School Closures and Respiratory Infections Transmission and Mortality: Evidence from School Holidays in Poland

Abstract

This study examines the impact of temporary school closures on influenza transmission and respiratory mortality, leveraging a natural experiment from winter break timings in Polish schools. Analyzing 12 years of ILI (Influenza-Like Illness) data and two decades of respiratory death records, findings indicate significant reductions in ILI incidence post-closures: 75% among school-aged children, 55% in adults, 32% in pre-school children, and 37% in the elderly. Notably, a 10% decrease in respiratory mortality was observed among the elderly, highlighting school closures as an effective public health intervention for reducing influenza spread and mortality among high-risk groups.

Keywords: Influenza, School Closure, Respiratory Mortality

1 Introduction

WHO [2023] estimates that influenza affects approximately a billion individuals globally each year, resulting in between 229,000 and 650,000 fatalities. Recovery from influenza does not preclude the long-term negative consequences, extending even through generations; infections among pregnant women cause adverse health and economic outcomes among their children [Almond, 2006, Schwandt, 2018]. To halt the spread of infectious diseases, policymakers have contemplated implementing school closures, acknowledging schools as significant vectors for transmission. Yet, most respiratory deaths are concentrated among the elderly [CDC, 2024], which raises questions regarding the efficacy of school closures in preventing such deaths. This paper documents the causal impact of temporary school closures on the prevalence of influenza and related respiratory mortality in Poland.

The underlying hypothesis posits that school closures reduce contact rates among students [Jackson et al., 2016], effectively reducing the spread of the virus. Schools serve as a prime environment for viral transmission, with children spending 5 to 8 hours daily in classrooms that typically house around 30 students. In such settings, a single ill student can spread the infection to numerous peers. Moreover, infected students may carry the virus home, transmitting it to family members across different age groups, including siblings, parents, and grandparents. This makes students pivotal vectors for transmitting the virus to more vulnerable populations. Interrupting this transmission pathway through school closures not only has the potential to reduce infections among school-aged children but also to limit the source of spillovers to other age groups.

Empirical evidence demonstrates that school closures indeed diminish the incidence of Influenza-Like Illness (ILI). Adda [2016] and Cauchemez et al. [2008] use French data[1] to show a significant decline in ILI incidence following schools holidays. This conclusion is further supported by Chu et al. [2017] who find a decrease in ILI among children and adults after school closures in Beijing. Similar results are obtained in studies throughout the world (Jackson et al. [2013]), such as Cowling et al. [2008] in Hong Kong, Ali et al. [2013] in India, Heymann et al. [2004] in Israel, and Wheeler et al. [2010] in the USA.

However, the onset of the COVID-19 pandemic has intensified scrutiny of the association between schooling and infectious disease transmission. While initial observational studies suggested a linkage between school closures and reduced COVID-19 case numbers [Bignami-van Assche et al., 2021, Auger et al., 2020], most of subsequent research shows no causal relationship. Investigations leveraging variations in school vacation timings have generally found limited or no-impact of such closures on COVID-19 transmission dynamics [Bismarck-Osten et al., 2020, Isphording et al., 2021]. Moreover, studies monitoring in-school cases and subsequent contact tracing efforts have consistently reported limited transmission within educational settings [Brandal et al., 2021, Falk et al., 2021, Gillespie et al., 2021, Ismail et al., 2021, Zimmerman et al., 2021]. Notably, these findings challenge the direct applicability of influenza-based models to the COVID-19 context, suggesting a more complex interplay between school operations and disease type. This limited impact is further corroborated by other studies using causal designs (Bravata et al. [2021], Fukumoto et al. [2021]). The two notable exceptions are Vlachos et al. [2021] who show that in-person schooling increases chances of infection among teachers and Chernozhukov et al. [2021] who find an association of in-person schooling with higher growth rate

[1] Similar to data used in this project

of cases.

This discrepancy between the impacts of school closures on COVID-19 versus influenza underscores the need to further investigate how these closures affect influenza transmission, particularly focusing on the unexplored aspect of preventing respiratory deaths. This paper leverages the plausibly exogenous variation in the timing of winter breaks across Polish schools as a natural experiment to identify the causal impact of temporary school closures on the incidence of Influenza-Like Illness and respiratory mortality. To achieve this aim, the study utilizes detailed surveillance and administrative data, encompassing 12 years of weekly, county-level reports of ILI cases and two decades of respiratory infection-related mortality data. The disaggregation of the data by age enables me to answer the critical question of whether this policy also affects groups at elevated risk of mortality.

The findings indicate that school closure serves as an effective intervention for reducing both the incidence of infections and mortality due to respiratory illnesses. Specifically, there is a pronounced decline in ILI incidence among school-aged children—by approximately 75%—in the weeks following the beginning of winter breaks. This protective effect extends beyond the school-aged population. Incidence among adults drops by 55%, among pre-school children by 32%, and among people aged 65 and older by 37%. Importantly, I demonstrate a sizable reduction in respiratory mortality in this last group. Conservatively, mortality decreases by about 10% compared to the pre-holiday average. Mortality in other age groups is not affected.

While the immediate health benefits of school closures are evident, such measures are not without their costs, particularly concerning human capital development and the productivity of caregivers. This paper focuses predominantly on the health implications of school closures. Readers interested in the broader socio-economic consequences of school closures are encouraged to consult existing literature on the topic (for instance Lempel et al. [2009], Adda [2016], Garcia and Cowan [2022], Jack and Oster [2023], Goldhaber et al. [2023]).

The rest of the paper is organized as follows: Section 2 describes the data and methods used, Section 3 presents the findings, and the Discussion closes the paper.

2 Methods

This study uses detailed surveillance data on ILI cases and mortality records, and is structured around a SIRS epidemiological model. It employs an event study framework leveraging the variation in timing of school vacations across Polish regions to capture the causal effects of school closures on ILI incidence and respiratory mortality.

2.1 Data

I use two primary datasets: surveillance data on ILI cases and administrative mortality records.

Surveillance Data : ILI case data are derived from weekly reports by primary care physicians as part of the national influenza surveillance initiative. For surveillance purposes, an illness is an ILI when a patient exhibits a fever of 38 °C (100 °F) or higher along with a cough that started within the last 10 days. The reports detail the number of patients presenting influenza symptoms, categorized into four age groups: 0-4, 5-14, 15-64, and 65+ years. The reporting is performed by physicians who voluntarily take part in the program. Nationally, about 1000 health practitioners participate in the program. Data is aggregated at the county and week level, with "county" here referring to the administrative division known as "powiat" in Poland. Access to these reports was facilitated through county and regional epidemiological stations, covering 168 of Poland's 380 counties from 2005 to 2019. Figure A.1 in the appendix shows counties that made the data available. The dataset includes the total reported cases and the contributing doctors per county each week, with disaggregated age group data available for the majority of counties. The surveillance period is organized into 48 epidemiological weeks per year. My main outcome of interest is the weekly incidence rates per age group and county, defined as the number of reported cases in a week per 10,000 persons in a given age group and county. Figure 1 illustrates the weekly averages of these rates. A clear seasonal pattern is observed, with incidence peaking typically in February-March, diminishing during the summer, and resurging in September, aligning with the start of the school year.

Mortality Data : The mortality dataset encompasses all Polish counties from 2000 to 2018, detailing deaths by cause, age group, county, week, and year. Weeks in Mortality data follow ISO norms. This analysis focuses on deaths attributed to respiratory system diseases (ICD-10 category J), using annual population data by age from the Polish Statistical Office (GUS) to compute mortality rates per 10,000. Similar to ILI incidence, a seasonal mortality pattern arises, particularly pronounced among seniors, with negligible rates in younger age groups (Figure 2).

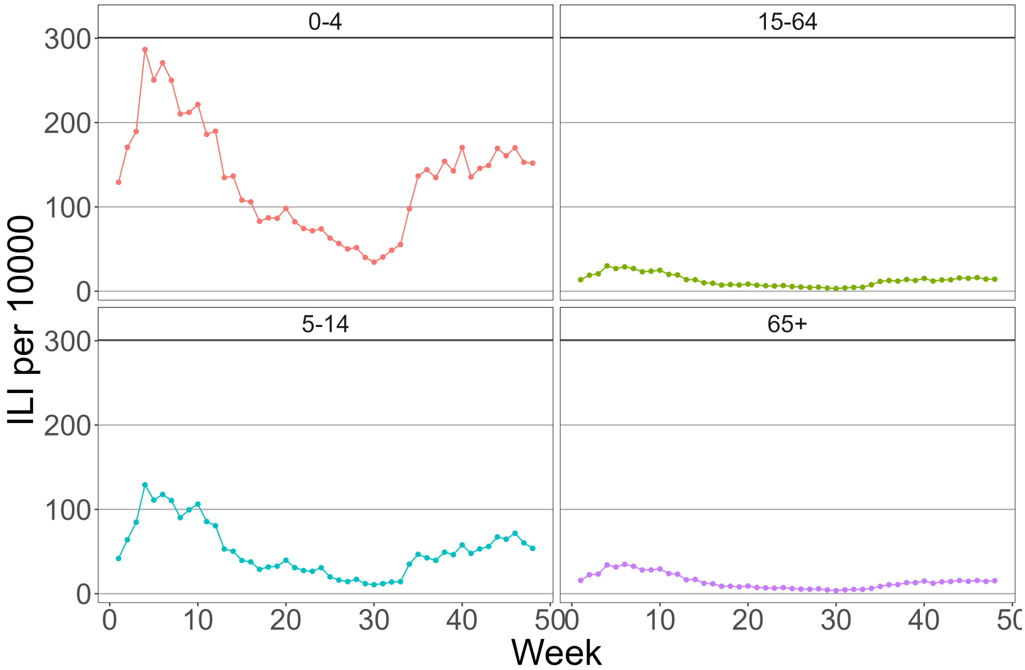

Figure 1: Average ILI Incidence by Week and Age Group
Note: Each dot represents the average weekly incidence of ILI cases per 10,000 people, aggregated across years and counties. Pre-school children (0-4 years) report the highest incidence, followed by school-aged children (5-14 years), the elderly (65+ years), and adults (15-64 years). *Source:* Author's compilation from epidemiological station data.

2.2 Motivating Model

The "Susceptible-Infected-Recovered-Susceptible" (SIRS) epidemiological model [Anderson et al., 1992] guides my analysis. It is a framework wherein an individual's state transitions through being susceptible, infected, and then recovered. This model allows for the re-entry of recovered individuals into the susceptible population upon immunity loss. The evolution of the infected population within this model is guided by both the inflow of new infections and the outflow of recoveries, as detailed in the following equation:

$$I_{t,i} = \alpha d_{ii} \frac{S_{t-1,i}}{P_{t-1,i}} I_{t-1,i} + \sum_{j \neq i} \alpha d_{ij} \frac{S_{t-1,i}}{P_{t-1,i}} I_{t-1,j} + (1-\beta) I_{t-1,i} \tag{1}$$

In this equation, $I_{t,i}$ represents the number of infected individuals in county i at time t, with the infection dynamics determined by three principal factors:

1. **Intra-county Infections**: New infections within county i are proportional to the contacts (d_{ii}) between susceptible and previously infected individuals in that county ($I_{t-1,i}$), adjusted for the per-contact transmission probability α and the proportion of the population still susceptible ($S_{t-1,i}/P_{t-1,i}$).

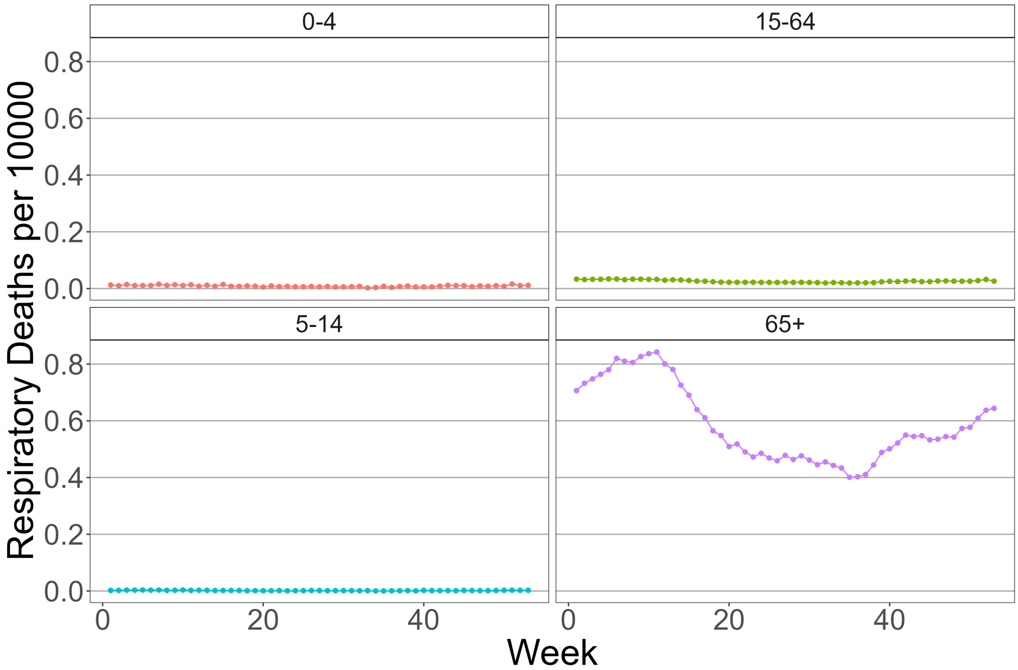

Figure 2: Average Respiratory Mortality by Week and Age Group
Note: Each dot represents the average weekly mortality from respiratory diseases per 10,000 people, aggregated across years and counties. Seniors exhibit the highest mortality rates, reflecting a seasonal pattern aligned with ILI incidence. *Source:* Author's compilation from administrative data.

2. **Inter-county Infections**: New infections stemming from contacts with individuals from county j (d_{ij}), summed over all counties.

3. **Continuing Infections**: Individuals who were sick in the previous time period and have not recovered. Note that β represents the recovery probability.

Equation 1 can be used to demonstrate how the policy of school closures impacts infection levels by temporarily reducing contact rates among children, leading to a decrease in the parameter d_{ii}[2]. This reduction in contact rates results in lower transmission and, consequently, an immediate decline in infections following the start of school vacations. Importantly, the effects of this intervention may extend beyond the vacation period, even after the contact rate has returned to its prior level. As the number of infected individuals decreases, the likelihood of new infections correspondingly falls, potentially maintaining reduced infection rates for an additional 2 to 3 weeks after the recess period.

It is important to mention two assumptions that are necessary to accommodate this model for the statistical analysis. Firstly, I assume a weekly cycle to align with the typical incubation period of influenza (Lessler et al. [2009]). Hence, in my setting

[2]Virtually all children attend schools in their county of residence

t represents an epidemiological week. Secondly, I assume that infected individuals visit physicians. While the propensity to report does not need to be equal among groups or across time, I assume it is not correlated with the timing of the school break. In the remaining analysis, I will argue that observed changes in incidence cannot be entirely driven by the changes in reporting.

The described model forms the analytical foundation for this study, guiding the empirical strategy.

2.3 Empirical Strategy and Statistical Methods

The empirical strategy leverages a unique natural experiment arising from the staggered timing of school breaks across Polish regions. During the winter months from January to March, schools close for a two-week period[3]. However, the specific timing of these breaks within a year varies by region (which encompasses multiple counties)[4]. Regions are divided each year into four groups. The first group begins their vacation in mid-January, while the last group starts in mid-February. Furthermore, the sequence in which these regions enter their vacation periods alternates annually. The school calendar, determined in June preceding the winter vacation, is set without prior knowledge of the impending flu season's dynamics, making the timing of these breaks plausibly exogenous to geographical and time variations in ILI incidence. This scenario creates an environment where counties within early and late vacation regions should be similar prior to the vacation start. This provides support for the necessary assumption that in the absence of school closures, the ILI trends would be parallel across these groups. Under this assumption, using late-vacation counties as a control, I can construct a counterfactual for early-vacation counties. Consequently, I can estimate the causal effects of school closures on ILI incidence and associated mortality rates.

To assess the dynamic, week-by-week effects of school closures, I employ an event study approach, which follows the equation 2:

$$y_{cwya} = \sum_{\substack{T=-6 \\ T\neq -3}}^{12} \beta_{Ta} I\{wy - (wy)_c^V = T\}_{cwy} + \delta X_{cwy} + \gamma_{wya} + \theta_{cwa} + \lambda_{cya} + e_{cwya} \quad (2)$$

This equation models the outcome variables y_{cwya}, representing either the number

[3] Pre-schools and care centers do not observe winter breaks.

[4] Region is an administrative unit larger than a county. There are 16 regions (wojewodztwa) in Poland

of reported flu cases or respiratory deaths per 10,000 individuals in county c, during week w, of year y, across different age groups a.

The treatment effect is captured through a series of indicator functions. Let $(wy)_c^V$ be the first week of vacation in year y and county c. Then $I\{wy - (wy)_c^V = T\}_{cwy}$ equals 1 if a county c is T weeks away from the start of the winter vacation. As T ranges from -6 to 12, the coefficients β_{Ta} capture effects from 6 weeks prior to the vacation to 12 weeks afterward. Therefore, β_{Ta} are the primary coefficients of interest showing the change in the outcome for each week relative to a counterfactual scenario where no vacation occurs. The key period of intervention is marked by $T = 0$, corresponding to the week when the recess begins. The third week before the vacation ($T = -3$) is excluded and serves as a reference point. Given the misalignment between the 48-week epidemiological calendar and the school year calendar, vacations may occasionally begin a few days before the designated week of $T = 0$, hence I do not exclude $T = -1$. It also allows for the examination of potential anticipatory effects, where individuals might alter their behavior in anticipation of the vacation, potentially affecting transmission dynamics.

In assessing the impact on infection rates, the model incorporates a control variable, X_{cwy}, representing the number of reporting doctors per 10,000 individuals. Additionally, the analysis includes a comprehensive set of fixed effects: week-year-age-group γ_{wya}, week-county-age-group θ_{cwa}, and year-county-age-group λ_{cya}. These fixed effects are designed to account for varying patterns of seasonality and reporting practices across counties and over years. The model is estimated separately for each age group to accurately capture age-specific effects. To address potential spatial correlations, standard errors are clustered at the regional level.

In the appendix, I present results for analyses using $log(y + 1)$ as the outcome variable, enabling to interpret the impact in percentage terms (see Figures A.3 and A.4). Given the challenges in interpreting outcomes derived from using $log(y + 1)$ with 0 outcomes [Chen and Roth, 2023], I apply Poisson regression models to the count data, with results detailed in Figures A.5 and A.6 of the appendix. To address potential concerns regarding treatment heterogeneity and its effect on the estimates in the event study, I perform a check with the robust difference-in-differences estimator from Callaway and Sant'Anna [2021], with findings shown in appendix Figures A.7 and A.8. Additionally, I extend the analysis to evaluate the policy's impact on the reproductive number, not merely incidence rates, detailed in Appendix Section A.1.1.

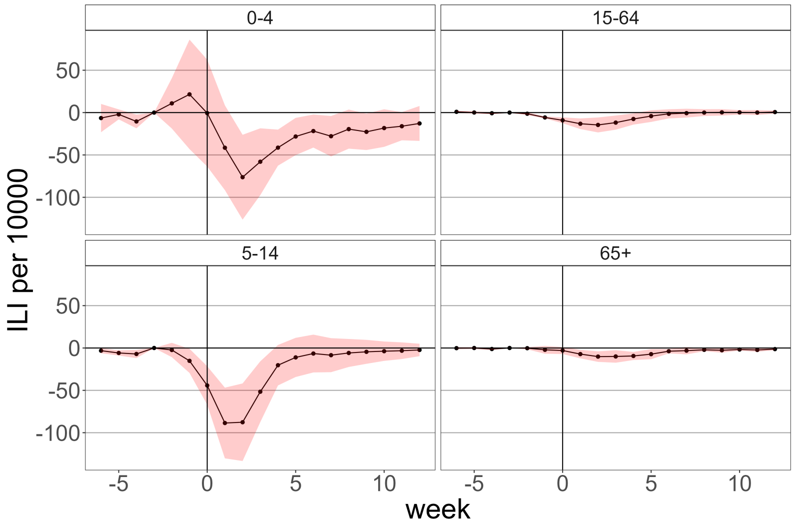

Figure 3: Event study: ILI Incidence

Note: Graph shows the impact of winter vacation on the ILI incidence by age group. Each sub-figure represents results of the estimation of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. Line represents estimates of the coefficients β_T from equation where the outcome is number of reported cases in a given county and week, per 10000 inhabitants (of a given age-group). These parameters show the change in incidence in week T, compared to three weeks before the vacation. Shaded area represents 95% confidence interval for the estimates. Standard errors are clustered at the region level. *Source:* own elaboration based on data collected from epidemiological stations.

3 Results

Temporary school closures significantly reduce the incidence of ILI among all age groups and respiratory mortality among the elderly.

Figure 3 graphically presents the estimated β_{Ta} coefficients, which reflect the impact of school closures on ILI incidence over time for various age groups. As depicted, the group most significantly impacted by school closures are children aged 5-14. The reduction in incidence begins during the vacation week and extends through to the fourth week after the start of the recess. In the vacation week, there is a decrease of 44 cases per 10,000, relative to the counterfactual, which is notable given the pre-vacation weekly average of approximately 91 cases per 10,000 in this demographic. The decline persists into the first and second weeks following vacation start, with 88 fewer cases each week, and remains lower by 51 cases in the third week—all statistically significant reductions. The continued decrease in the third week is particularly interesting since it occurs despite students having returned to school. Undeniably, the boost in travel and related absence may contribute to the decrease in reporting during the recess. However, the subsequent drop cannot be attributed to an absence during the vacation, as children need to be back in school in the following week. The persistence is consistent with an initial decrease in the pool of infected individuals due to fewer interactions, and it is inconsistent with a temporary decrease in reporting. Most coefficients preceding vacation start are zero, suggesting that early and late counties indeed have parallel ILI trajectories without vacation. The sole deviation at $T = -1$ may arise from discrepancies between epidemiological and school calendar alignment. Aggregating the significant effects over all relevant weeks, the vacation causes a decrease of around 272 cases per 10,000—amounting to a roughly 75% reduction in incidence from the pre-vacation period. It is also worth noting that the impact is evident as the winter vacation happens during the typical peak of the epidemic [5].

The implementation of school closure policies effectively halts the spread of ILI among school-aged children and diminishes the risk of exposure for high-complication-risk groups. While children of school age typically exhibit mild symptoms and recover quickly, very young children and the elderly are more susceptible to severe influenza-related complications, making their cases more impactful from a healthcare perspective. Fortunately, school closures appear to also mitigate the incidence rate in these vulnerable age groups.

For pre-school children (0-4 years), a decrease in infection incidence begins in the second week following the start of the break, with 76 fewer infections per 10,000 relative to the counterfactual. This lower incidence persists until the fifth week, accumulating to a 32% reduction compared to the pre-vacation average for this age group.

Adults, too, show a decline in ILI cases post-vacation. Although the absolute decrease is smaller, the relative reduction is more pronounced. Starting with a significant drop of 9 cases per 10,000 in the first week of vacation, the decrease extends until the third week, accumulating to a 55% decrease in incidence. This result highlights that school-aged children are a significant source of infections for adults.

Finally, the elderly population (65+ years) also experiences a significant decline in infections. Beginning with the first week of vacation, there are 7 fewer cases per 10,000 compared to the counterfactual. The protective effect extends over the following five weeks, though it gradually wanes. Overall, the vacation period contributes to averting 27 cases per 10,000 in this age group, equating to a 37% decrease from the pre-vacation average.

The reduction in ILI cases across various age groups is likely due to decreased

[5] A similar exercise is not feasible for summer vacation because the flu level is negligible and all counties have summer recess at the same time every year

intra-household transmission, with school-age children serving as common vectors. This highlights the broader protective impact of school closures beyond the immediate school environment.

Given the observed positive spillovers of school closure policies on at-risk age groups, we might expect a decrease in their mortality. Figure 4 presents the results of the estimation where the outcome variable is respiratory mortality, indicating that school closures indeed contribute to a decline in respiratory disease-related deaths among the elderly population aged 65 and above.

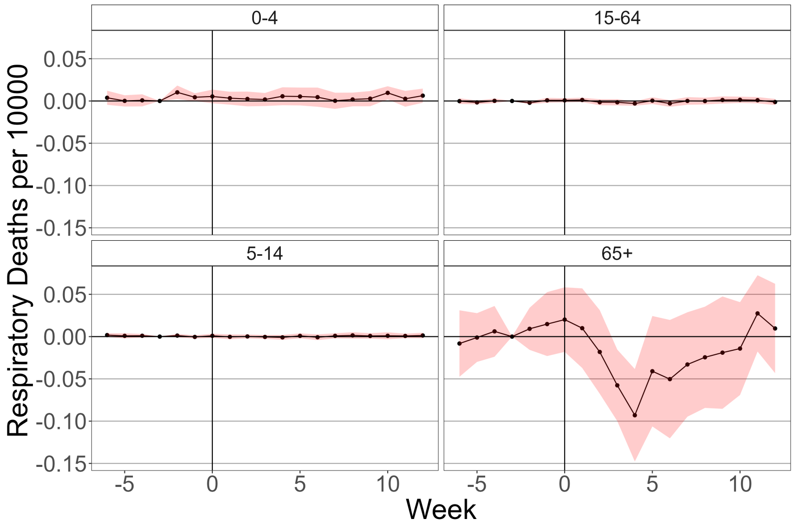

Figure 4: Event study: Respiratory Mortality

Note: Graph shows the impact of winter vacation on the ILI incidence by age group. Each sub-figure represents results of the estimation of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. Line represents estimates of the coefficients β_T from equation where the outcome is number of reported cases in a given county and week, per 10000 inhabitants (of a given age-group). These parameters show the change in incidence in week T, compared to three weeks before the vacation. Shaded area represents 95% confidence interval for the estimates. Standard errors are clustered at the region level. *Source:* own elaboration based on mortality data.

Prior to the vacation period, the baseline weekly respiratory mortality among the elderly stands at 0.73 per 10,000 individuals. Following the vacation start, significant declines are observed: mortality decreases by 0.0576 in the third week and by 0.093 in the fourth week. While the coefficient at later dates are negative, they are not statistically significant at traditional thresholds. These reductions are statistically significant and their timing aligns with the incubation to death period for influenza, consistent with the hypothesized impact of school closures. The cumulative effect of these significant reductions represents approximately a 10% decrease from the pre-vacation average mortality rate in this demographic.

Collectively, these results confirm that interactions among students significantly propagate Influenza-Like Illnesses. Furthermore, the evidence suggests that school closures serve as an effective tool not only to halt viral transmission across age-groups but also to reduce seasonal mortality among high-risk groups, such as the elderly. These findings offer compelling justification for the implementation of school closures as a public health strategy during peak influenza seasons.

4 Discussion

This study's causal estimates on the effects of school closures on influenza-like illnesses (ILI) and respiratory mortality highlights the significant public health benefits of such interventions. Analyzing data from a natural experiment involving staggered school vacation schedules reveals substantial reductions in ILI incidence across all age groups, with the most significant 75% decrease among school-aged children. Moreover, the implementation of this policy significantly attenuated respiratory mortality among the elderly, a group particularly vulnerable to severe outcomes from influenza.

School closures break the chain of transmission within the community, demonstrating that school-aged children play a crucial role in the spread of influenza. The resulting declines in illness and mortality not only lessen the burden on healthcare systems but also emphasize the efficacy of school closures as a temporary public health measure to mitigate influenza outbreaks.

The impact on incidence observed in this study places it at the higher end compared to other findings in the literature. Methodologically similar work of Adda [2016], reports a decrease of $30 - 40\%$ in children, $20 - 30\%$ in adults, and 20% in the elderly. Adda's inclusion of preschool children and older teenagers in the children's group may account for the smaller effect size. Furthermore, the confidence intervals for the elderly in Adda's study contain the estimates reported here.

Comparative studies from France [Cauchemez et al., 2008], China [Chu et al., 2017], Argentina [Garza et al., 2013], Israel [Heymann et al., 2004], and the USA [Wheeler et al., 2010] typically demonstrate smaller effects ranging from $13 - 42\%$ decline for children. Nonetheless, these studies often compare incidence ratios during or post-break to the periods before, rather than to a counterfactual scenario in the absence of holidays—potentially underestimating the effects relative to the causal estimates presented here. Chowell et al. [2014] in Chile found reductions similar to this study, with a 67% decline in children and 37% in adults.

Regarding mortality, while no direct comparisons exist, the magnitude of significant effects on the elderly in this study is more than double the increase in influenza mortality linked to local events, such as the presence of a home team in the Super

Bowl, associated with a mortality increase of 0.07 per $10,000$ among the elderly **?**.

According to my estimates, winter vacations may prevent approximately $107,400$ infections annually among school-age children, $25,736$ infections in the $0-4$ age group, $125,580$ cases among adults aged $15-64$, and $18,177$ cases among those aged 65 and older. Crucially, disrupting transmission during the winter vacation is estimated to prevent 101 deaths in the elderly population annually.

Nonetheless, this study has limitations. The data comes from primary care reports, which could lead to under-detection of infections if individuals refrain from seeking medical attention. Moreover, not all doctors report, resulting in missing cases, and not all reported cases are laboratory-confirmed as influenza. Additionally, vacation periods may influence the propensity to visit a doctor, although this is unlikely to account for the observed post-vacation decline. These reporting issues do not affect mortality data, which is derived from administrative records and is not subject to timing adjustments based on vacation schedules. A further limitation is the imperfect alignment between epidemic and school calendars, potentially misassigning vacation periods by up to three days. Lastly, the generalizability to other diseases is limited, as transmission patterns may differ and not be as dependent on children.

Despite these limitations, the results appear robust, as substantiated by the various robustness checks in the appendix section A.1, exploring alternative outcome definitions, specifications, and methodological approaches.

While school closures can effectively reduce infections and mortality, this benefit is just one part of the decision. Policymakers need to consider the trade-offs, balancing health gains against educational disruptions and the extra caregiving load on families.

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A Appendix: For Online Publication

Figure A.1: Counties with data available

Note: Shaded areas represent counties which made their data available

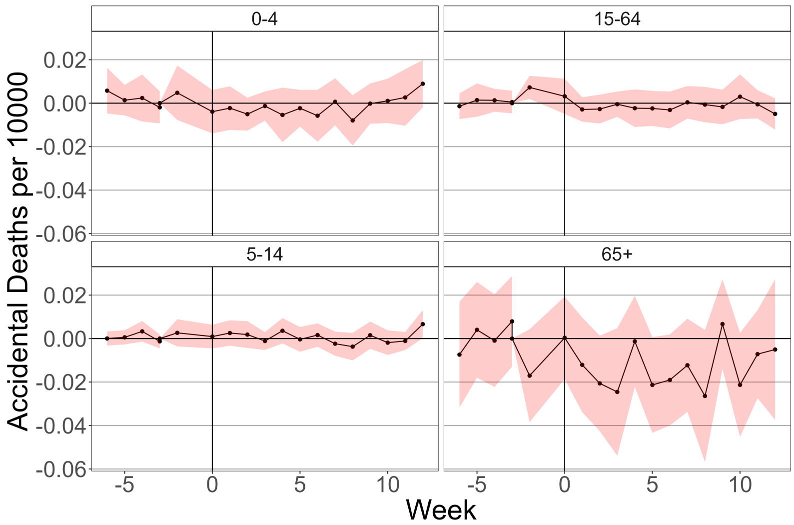

Figure A.2: Event study: Mortality due to external causes by age

Note: Graph shows the impact of winter vacation on the external causes mortality (cat. V in ICD-10) by age. Each sub-figure represents results of the estimation of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is the number of deaths due to external causes in the given age category in a county i and week t per 10 000 of inhabitants (of given age). Hence the coefficients show the change in the number of deaths in each week prior and after the vacation, where week 0 is the first week of vacation. Shaded area represents 95% confidence interval for the estimates. *Source:* own elaboration based on mortality data.

A.1 Robustness Checks

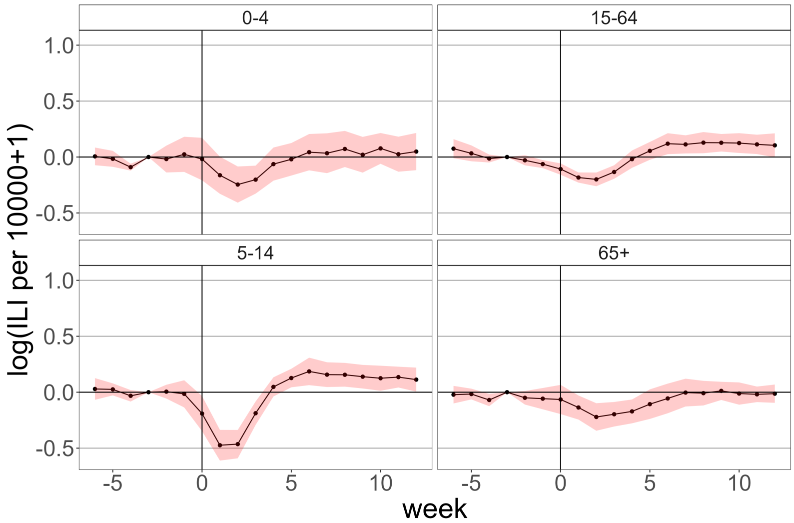

Figure A.3: Event study: log(Incidence+1)

Note: Graph shows the impact of winter vacation on the weekly incidence of infections. Each sub-figure represents results of the estimation of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is log of the incidence plus 1. Hence the coefficients show the percentage change in the incidence in each week prior and after the vacation, where week 0 is the first week of vacation. Shaded area represents 95% confidence interval for the estimates. Errors are clustered at the region level. *Source:* own elaboration based on epidemiological data.

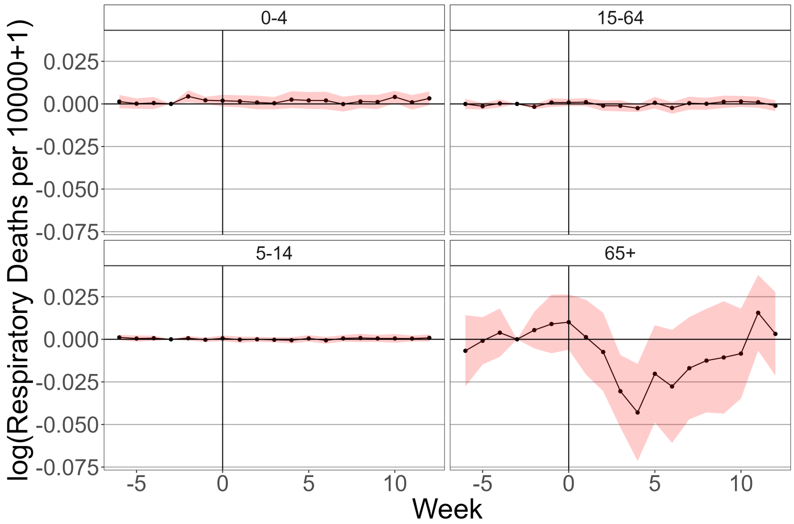

Figure A.4: Event study: log(Mortality+1)

Note: Graph shows the impact of winter vacation on the weekly respiratory mortality. Each sub-figure represents results of the estimation of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is log of the mortality plus 1. Hence the coefficients show the percentage change in the mortality in each week prior and after the vacation, where week 0 is the first week of vacation. Shaded area represents 95% confidence interval for the estimates. Errors are clustered at the region level. *Source:* own elaboration based on mortality data.

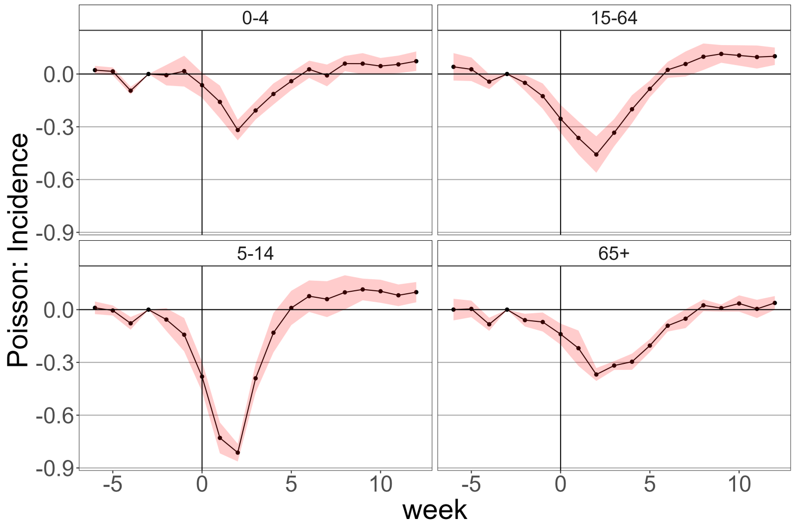

Figure A.5: Poisson Regression: Infections

Note: Graph shows the impact of winter vacation on the external causes mortality (cat. V in ICD-10) by age. Each sub-figure represents results of fitting a Poisson regression following the specification of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is the number of reported infections in a given county and week. Hence the coefficients show the percentage change in the number of infections in each week prior and after the vacation, where week 0 is the first week of vacation, compared to week -3. Shaded area represents 95% confidence interval for the estimates. *Source:* own elaboration based on epidemiological data.

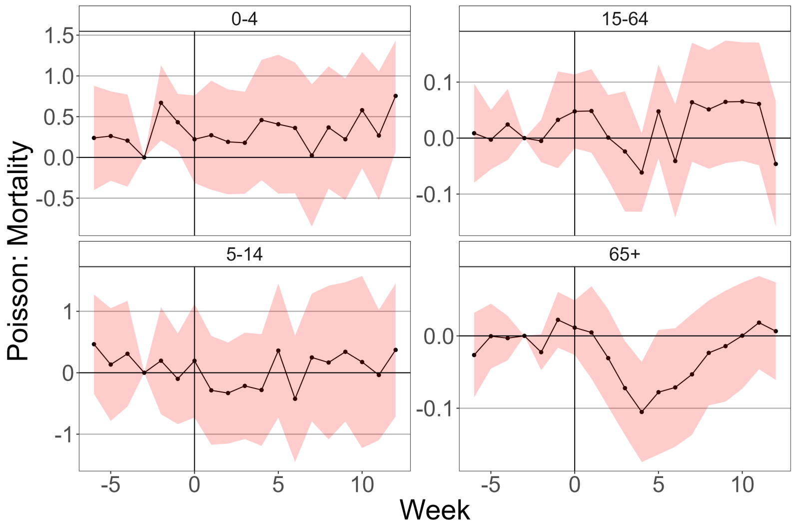

Figure A.6: Poisson Regression: Deaths

Note: Graph shows the impact of winter vacation on the external causes mortality (cat. V in ICD-10) by age. Each sub-figure represents results of fitting a Poisson regression following the specification of the event study in equation 2 on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is the number of respiratory deaths in a given county and week. Hence the coefficients show the percentage change in the number of infections in each week prior and after the vacation, where week 0 is the first week of vacation, compared to week -3. Shaded area represents 95% confidence interval for the estimates. *Source:* own elaboration based on epidemiological data.

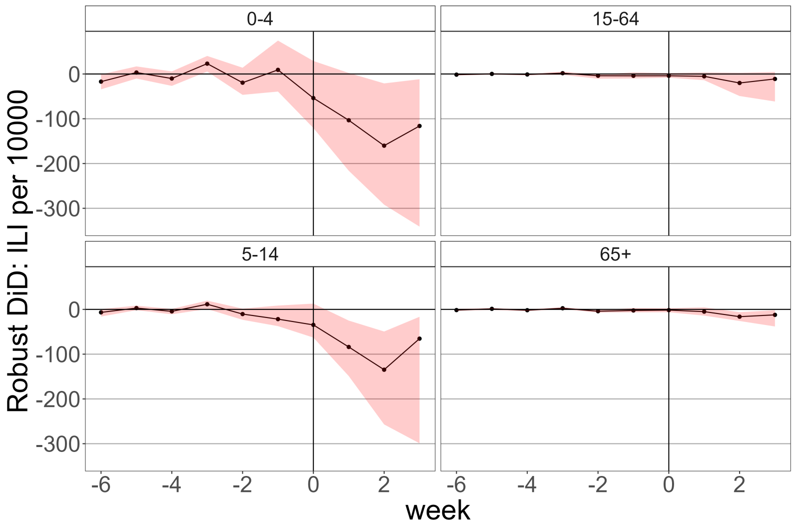

Figure A.7: Robust DiD: Incidence

Note: Graph shows the robust event study estimates based on Callaway and Sant'Anna [2021]. Each sub-figure represents results of the estimation on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is the number of reported infections in the given age category in a county c and week w per 10 000 of inhabitants (of given age). Each season is treated as a separate experiment. Only the effect up to week 3 can be estimated, because the latest region starts vacation 4 weeks after the earliest region and hence there is no more untreated units. Standard errors are boostrapped, with randomization at the regional level. Shaded area represents 95% confidence interval for the estimates. *Source:* own elaboration based on epidemiological data.

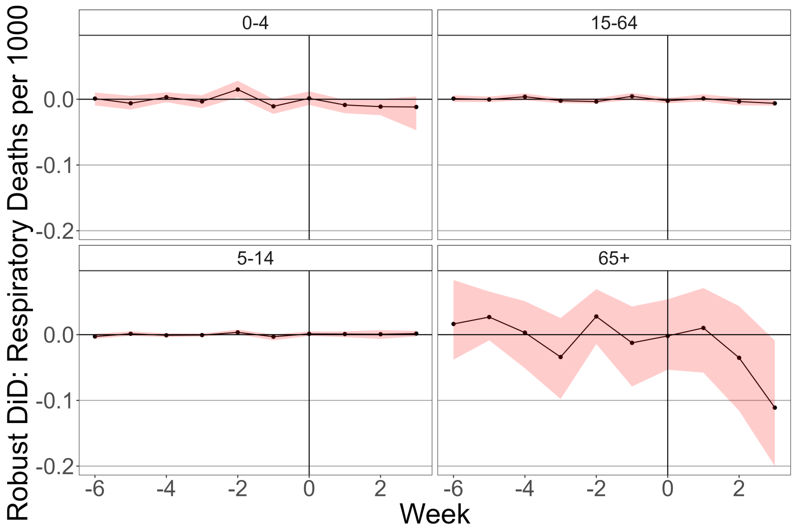

Figure A.8: Robust DiD: Mortality

Note: Graph shows the robust event study estimates based on Callaway and Sant'Anna [2021]. Each sub-figure represents results of the estimation on a sub sample restricted to age groups 0-4,5-14,15-64, 65+. The outcome is the number of deaths in the given age category in a county c and week w per 10 000 of inhabitants (of given age). Each season is treated as a separate experiment. Only the effect up to week 3 can be estimated, because the latest region starts vacation 4 weeks after the earliest region and hence there is no more untreated units. Standard errors are boostrapped, with randomization at the regional level. Shaded area represents 95% confidence interval for the estimates. *Source:* own elaboration based on epidemiological data.

A.1.1 Event study: impact on transmission

This event study looks at the impact of the winter vacation on the transmission of the virus. It measures the impact of the break on the interactions which fuel the spread of the virus. School recess disrupts interactions in weeks 0 and 1 (recess lasts two weeks). Hence the virus will have a lower reproduction rate from week 0 to 1 and from week 1 to 2. The event study follows the equation:

$$\frac{I_{cwy}}{L_{cwy}} = \sum_{T=-5}^{10} \alpha_T I\{wy-(wy)_c^V = T\}_{cwy} * \widetilde{S_{cwy}} \widetilde{\frac{I_{cwy}}{L_{cwy}}} + \alpha_0 \widetilde{S_{cwy}} \widetilde{\frac{I_{cwy}}{L_{cwy}}} + \delta X_{cwy}. + e_{cwy} \quad (3)$$

Where the L_{cwy} represents the number of reporting doctors in county c, week w and year y. The number of infected individuals (I_{cwy}) is the number of newly reported cases. The susceptible share $\widetilde{S_{cwy}}$ is the total population minus the cumulative number of reported infections since the start of the epidemic season (epidemiological week 24).

Figure 15 shows the results. Vacation clearly disrupts the transmission of the flu, as evidenced by the high decline in the reproduction of the virus in weeks 1 and 2. In other words, the same amount of infections results in fewer secondary cases in weeks 1 because of fewer interactions among children in respective previous weeks. As expected, the parameter returns to the pre-vacation value three weeks after the vacation began as children start interacting again at a usual rate in week 2.

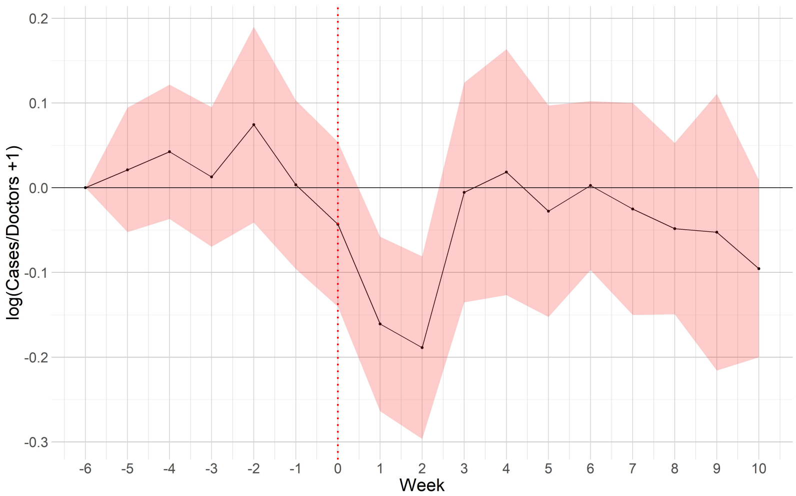

Figure A.9: Impact of winter vacation on transmission

Note: Graph shows the impact of winter vacation on the reported influenza cases. Lines represents estimates of the coefficients α_T from the event study in equation 3 where the outcome has been changed to $log(\frac{I_{i,t}}{L_{i,t}} + 1)$. Shaded area represents 95% confidence interval for the estimates. *Source:* own elaboration based on data collected from epidemiological stations.