) log(PositiveNum)	(4) log(PositiveNum)
MaskBan	0.774^{***} (0.080)	0.635^{***} (0.062)	0.282^{***} (0.031)	-0.061 (0.049)
MaskBan × EconDisadv	-0.995^{***} (0.121)			
MaskBan × Minority		-0.855^{***} (0.095)		
log(SearchVolume)			0.004 (0.007)	
MaskBan × log(SearchVolume)			-0.109^{***} (0.021)	
MaskBan×Size				0.300^{***} (0.053)
AveHighTemp	0.030^{***} (0.004)	0.028^{***} (0.004)	0.031^{***} (0.004)	0.032^{***} (0.004)
AveLowTemp	0.002 (0.001)	0.002 (0.001)	0.003^{*} (0.002)	0.003^{*} (0.001)
AveAQI	-0.009^{***} (0.001)	-0.009^{***} (0.001)	-0.009^{***} (0.001)	-0.009^{***} (0.001)
UnemployRate	-0.198^{***} (0.024)	-0.168^{***} (0.025)	-0.197^{***} (0.023)	-0.199^{***} (0.023)
VaccRate	-0.028^{***} (0.002)	-0.022^{***} (0.002)	-0.027^{***} (0.002)	-0.028^{***} (0.002)
School FE	Yes	Yes	Yes	Yes
Weekly FE	Yes	Yes	Yes	Yes
Observations	25,660	25,660	25,660	25,660

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$; Robust standard errors clustered at the school level are in parentheses.

Next, we used *SearchVolume$_{it}$*, which represents the search volume for the term "mask" in the city where school *i* is located in time period *t*, to examine the moderating role of search volume. We chose to use Google Trends data to measure search volume for several reasons. First, Google's search engine has a dominant market share, making it likely to be representative of the internet search behavior of the general population (Huang et al. 2020). Second, search behavior is considered a revealed attention measure, as noted by Da et al. (2011). For example, when individuals search for "mask" on Google, it indicates that they pay attention to the topic. Hence, the search frequency of the term "mask" in Google can be used as a measure of attention. The estimation result, presented in column 3 of Table 4, shows that the coefficient of the interaction term (*MaskBanit × log(SearchVolume$_{it}$)*) is significantly negative. This implies that the detrimental impact of the mask mandate ban is smaller for schools with higher search volumes for the term "mask" One possible explanation for this finding is that people who are paying more attention to "mask" may be actively seeking information about the benefits of wearing masks. Therefore, even if the school district of a county chooses to follow the mask mandate ban policy, parents may still choose to have their children wear masks based on the information they gather from their increased search activity. Therefore, the impact of the mask mandate ban is limited.

Lastly, we examine the moderating role of school size. We use $Size_i$, which is the number of enrolled students (in thousands), to measure the school size. The estimation results are presented in column 4 of Table 4. We find that the coefficient of the interaction term ($MaskBan_{it} \times Size_i$) is significantly positive, which implies that the detrimental impact of the mask mandate ban is larger for larger schools. In fact, since the coronavirus transmits through human contact, the disease spreads more rapidly in areas where more people gather (Bhadra et al. 2021). Thus, when the mask mandate is lifted, the consequences of increased transmission will be more severe for large schools. Note that while a larger school size does not necessarily equate to a higher level of congestion, it is likely to increase human contact, potentially leading to more coronavirus transmission.

4. Conclusion and Discussion

The effectiveness of mask mandates in schools has been a topic of debate, but there is limited understanding of their causal impact on COVID-19 transmission. This study aimed to address this gap by using a natural policy shock that occurred in Florida, where the "Mask Mandate Ban" policy allowed school districts to decide whether to enforce mask-wearing. Our results demonstrate a 20.6% increase in COVID-19 cases among students when mask mandates were banned. Additionally, we examine the impact of the mask mandate ban on different school sizes, search volume for "mask," and racial and poverty groups. Our findings show that schools with smaller enrollments, higher local search volumes for "mask," and higher percentages of economically disadvantaged or minority students experienced lower COVID-19 transmission rates after the ban.

4.1. Theoretical and Managerial Implications

Our work has important implications for both research and practice. From a theoretical perspective, our study contributes to the ongoing debate on mask-wearing in educational settings. Our natural experiment approach has two notable advantages over traditional randomized controlled trials when it comes to establishing causation in our specific situation. Firstly, randomized controlled trials often face difficulties in ensuring high compliance rates of mask-wearing, especially among children in the treatment group. In contrast, our natural experiment approach circumvents these challenges. Secondly, while most randomized controlled trials primarily focus on assessing the effects of mask-wearing on the individuals wearing them, our approach considers the broader impact of masks by considering how they can potentially reduce virus transmission to others if the mask wearer is already infected. Determining this aspect can be more complex in traditional trials. Furthermore, prior research has mainly focused on the effectiveness of masks in public settings during the early stages of the pandemic, from March 2020 to early 2021 (Chernozhukov et al. 2021; Karaivanov et al. 2021). To the best of our knowledge, our study is the first empirical research to use natural experiments to investigate the causal relationship between mask mandate policies and COVID-19 transmission in schools. Our findings reveal a significant 20.6% increase in COVID-19 cases among students when mask mandates are banned, emphasizing the importance of enforcing mask mandates in schools. Additionally, we examined the moderating effects of school size, search volume for "mask," and racial and poverty groups on the impact of the mask mandate ban. Our results demonstrate that schools with smaller enrollments, higher local search volumes for "mask," and higher percentages of economically disadvantaged or minority students experience lower COVID-19 transmission rates after the ban. These results contribute to the ongoing debate on mask-wearing in educational settings and show the causal impact of mask mandates in different types of schools.

From a managerial perspective, our study highlights the significant impact of mask mandates in mitigating the spread of COVID-19 in schools. School administrators should consider implementing mask mandates, especially during times of high community transmission. The study also provides insights into the impact of the mask mandate ban on different school sizes, search volume for "mask," and racial and poverty groups. School administrators should consider these factors when making policy decisions related to mask mandates. Furthermore, policymakers can use the findings of this study to inform their decision-making on mask mandate policies in schools. They can evaluate the effectiveness of existing policies and make evidence-based decisions that prioritize the health and safety of students and staff. Finally, this study uses "Mask Mandate Ban" in Florida as an exogenous shock to investigate the causal impact of mask mandate on COVID-19 transmission in elementary and middle schools. By employing this natural experiment, policymakers can not only gain valuable insights into the effectiveness of mask mandates, but also enabling them to make informed decisions during the post-COVID period or to enhance preparedness for future pandemics.

4.2. Limitations and Future Research Directions

Our research is not without limitations. One limitation of our study is the potential endogeneity of the natural policy shock in Florida, as the treated schools were not randomly selected. The decision of counties to enforce or not enforce the mask ban policy could have been influenced by various factors such as the level of COVID-19 transmission, school size, funding, and the percentage of minority students. While we employed several robustness checks and control variables to address this issue, there remains the possibility of unobserved confounders affecting our results.

Our research can be extended in several ways. First, based on our result showing mask mandates plays a vital role in preventing COVID-19 transmission in elementary and middle schools, future research could investigate the effectiveness of different types of masks and how compliance with mask mandates can be improved in school settings. Second, we only examine the effectiveness of mask mandates in protecting students' physical health. Future research could explore the effectiveness of mask mandates on students' and teachers' mental health. Finally, future research could focus more on examining the causal impact of mask mandates on COVID-19 transmission in high schools or universities.

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