School Closures and the Balance of Health and Parental Labor Supply in Russia*

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ABSTRACT: Do the benefits of school closure outweigh the costs? This paper analyzes the tradeoff of the consequences of school closure during the COVID-19 pandemic. We analyze the effect of school closure on children's health, parents' health, and parental labor supply. The study uses the Russian household survey linked with the grade-specific daily dataset on regional school closures. We leverage the published dates of survey interviews to exploit within-round variation in schooling disruptions. Specifically, we aggregate daily data on schooling policies to match the timeframe of survey questions. Employing fixed effects models across a 5-year (2017-2021) panel, we find that school closures significantly decrease the probability of children experiencing flu-like symptoms and having other health issues. Parents indirectly benefit from school closure via reduced contagion. On the other hand, school closures significantly disrupted parental labor supply.

KEYWORDS: school closure, school breaks, child's health, parent's health, labor supply, work from home, contagion, tradeoff, COVID-19, Russia.

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1 Introduction

The COVID-19 pandemic caught policymakers worldwide off guard. Governments chose different strategies to combat and mitigate this new, unexpected infection. Some of these strategies have been more efficient than others. As new pandemics are likely to occur (see, e.g., Morens and Fauci, 2020), it is important to draw lessons from the COVID-19 pandemic, compare the efficiency of mitigating strategies, and analyze policy trade-offs by building on the experience of different countries. One of the most common measures the authorities undertook has been closing schools and shifting classes to online mode. School closings have aimed to reduce the harm of the pandemic to public health and to prevent the illness-related loss of labor productivity. However, the potential decrease in illnesses comes with a considerable cost of additional childcare that parents have to bear.[1] School closure is especially challenging for working parents who have to adjust their work schedule, shift to working from home, cut work hours, leave the labor force, or find other arrangements for childcare.

Do the benefits of school closure outweigh the cost? It is almost impossible to quantify the answer when the benefits concern people's lives and health, and the costs are multifaceted. In this study we introduce the benefit-cost tradeoff into the analysis of the consequences of school closure. On the benefit side, we consider illness prevention and a reduction of time lost from work due to a child's or parent's illness. On the cost side, we examine the loss of worktime and the switch to remote work due to a higher demand on parents' time to care for their children and to be more involved in the child's education. We also consider the mental health costs of school closure. We study both sides of the policy trade-off related to epidemiological school closure.

Previous studies examine health and labor market outcomes of school closure separately, not through the lens of the tradeoff. Part of the reason for separate analysis is the lack of microdata with time-varying measures of parent's employment and hours, parent's and child's health. Studies analyzing the health consequences of school closure often use macro (e.g., county-level) data and look at the aggregate rates of infection and deaths (e.g., Chernozhukov et al., 2021; Goldhaber et al., 2021; Koppa and West, 2022). They find a significant increase in the number of COVID-19 cases

[1] Other costs also include learning losses (Agostinelli et al., 2022; Donnelly and Patrinos, 2021), mental health issues (Lee, 2020; Li at al., 2022; Yamamura and Tsustsui, 2021), increased inequality among parents (Couch et al., 2020; Deryugina et al., 2021) and children (Agostinelli et al., 2022; Blanden et al, 2022; Donnelly and Patrinos, 2021; Goldhaber et al., 2023; Grewenig et al., 2021), etc.

and deaths after schools re-open for in-person learning. These results are consistent with the pre-COVID epidemiological literature evaluating the effect of school closure on the spread of influenza; see Nafisah et al. (2018) for the review of 31 studies from 12 countries on this issue. From this review, we conclude that epidemiologists consider school closure as an effective tool in delaying an epidemic peak and limiting the infection spread, especially if schools are closed at the start of the pandemic wave. Thus, when childcare needs are not an issue, school closure may have a positive effect on labor supply during the pandemic by preventing a worktime loss from child's and/or parent's illness.

On the other side of the literature spectrum, there is a growing number of studies examining the consequences of school closure on the labor market. Much of the work has been done at the micro level using popular household surveys, and the focus is on the labor cost of school closure. Many studies find that the pandemic-related schooling disruptions are costly, as they reduce labor market participation and hours of work among mothers of school-age kids (see Amuedo-Dorantes et al., 2023; Collins et al., 2021; Couch et al., 2022; Garcia and Cowan, 2022; Hansen et al., 2022; Lofton et al., 2021, among others).[2] The corresponding effects on fathers' working hours tend to be smaller. The labor supply response to canceling in-person classes is mainly explained by the necessity to provide additional childcare. What is missing in the literature is the micro-analysis of the health effects of school closures and the impact of these health consequences on parental labor supply. So far, child's and parent's health have not been part of employment equations, nor they have been considered to be the outcomes of school closure.

Only one study that we know of analyzed the impact of school re-opening on both outcomes – employment and the COVID-19 spread. Using aggregate, county-level data, Koppa and West (2022) find no effect of school reopening on county employment but a strong positive effect on COVID-19 deaths in the U.S. We take it further by looking at the individual work-related choices among parents of school-age kids, incorporating child's and parent's health in labor supply functions, as well as examining indirect child-to-parent contagion effects of school closure. We calculate this indirect effect as the product of the estimated coefficient on school closure in the child's health issues equation and the estimated coefficient on the child's health issues in the parent's

[2] These studies are part of a broader literature on the relationship between childcare cost and parental labor force supply. The pre-pandemic literature has generally concluded that a decrease in childcare costs by either direct subsidy or public-school enrollment increases maternal labor supply (e.g., Averett, 1997; Baker et al., 2008; Gelbach, 2002).

health equation.

We undertake this paper using the Russia Longitudinal Monitoring Survey-Higher School of Economics (RLMS-HSE), a representative annual longitudinal survey of Russian households. Our choice of country is partly owed to the rare opportunity to have measures of work duration, remote work, child's health, and parent's health all in one survey and for the periods before and after the start of the pandemic. RLMS-HSE data enables us to analyze two waves of COVID-19 pandemic that occurred in Fall 2020 and Fall 2021. In addition to these two RLMS-HSE rounds, we also use the previous three rounds for the years 2017-2019. All RLMS-HSE surveys always happen in Falls.

Another reason behind our choice of country is the high-quality data on school closure we collected within a large-scale NIH-funded cross-country project on the effects of COVID-19 mitigation policies on social and economic behavior and outcomes. Our data on school closures is unique as it is daily, grade-specific, gathered directly for each decision maker (governor or government of a region), and covers the entire duration of the COVID-19 pandemic. Most existing studies use aggregate or indirect data on school closures, and the data is often taken from the early pandemic period.[3] We determine a schooling mode for each school grade, all Russian regions, and every day over three academic years from September 1, 2019, to May 31, 2022.

We merge RLMS-HSE data with our data on school closure using the recorded dates of survey interviews. To merge our data on school closures with RLMS-HSE data, we compile daily data pertaining to school closures so that it corresponds with the same period covered by the RLMS-HSE survey questions. For example, RLMS-HSE has a variable that reflects whether parents are employed in the 30 days before the interview. To analyze this variable, we count the number of days the schools were closed for a given grade and region 30 days before each RLMS-HSE interview date and then merge this measure with RLMS-HSE data using the interview date.

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[3] Some examples of previously used school closures measures include individual responses on the teaching modes aggregated at the state-level (Lofton, et al., 2021), change in school visits based on mobile phone data (Garcia and Cowan, 2022; Hansen et al., 2022), percent of the state's population exposed to school closure, which is calculated as the population-weighted average of the fraction of days when schools were closed in each county in Spring 2020 (Amuedo-Dorantes et al., 2023), the weighted share of school districts offering in-person, remote, and hybrid instruction models for elementary schools by state in September 2020 (Collins et al., 2021). More disaggregated measures include the dominant teaching mode of the biggest school district in each county in October 2020 (Koppa and West, 2022) and instructional modality (in-person or hybrid) by school district and month available for Michigan and Washington states only (Goldhaber et al., 2022).

Another unique feature of our research is that we separate the effects of COVID-related school closures from the effects of regular school breaks. No other study makes such a distinction. Among earlier published papers, Graves (2013) uses heterogeneity in the length and timing of school breaks in the U.S. to conclude that more frequent and shorter breaks decrease maternal employment. In an epidemiological study, Garza et al. (2013) show that winter school breaks in Argentina noticeably decrease the rate of influenza infection among children aged 5-14. School breaks in Russia are announced before the start of school year, while COVID-related school closures are largely unanticipated and announced immediately or at best a few days in advance. This could explain why we find a relatively small positive effect of school breaks on work from home. The lack of variation in the length of school breaks across regions and little variation over time may also explain this result.

Above all else, the Russian school closure policies and their consequences have not been studied yet. In the comprehensive review of literature on school disruptions and parental employment (Lillard et al., 2023), the overwhelming majority of studies are done on the U.S. or other developed economies. Going forward, it is important to draw on the experiences of a variety of countries with different types of policies and institutions. The Russian case is particularly interesting as school policies were not imposed at the federal level but at the regional one, creating a considerable regional variation in the timing and length of school closures.

Depending on the type of response variable and the level of analysis, we use two samples: parent-based and child-based. The parent-based sample comprises mothers and fathers of children aged 6-14 who are enrolled in grades 1 to 8, encompassing both biological and adoptive parents between the ages of 18 to 60. We exclude preschool children's parents unless an older sibling goes to school. If a parent has more than one child in grades 1 through 8, then the grade level of the youngest school-age child is chosen to link with a corresponding grade-specific schooling policy. Our child-based sample comprises all surveyed school-age children in grades 1 to 8. We note that instances of these school-age children not attending school are exceedingly uncommon, less than 1 percent. Such outliers are removed from our analysis. The child survey is filled out by a parent or another adult family member who looked after the child in the past seven days.

We employ and compare results from two estimation methods. The first one is the standard difference-in-difference (DID) approach with two-way fixed effects for region and time. We also leverage the panel feature of our dataset by incorporating individual fixed effects in our equations. Individual fixed effects models are relatively uncommon in the literature on school closures as the estimation of these models requires significant within-variation in the duration of school closures.

The main empirical identification concern about our research design is the non-random assignment of school closures and the imperfection of our data on COVID-19 cases. As we show, school closures coincided with the spikes in COVID-19 cases. Our paper uses the best available data on COVID-19 cases, but as we acknowledge in the next section, these data suffer from undercounting. Despite this, our data are likely to reflect the general trend in COVID-19 cases and reflect the peaks and bottoms of each pandemic cycle well.

Our findings indicate that, on average, epidemiological school closure significantly decreases the probability of children having health issues, illness-related school absences, and the likelihood of having flu-like symptoms. No such effect is found for school breaks and holidays. Parent's health is also affected by school closure during the pandemic, both directly and indirectly through children. Conditional on the observed measures of children's health, the direct policy effect on parent's illness is positive, but the estimate has a large variance. Simultaneously, there is an illness-reducing indirect effect of school closure through lowered child-to-parent contagion. With higher rates of COVID-19, the average size of direct effect decreases up to the point when it becomes negative at the highest rates of COVID-19, thus, indicating that parents are more likely to benefit from school closures in terms of health when the numbers of COVID-19 cases are particularly high.

With regard to labor supply effects, we find no statistically significant effect of pandemic-driven school closure on maternal employment and hours of work. The results for fathers are mixed, with one specification indicating a potential decrease in total hours of work in response to school closings. While investigating the reasons for the seeming lack of maternal labor supply response, we find evidence of shifting hours across space by working more hours remotely and across time by working more hours per day of work. The probability of mothers working at home increases by 5 pp and hours of remote work rise by 22 per month in response to closing schools for 10 business days. The likelihood and duration of mother's remote work also increases with each day of regular school break but at a lower rate than under school closures for epidemiological reasons. Predictably, we estimate that mothers and fathers experiencing health issues tend to work fewer hours and spend more time working at home. Yet, when children become sick, only mothers, and not fathers, change their labor supply by leaving their jobs, cutting working hours, and working more hours from home. As a result, the indirect effect of school closure through lower children's illness is found only among mothers. However, the magnitude of such an effect is rather trivial, so the overall labor supply remains unchanged. Despite the lack of labor supply response, school closure was costly for businesses and families. In conclusion, we discuss potential losses in education quality and productivity emerging from the distant nature of classes and work.

As our study is the first one to analyze the health effects of COVID-19 school closures using microdata, we can compare our results either to previous estimates of COVID-19 school closures health effects obtained by macro-level analysis or to the existing estimates of school closures effects on the spread of other respiratory diseases. In contrast to papers based on macro-level data on COVID-19, our health measures are not COVID-19 cases and mortality but health problems and flu symptoms (in our paper, children have flu symptoms if their parents say their children have cough, cold, earache, or sore throat). Chernozhukov et al. (2021) and Koppa and West (2022) conclude that school openings lead to a 5-10% increase in COVID-19 cases. This aligns with our result that school closures decrease the probability of children's flu-like symptoms by 10%. We are aware of only one other paper that performed a micro-level analysis of school closures' effects on the incidence of respiratory diseases. Adda (2016) analyzed the effects of school breaks on the prevalence of flu-like illnesses in France. In contrast to her paper, we study not only the effects of regular school breaks on the incidence of flu-like symptoms but also the effects of COVID-19-related school closures. Contrary to our results, Adda (2016) concludes that regular school breaks decrease the incidence of flu-like illnesses. However, her estimates are close to those we have for the effects of COVID-19-related school closures. The difference in the conclusions on the effects of regular school breaks can be attributed to the fact that Adda (2016) analyzes school breaks throughout the whole calendar year, while we have data only for the Fall periods.

As regards the comparison of our findings with existing literature on school closures' labor supply effects, we observe variations. Some studies did not find statistically significant changes in fathers' employment (Garcia & Cowan, 2022), and others reported no changes in the employment of either fathers or mothers (Amuedo-Dorantes et al., 2023). A few papers showed that the employment of both mothers and fathers decreased due to school closures (Hansen et al., 2022 and Kozhaya, 2022), with the employment of mothers decreasing more than that of fathers (Hansen et al., 2022 and Garcia & Cowan, 2022). Some studies even used fathers as a control group (e.g., Couch et al., 2022). Discrepancies extend to the effects on working hours, with some studies concluding that school closures decreased average working hours (Amuedo-Dorantes et al., 2023), while others reported decreases in both average employment rates and working hours (Couch et al., 2022; Hansen et al., 2022, and Kozhaya, 2022). The literature on the effects of school closures on the hours parents work from home presents mixed conclusions. Some researchers found that both fathers and mothers increased their hours working from home by similar amounts (Garcia & Cowan, 2022), while others reported that only mothers increased these hours, with fathers either maintaining or decreasing their hours working from home (Hansen et al., 2022; Yamamura & Tsutsui, 2021). These differences in average results may arise from variations in school closure measures alone.

Overall, our paper contributes to the literature by analyzing the health consequences of school closures at the micro level and the effect of these consequences on parental labor supply. In our research we use unique daily grade-specific data gathered directly for each decision maker (governor or government of a region). We collect data both on COVID-19-related school closures and regular school breaks. This allows us to separate the effects of regular school breaks from those of pandemic-related school closures. Our results imply that children experience significant health benefits because of school closures. Parents also benefit from school closures in terms of health too due to reduced contagion. However, these health benefits come with labor supply adjustment costs. School breaks affect all these children and parental outcomes in a similar way but to a lesser degree. Future research on bigger samples than ours is needed to establish the lifesaving effects of school closures. While the primary benefits of school closures are undeniably health benefits, the forthcoming research has yet to establish the primary costs of school closures for parents and children and conclude whether the benefits outweigh the costs or not.

The rest of the paper is structured as follows. Section 2 describes our survey data and measures of schooling disruptions. Section 3 discusses the estimation methods. In Sections 4 and 5, we present the effects of school closure on children and parents, respectively. We discuss the results in Section 6 and make concluding remarks in Section 7.

2 Data

2.1 RLMS-HSE

To account for health factors in estimating the impact of school closure on labor supply, the data source should meet certain requirements. At a minimum, the dataset should have good measures of working hours and the distribution of hours between home and workplace, contain information on episodes of illness for both parents and children and be linked to school closing policies that have both intertemporal and cross-sectional variation (e.g., spatial and/or by child's grade). Preferably, the dataset can distinguish between school closings for health-related reasons and regular pre-planned school breaks. We created such a dataset on the basis of the Russia Longitudinal Monitoring Survey-Higher School of Economics (RLMS-HSE), a representative annual longitudinal survey of Russian households. The data collection effort is part of the NIH-funded project on the cross-country comparison of the effects of COVID-19 mitigation policies on social and economic behavior and outcomes (1R01AG071649-01).

In this study, we use the 2017-2021 survey rounds of the RLMS-HSE. The average sample size is about 16,000 respondents per round. The survey is conducted in 38 randomly chosen primary sample units from 32 out of 83 regions of the Russian Federation.[4] As we show below, there is considerable regional variation in schooling policies. The interviews take place from September to December of each year and early January of the following year in rare instances. Thus, the survey covers two of the biggest COVID-19 waves in the Fall 2020 and Fall 2021. Even though the data did not include the first large-scale implementation of restrictive measures in Spring 2020, it would not be possible to isolate the effects of school closure from the effects of other restrictive measures during the complete lockdown period. Starting in Fall 2020, the isolation of net effects becomes feasible, as we discuss below. In the descriptive analysis, we also use a retrospective module on COVID-19, referring to the onset of the COVID-19 pandemic in Spring 2020. The respondents participated in this module in the Fall of 2020.

Our approach to data sampling varies depending on the response variable and the level of

[4] In its sampling design, the RLMS-HSE is similar to the U.S. Panel Study of Income Dynamics (PSID). It is based on a stratified multistage random sample that represents the general population of the country but does not represent each region. Like in PSID, geospatial variables have to be obtained from external sources since they cannot be constructed within the survey. See section 3.3 on external regional controls used in this study.

analysis, wherein we opt for either parent-based or child-based samples. The parent-based sample consists of mothers and fathers of school-age (6-14) children in grades 1 to 8. It includes both biological and adoptive parents aged 18 to 60. In cases where a family has preschool children, these parents are part of the sample only if there is also an older child attending school.[5] For parents with multiple children in the specified grade range, we use the grade of the youngest child currently in school to align with the grade-specific educational policy.[6] The child-based sample consists of all surveyed school-age children attending grades 1 to 8. The cases of school-age children not attending school are very rare, less than 1 percent. These cases are removed from the estimation. The child questionnaire is completed by a parent or other adult family member who took care of the child in the previous week.

Table 1 describes the variables, whereas Table 2 reports summary statistics of key variables. Appendix 2 provides additional tables describing the sample's structure. We note that the numbers presented in Table 2 are for the fall of each year. Thus, they exclude the period of the stay-at-home order in Spring 2020.

2.2 Measures of Schooling Disruptions

The measures of schooling disruptions come from the dataset "The Schooling Policy Tracker during the COVID-19 Pandemic in Russia" (SP Tracker thereafter), a daily dataset on COVID-related regional restrictive measures for each school grade level. The SP Tracker covers 83 regions and three academic years from September 1, 2019, to May 31, 2022. The dataset is assembled by authors based on 1200+ official documents and news media reports on coronavirus-related restrictions of educational activities.

Each calendar day in the SP Tracker is determined as either a business or non-business day. Non-business days include weekends and public holidays, which could be federal or regional.[7] In turn, each business day is further classified into four categories depending on whether a typical

[5] By the start of the survey in mid-September 2020, most pre-schools were re-opened. A short episode of pre-school closure in Fall 2021 coincided with non-working days, which we control in our empirical analysis.
[6] This is done to avoid multiple observations per parent year. The youngest child will likely require more effort on childcare arrangements when schools are closed and more parental time when the child gets sick.
[7] We count non-working regional holidays when schools are closed. These are mostly religious holidays and memorable days celebrated in the republics with dominant Islam or Buddhism religion. Only two RLMS regions - the Republic of Kabardino-Balkaria and the Republic of Tatarstan - had regional non-working holidays during the fall survey period.

student at a given grade level can attend school on that day: (1) in-person schooling when schools are fully open, (2) no in-person schooling for COVID-19 reasons, (3) scheduled school break, and (4) other schooling disruptions, e.g., classes are partly in-person (hybrid schooling) or they are canceled for non-COVID reasons such as inclement weather, security threats, voting, etc.[8] We had to omit the fourth category from the analysis because the occurrence of such events was extremely rare during the fall months of the household survey. In this study, school closure means that schools are closed for in-person learning due to coronavirus-related reasons, i.e., category 2. When schools are not in-person, they are considered to be closed even if learning continues in different formats such as on-line classes with teachers or study at home with parents. Since we are interested in accounting for the potential contagion effect, the key distinction here is between in-person school attendance vs. staying at home.

Main decisions regarding school closure in Russia are made by regional authorities, causing substantial regional variation in schooling policies. The country map in Figure 1 shows the geographic distribution of total in-person school days in 2020 (averaged across school grades). The regional dispersion is large, with in-person days varying from 71 days in Zabaikalsk Krai to 129 days in Chuvash Republic; in comparison, a normal year is about 170 in-person school days. The map does not reveal any visible clustering of in-person days within a broader geographic area. Both the map and our reading of regional government policies suggest that regional authorities made their own schooling decisions in response to the COVID-19 spread, and the spatial spillover effect is not evident.

Most executive orders on school closure were issued when daily COVID-19 cases and deaths were on the rise. We observe this in Figure 2, which shows the relative number of regions that mandated schools to be closed at different stages of the COVID-19 pandemic. At the start of the pandemic in Spring 2020, all regions closed schools for in-person learning. With each subsequent wave of the pandemic, the number of regions implementing restrictive measures declined despite a higher spike in daily confirmed COVID-19 cases. Our study focuses on the second and fourth COVID-19 waves which coincided with the RLMS-HSE Fall survey period in 2020 and 2021. There were no school closures during the summer break in 2021 when the third wave of coronavirus hit.

[8] Related to these reasons are teacher's strikes. Jaume and Will'en (2018) find that temporary school closures due to teachers' strikes have a negative impact on employment.

To visualize the sequence of schooling restrictive measures, we create their timeline for each RLMS region and every grade level. An example of a timeline for the 5th grade can be seen in Figures 3 and 4 for Fall 2020 and Fall 2021, respectively. The timeline indicates in-person days, no school days for COVID-related reasons, regular school breaks, and holidays.[9] Weekends are excluded from the timeline. In Figures 3 and 4, we observe again considerable heterogeneity in schooling policies, with some regions not implementing any restrictive measures and some regions closing schools for a prolonged time, up to 45 days out of 87 business days in Fall 2020. The number of regions ordering schools to close decreased in Fall 2021 despite COVID-19 being more widespread. Typical arguments against school closure came down to the high cost to the economy of past restrictive measures and/or the lack of confidence in the effectiveness of such measures.

The unique feature of Russian school closure policies is that they are grade-specific. Regional authorities in one executive order can permit students at certain grade levels to attend school in person while sending other students for an extended break or to study on-line. Yet, during our sample period, the variation in schooling modes from grade to grade was not as drastic as from region to region. From Figure 5, we can see that differences between grades were most apparent in the Fall of 2020, when older students experienced more school attendance restrictions than younger ones, on average.

In addition to considerable regional variation in school closures and some variation by child's grade, there is also a large variability in school closures over time within the same survey round. It is evident from timelines, Figures 3 and 4, and from Table 3, where we report the overall distribution of business days by schooling mode for each survey month. The month-to-month shifts in the distribution are apparent, with most schooling disruptions occurring in November 2020 and 2021. We take advantage of the published dates of survey interviews to examine variations in schooling disruptions that occurred during the same survey cycle. Specifically, we aggregate daily data on schooling policies to align with the timeframe of survey questions. Since employment and health questions in the RLMS-HSE refer to the last 30-day period before the day of the interview, we construct schooling policies for the same period. We calculate the rolling sum of days in each category within a 30-day moving interval and divide the sum by the number of business days within

[9] The length of school breaks is more or less the same across regions, but their timing varies. Most schools in Russia are on a quarterly schedule and go on fall break at the end of October. It was not uncommon to order school closure as an extension of school break.

the same interval, where business days are defined as 30 minus weekends minus federal and regional holidays. The regional variation in business days is minimal, as we can see from the timeline of schooling modes in Figures 3 and 4. To account for small differences in the duration of holidays, we create a dummy variable indicating if holidays lasted for more than one working day in the last 30 days. All these rolling measures of schooling disruptions are then linked to the RLMS-HSE using the date of the interview, region of residence, and the grade level of child.

2.3 Regional Factors

School closure policies were often implemented together with other government responses to the COVID-19 pandemic. This creates a challenge of disentangling policy effects one from another. Only a handful of studies on school closure attempted to account for other concurrent COVID-19 restrictive measures (e.g., Amuedo-Dorantes et al., 2023; Garcia and Cowan, 2022). In Russia, by the time the survey interviews started in September 2020, the major restrictions on people's movement, such as stay-at-home orders, were lifted. The self-isolation regime remained in place for people older than age 60 in several regions, and we exclude this population from the analysis. However, there might be concerns about the possible confounding effect of workplace closure on the association between school closures and labor supply. Following the coronavirus spike in Fall 2021, Russia declared 3 business days in early November as "non-working days" paid by employers. During non-working days, all enterprises and schools were mandated to close, with the exception of essential businesses. Of 32 RLMS regions, nine regions prolonged federal non-working days by starting the no-work period as early as October 25 and ending it as late as November 15. To separate the effect of school closure from the effect of workplace closure, we construct an additional control variable as a rolling sum of non-working days due to COVID-19 in the last 30 days for each interview date and region.[10]

At the regional level, we also control for the monthly unemployment rate and the COVID-19 spread. If the former measure is standard (see Table 1), the latter one needs to be explained. For each interview date and region, we calculate the number of new coronavirus cases per 100 people in the last 30-day period. The number of confirmed cases is taken from the Yandex coronavirus database, which, in turn, is assembled from the daily reports by the Russian government published in

[10] The workplace closure measure does not account for industry-specific restrictions that were put in place on the time of operation and the size of specific businesses such as restaurants, stores, entertainment facilities, sporting venues, cultural events, etc.

стопкоронавирус.рф. Although this data source is widely used by reputable data aggregators such as the World Health Organization, the Coronavirus Resource Center at Johns Hopkins University, Our World in Data, etc., the daily numbers of COVID-19 cases and especially deaths are severely undercounted. There is a vast discrepancy between the sum of daily government reports and the final end-year statistics provided by the Russian Ministry of Health Care on COVID-19 morbidity levels and death certificates.[11] By our estimates, daily reports account for 62 percent of confirmed cases and 54 percent of COVID-19 deaths, on average. Yet, the correlation in annual coronavirus cases between the two data sources across regions is relatively high, 0.72. Despite undercounting, daily reports are likely to reflect the general trend in COVID-19 cases and depict the peaks and bottoms of each pandemic cycle. In sum, our final dataset is a result of linking the survey data on parents and children with high-frequency policy measures and regional information.

2.4 Summary Statistics and Descriptive Trends

In Table 2 we present summary statistics for two groups, 'stayers' and 'movers,' and two time periods, before the pandemic (2017-2019) and after the onset of the pandemic (2020-2021). The group of 'movers' includes parents whose children in grades 1-8 have experienced COVID-19-related school closures during the 30-day period preceding their date of interview, while the group of 'stayers' includes parents who have never been treated. These summary statistics are for the Fall of each year, excluding the period of the stay-at-home order in Spring 2020.

Prior to the pandemic, movers have reported children's health problems and flu symptoms more frequently than stayers. However, after the start of the pandemic movers and stayers were equally likely to report that their children had health problems and flu symptoms, implying that school closures have decreased the prevalence of health problems and flu symptoms among movers' children. Simultaneously, after the start of the pandemic, movers were slightly more likely to become depressed, though this difference in depression frequency between movers and stayers is statistically insignificant. Before the pandemic, we do not see any statistically significant difference in the

[11] The COVID-19 was cited as a primary cause of death on 465,525 death certificates in 2021 alone, which corresponds to 316 deaths per 100,000 people per year, and that is one of the highest mortality rates in the world. For the same year, the daily mortality numbers sum to 251,841 deaths. The Ministry of Health Care also published the COVID-19 morbidity rate of 81 illnesses per 1,000 population in 2021. The morbidity statistics counts people, not cases; each person is counted once when coronavirus diagnosis is established for the first time. Even so, morbidity statistics significantly exceeded the total number of confirmed COVID-19 cases from daily reports, which is equal to 50.7 cases per 1,000 population in 2021.

prevalence of parental health problems, but after the start of the pandemic, movers were more likely to have health problems.

Table 2 shows that the employment rate of individuals who have never been treated was not statistically significantly different from that of treated individuals before the pandemic. However, after the pandemic started, the difference in their employment rates became statistically significant. Contrary to our expectations, the employment rate of the treated group increased rather than decreased since the start of the pandemic, while the employment rate of those who have never been treated remained unchanged. No statistically significant differences were observed in the total hours of work for both never-treated and treated parents, both before and after the pandemic.

Treated individuals were more likely to work from home even before COVID-19. Combining this with the observation that treated parents had higher college education rates (0.38) than untreated ones (0.36) and lived in regions with lower unemployment rates prior to the pandemic, suggests that COVID-19-related school closures were more likely in affluent regions. However, this explanation is not supported by the fact that treated and never treated respondents lived in regions with approximately the same poverty rate.

The initial difference in the percentage of people working from home between the two groups considered widened after the start of the pandemic. This percentage remained unchanged for never- treated individuals (around 8%), while for those who experienced at least one day of school closures in the last 30 days prior to the interview, it increased from 10% to 13%.

The average number of hours parents worked from home increased for both the never-treated and treated groups by approximately the same number of hours. Both groups of parents worked around 34-35 hours from home before the pandemic and 58-60 hours after its onset.

On average, parents who experienced COVID-19-related school closures in the 30 days prior to their interview did so for only about five days. Interestingly, treated parents, on average, had a greater number of days of school breaks in the last 30 days before the interview than those who had never been treated. This difference can be explained by a tendency of Russian policymakers to introduce COVID-19-related school closures just before or after school breaks.

Finally, there is a difference in COVID-19 rates for treated and untreated groups. Parents who experienced school closures in the last 30 days prior to the interview resided in regions with higher COVID-19 rates before their interview.

Figure 6 shows health patterns of children and parents by the level of exposure to COVID-19-related school closures. Children are less likely to have health problems and flu symptoms after long periods of COVID-19-related school closures. However, parents' health problems and depression show little dependency on the number of days of pandemic-related school closures.

3 Estimation Methods

Next, we introduce three different methods employed in this study to estimate the effect of school closures on labor supply. Our initial approach relies on the standard DID model with two-way fixed effects for region and time. In this model, a variable of interest, Y_{it} , is assumed to be influenced by school closure mandates (S_{it}), other covariates (X_{it}), calendar year (θ_t), and the region of residence captured through the regional fixed effects, η_r.

$$Y_{it} = \gamma S_{it} + \beta X_{it}^R + \theta_t + \eta_r + \epsilon_{it}, \qquad E(\epsilon_{it} | S_{it}, X_{it}^R, \theta_t, \eta_r) = 0, \tag{1}$$

where S_{it} represents the number of days of COVID-related school closings in the last 30 days, varying by region, child's grade level, and the time of the survey interview. ϵ_{it} is assumed to be independently distributed across clusters (regions).

A dependent variable, Y_{it} , in our study, is either various parental labor supply outcomes, L_{it}^P, parental health outcomes, H_{it}^P, or children's health outcomes, H_{it}^C. These labor supply outcomes include employment and total hours of work in primary and secondary jobs, with the binary employment variable taking the value of one if the parent worked for pay or profit at primary or secondary jobs in the last 30 days. Additionally, we explore outcomes that characterize working from home, including the probability of engaging in such work and the number of hours spent working at home. To accommodate cases with zero hours of work at home for those who worked elsewhere for at least one hour, we apply the MaCurdy and Pencavel (1986) transformation log (hours+1). As for health outcomes, we analyze the presence of parental health problems, children's health problems, and children's flu symptoms. All labor supply outcomes and health problems pertain to the last 30-day period preceding the survey interview, while children's flu symptoms – to the last 7-day period preceding the survey.

The X_{it}^R vector comprises a diverse set of covariates. Several variables account for other reasons why schools may not be functioning, including the length of school breaks, the duration of closures due to inclement weather and other reasons, extended holidays, and the period of workplace closure when both businesses and schools were mandated to shut down due to the heightened spread of COVID-19. All four variables refer to the 30-day period preceding the interview date. These variables are intended to separate the labor supply effect of COVID-19 school closures from the influence of the business shutdown and other non-school days. The X_{it}^R vector also includes:

- Other school and workplace interruptions: school breaks, long holidays, and COVID-19-related workplace closures.
- Other COVID-19-related policies: self-isolation and social distancing policies.
- Characteristics of parents: age categories, level of education, ethnicity, place of birth, and pre-pandemic chronic illnesses.
- Characteristics of children: the child's grade, current health problems, and pre-pandemic chronic diseases.
- Household characteristics: living with a spouse or a partner, the presence of an older caregiver in the household, having an outside family helper, receiving children's benefits, receiving unemployment benefits or other government assistance.
- Regional characteristics: the unemployment rates and the number of new COVID-19 cases.
- Occupational characteristics capturing the potential of workers to work remotely from home: unstructured job (indicating the extent to which a job allows the worker to determine tasks, priorities, and goals) and indoor occupation (indicating the extent to which a job requires working indoors). These variables are only included in the equations for hours of work and work from home, not in the employment and health equations.

A detailed description of all the variables employed in the estimation can be found in Table 2.

The second approach entails estimating Equation (2) with individual FEs, thereby accounting for individual variations in consumption-leisure preferences, attitudes towards work, propensity for home-based work, and other time-constant elements of individual heterogeneity.

$$Y_{it} = \gamma S_{it} + \beta X_{it}^{F} + \theta_t + \alpha_i + \epsilon_{it}, \qquad E(\epsilon_{it}|S_{it}, X_{it}, \theta_t, \alpha_i) = 0. \tag{2}$$

The X_{it}^{F} vector, in comparison to X_{it}^{R}, excludes time-invariant variables: parents' ethnicity and place of birth and the pre-pandemic diseases of both parents and children. This approach is relatively uncommon in the literature on school closure, as it requires a longitudinal dataset with a sufficient level of within-variation in school closure variables. To test whether the treatment effects vary with observed characteristics, we interact the school closure variable with select covariates one at a time.

Our data structure is complex as we have repeated observations per parent and child, cluster sampling, and clustered policy assignment. We are aware of the recent study by Abadie et al. (2022) that shows that when the number of clusters in the sample is a non-negligible fraction of the number of clusters in the population (which is our case), traditional cluster standard errors can be severely inflated. However, their correction methods are not suitable for our case as they apply to binary treatment. Our decision is to report the most conservative standard errors, even if they are inflated. For main models, we compute different standard errors: robust, bootstrapped, clustered at the level of parent or child, and clustered at the level of region. Clustering at the regional level produces the highest standard errors which we report. If the choice of the clustering level influences our conclusions, we will make a note of it.

4 Effects of School Closure on Children's Health

Policymakers face a difficult choice when deciding whether (and when) to close schools for epidemiological reasons. The ultimate question is how big the health benefits are to justify immense social and economic costs. Answering this question is not achievable within a household survey that lacks objective health assessments and confirmed COVID-19 test results. Given that household survey we use does not have such objective health measures, our goal here is modest, albeit important. It is to assess if there are any health gains (e.g., reduction in the illness rate) associated with school closure mandates.

We estimate a simple linear probability model of a child's and parent's illness as a function of school closure, with a rich set of controls. Since we lack time-varying individual data on COVID-19 infection status, the main dependent variables we use for both children and parents are the answer to the survey question of whether an individual experienced any health problems in the last 30 days. While imperfect, it is the best available measure that matches the timing of employment questions as well as the timing of schooling policies, and it should encompass health issues caused by the COVID-19 pandemic.[12] Two additional variables are available to measure the child's illness – having flu-like symptoms in the last 7 days and having upper respiratory tract illnesses.

In region fixed effects model, the probability of illness for a school-age child *k* in a 30-day period *t* is assumed to linearly depend on school closure, S_{kt}, control variables, X_{kt}^{CR}, pre-pandemic chronic diseases of parents and children, Z_k^C, year fixed effects, θ_t^{CR}, region fixed effects, η_r^C, as shown in Equation (3):

$$H_{kt}^C = \gamma^{CR} S_{kt} + \beta^{CXR} X_{kt}^{CR} + \beta^{CZR} Z_k^C + \theta_t^{CR} + \eta_r^C + \epsilon_{kt}^{CR}. \tag{3}$$

In the individual fixed effects model, the equation is slightly different, we control only for X_{kt}^{CF}, year fixed effects, θ_t^{CF}, and child fixed effects, α_k^C:

$$H_{kt}^C = \gamma^{CF} S_{kt} + \beta^{CXF} X_{kt}^{CF} + \theta_t^{CF} + \alpha_k^C + \epsilon_{kt}^{CF}. \tag{4}$$

The key independent variable, S_{kt}, is the number of days of COVID-related school closings in tens of days in the last 30 days. It varies by region, child's grade level, and the time of the survey interview. Z_k^C denotes two variables indicating whether a child or a parent acquired chronic illnesses before 2020. The rationale for the Z_k^C variables is to control for initial conditions related to health prior to the pandemic and before our sample period.

The X_{kt}^{CR} vector has a multitude of control variables. Three variables account for other reasons why schools may not be open, including the length of school breaks, longer holidays, and the duration of workplace closure when all businesses along with schools were mandated to be closed due to the high spread of COVID-19. All three variables refer to the 30-day period before the

[12] Other health-related survey questions refer to a different time frame such as hospitalizations in the last 3 months, the number of missed working day due to illness in the last 12 months, or individual health self-assessment on the day of interview.

interview date. These variables are necessary to isolate the health effect of COVID-19 school closure from the influence of the other COVID-19 mitigating polices and school closure mandated for other reasons. The X_{kt}^{CR} also includes other COVID-19-driven policies, namely, self-isolation and social distancing policies, individual and household characteristics such as child's age, mother's age, mother's level of education, living with a married parent, mother's ethnicity and place of birth, cohabiting with an older household member who can take care of a child, receiving child and home care by a helper outside of household, and receiving child benefits or other government assistance. We focus on the characteristics of mothers, because 18% of our children's sample live with single mothers and less than 2% live with single fathers. If the mother is absent, then the father's age and education are used. Lastly, we control for the regional number of new confirmed COVID-19 cases in the last 30 days and monthly unemployment rate as a proxy for current regional economic conditions. The only difference between X_{kt}^{CR} and X_{kt}^{CF} is that X_{kt}^{CF} omits time-invariant variables, specifically, parent's ethnicity and place of birth.

Table 4 shows the key parameter estimates of Equations (3) and (4) for all children aged 6 to 14 who are in school. Full estimation results, as well as results for the youngest school-age student in the family, are reported in Appendix 2; both sets of estimates are very similar. We find that COVID-19-driven school closure for 10 business days during the pandemic reduces the probability of children's health problems by 5-7 pp and the probability of having flu-like symptoms in the last 7 days by 3-6 pp, ceteris paribus. The health effects of school breaks and long holidays tend to be smaller. Only one out of 6 regression shows the health effects of school breaks larger than those of COVID-19-related school closures. Namely, in an individual fixed effects regression for children's flu symptoms, the coefficient on COVID-19-driven school closures is statistically insignificant at -0.03, while the coefficient on school breaks is statistically significant -0.04. The smaller effects of school breaks on the prevalence of children's diseases can be attributed to the fact that during school recess, children might have even more intense interaction with their peers relative to the regular school year period. By contrast, it is reasonable to expect an unambiguous decrease in the intensity of children's social interactions during COVID-19-related school closures. Predictably, the probability of illness decreases with a child's age, and it is highly dependent on the parent's and child's chronic illnesses acquired before the pandemic. The effect of COVID-19 cases on a child's illness is not statistically significant. We find a much stronger negative impact of school closure on children's health problems and flu symptoms at higher rates of COVID-19 cases: no statistically significant effect at the lowest quintiles and statistically significant 8-12 pp at the highest quintiles.

Figures 7 and 8 visualize our results and show how the effects of school closures on children's health vary with the levels of COVID-19 exposure. Unequivocally, we can observe an increase in the efficacy of school closures with rising COVID-19 cases. At the highest levels of COVID-19 spread, both the region and year fixed effects model and the individual and year fixed effects model show a decrease in the prevalence of children's health problems and flu symptoms. To sum up, our results reveal unambiguous health benefits of school closures for children.

5 Effects of School Closure on Parental Health and Labor Supply

The following section switches to parental viewpoint and discusses the impact of closed schools on their health and supply of labor. The equations for the parent's illness have a structure similar to those for the children's illness:

$$H_{it}^{P} = \gamma^{HR} S_{it} + \beta^{HHR} \widetilde{H}_{it}^{C} + \beta^{HXR} X_{it}^{PR} + \beta^{HZR} Z_{i}^{P} + \theta_{t}^{HR} + \eta_{r}^{H} + \epsilon_{it}^{HR}, \tag{5}$$

$$H_{it}^{P} = \gamma^{HF} S_{it} + \beta^{HHF} \widetilde{H}_{it}^{C} + \beta^{HXF} X_{it}^{PF} + \theta_{t}^{HF} + \alpha_{i}^{H} + \epsilon_{it}^{HF}. \tag{6}$$

The differences with children's health equations are minor. In parent's health estimations, we take schooling policies corresponding to the grade level of the youngest school-age (6-14) child. To account for the potential child-to-parent contagion effect and other common within-family hazards, we include $\widetilde{H}_{it}^{C}$, which indicates health issues for any child under age 15 in the last 30 days. Equations (5) and (6) are estimated separately for mothers and fathers. Pre-pandemic chronic conditions in Z_{i}^{P} and other individual characteristics in X_{it}^{PR} and X_{it}^{PF} are chosen for the corresponding parent.

Table 5 reports the key parameter estimates of the parent's health equations (5) and (6). Full results can be found in Appendix 2. We see that parent are more likely to get ill when their kids are ill. Since children are less likely to get ill when schools are closed due to COVID-19, school closures have an indirect child-to-parent contagious effect on parents' health. We calculate this indirect effect by multiplying the estimated coefficient on school closure pertaining to the child's health equation with the estimated coefficient on the child's health issues pertaining to the parent's health equation.

Because of a decreased child-to-parent contagion, the COVID-19 school closure reduces the probability of parental health problems in the last 30 days by 0.7 pp for mothers and by 0.5 pp for fathers.

Yet, the average direct effect of school closure on parents' illness is actually reverse, it is positive, 3-4 pp for mothers and around 5 pp for fathers, but not statistically significant at the 5 percent level. This result indicates that school closure may deteriorate parents' health, conditional on holding children's health constant. It can plausibly occur via the mental health channel. School closure may increase parents' anxiety because of additional childcare problems and changed daily life routines; it may have an adverse effect on parents' mental health, which in turn may exacerbate other health issues. Our survey data is not suitable for the high-quality empirical analysis of the effect of school closure on mental health. However, in Appendix 3, with some limited data and school closing measures for the 12-month period, we find a relationship between school closure and parent's depression. The estimated results in Appendix 3 suggest that the longer schools remain closed during the pandemic, the more elevated parental stress is. This negative effect of school closure on mental health is statistically significant for fathers, and it is noisy for mothers. Due to the lack of data, we cannot perform such an analysis for children. To the extent that worsened children's psychological well-being during school closure triggers children's health issues reported in the survey, the average effects shown in Table 4 should reflect some of the mental health consequences of school closure for children.

We analyze the heterogeneity of direct, indirect, and total effects of school closures by the intensity of exposure to COVID-19. With higher levels of exposure, the direct effects of school closures on parental health problems diminish and eventually turn negative. The indirect effects are negative at all COVID-19 levels and become larger in absolute values at higher rates of COVID-19. Summing up the direct and indirect effects of school closures, we see that at the highest levels of COVID-19 exposure, parents benefit from school closures in terms of health.

Next, we examine the potential costs of school closure for the labor market by estimating labor supply equations. Health conditions are often omitted from labor supply estimation, mainly due to health questions not being asked in censuses and standard labor force surveys.[13] Yet, in the

[13] For example, the two largest U.S. surveys used in official labor force statistics – the monthly Current Population

context of our study, health is an important mediating factor since the whole purpose of school closings was preventing the spread of coronavirus. We specify the following labor supply equations with health conditions included:

$$L_{it}^{P} = \gamma^{LR} S_{it} + \beta^{LHR} \widetilde{H}_{it}^{C} + \beta^{LXR} X_{it}^{PR} + \beta^{LZR} Z_{i}^{P} + \beta^{IR} I_{it} + \theta_{t}^{LR} + \eta_{r}^{L} + \epsilon_{it}^{LR}, \tag{7}$$

$$L_{it}^{P} = \gamma^{LF} S_{it} + \beta^{LHF} \widetilde{H}_{it}^{C} + \beta^{LXF} X_{it}^{PF} + \beta^{IF} I_{it} + \theta_{t}^{LF} + \alpha_{i}^{L} + \epsilon_{it}^{LF}, \tag{8}$$

In addition to the abovementioned variables, in the equations for hours of work and work from home, we also include I_{it} - industry fixed effects and standardized scores for two occupational characteristics – unstructured job (or the extent to which a job allows the worker to determine tasks, priorities, and goals) and indoor occupation (or the extent to which a job requires working indoors).[14] We think these characteristics can capture the ability of workers in a given occupation to switch to remote work from home. The characteristics are taken from the O*NET occupational database using the crosswalk to the 4-digit ISCO-08 (International Standard Classification of Occupations) codes. Although occupational characteristics are created for the U.S. occupations, the ranking of occupations in terms of job flexibility and indoor work makes a lot of sense in the Russian context as well.

We examine the impact of school closure on the following labor supply outcomes, L_{it}^{P}: employment, total hours of work in primary and secondary jobs, hours of work at the main job, the probability of any work from home and hours spent on working at home. We keep zero hours of work at home by using MaCurdy and Pencavel (1986) transformation, log (hours+1), for working parents. All labor supply outcomes refer to the last 30-day period prior to the survey interview.

We report the key parameter estimates of Equations (7) and (8) in Table 6 and full results in Appendix 2 separately for mothers and fathers. We find no statistically significant effect of school closure on employment and hours of work. If the employment result may be explained by the rigidity of the overall labor force structure in Russia, the results for hours may seem puzzling[15] as it

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Survey (CPS) and the annual American Community Survey – do not have health measures. The CPS March annual supplement only has a self-assessed health status on the day of the interview.

[14] We do not include industry and occupational characteristics in the employment equation, as they are only available for the employed individuals.

[15] Working hours are more flexible than the labor force structure in Russia. For example, average hours of work decreased by more than 25 percent during the lockdown period in Spring 2020 (Rosstat, 2020). At the same time, the Russian labor force composition changed inconsequentially during the same period; the unemployment rate increased

is an outlier among recent studies from other countries where school closure is found to bring a reduction in parents' hours of work (e.g., Amuedo-Dorantes et al., 2023; Beauregard et al., 2022; Couch et al., 2022; Garcia and Cowan, 2022).

We hypothesize that Russian families might have been able to adjust to school closure and retain the same working hours (1) by arranging alternative childcare or (2) by reallocating hours across space or (3) by reallocating hours across time. We find no support for the first hypothesis, strong support for the second one, and some support for the third one. As Table 6 shows, the longer the schools remain closed for COVID-19 reasons, the more likely mothers choose to work from home; the probability of working at home increases by 4-5 pp in response to closing schools for 10 days. Hours of work at home are also predicted to go up by 0.19-0.22 log points, which is equivalent to about 8 hours at home per month, conditional on working remotely. The effect of remote work is only found for mothers. We further examine why parents do not decrease total hours of work when schools are closed in Appendix 4 by looking at alternative childcare arrangements and intertemporal reallocation of hours. The most interesting result is that families employ or invite non-household members and relatives to care for children during regular school breaks but not during pandemic-related school closures. Perhaps, out of concerns over infection risks or because epidemiological school closures were not anticipated in advance, an average family's response to school closure was mainly reallocating hours across space and time rather than finding outside childcare options.

The labor supply estimates, together with the estimates of health effects, on the one hand, predict an increase in mothers' hours of work during school closure because of a lowered risk of a child's illness, but, on the other hand, they predict a decrease in hours because of an amplified risk of own illness. The total effect of school closure on hours worked through the health channel is close to zero.[16]

Our estimates reveal a few other interesting relationships. All estimates of the effects of school breaks on parental labor supply are smaller than those of COVID-19-related school closures.

marginally from 4.6 percent in February 2020 to 6.2 percent in May 2020 (Rosstat, 2020). Employers were not allowed to lay off workers during so-called non-working days.

[16] The total indirect effect is obtained as the product of the estimated coefficient on school closure in the child's health equation and the estimated coefficient on the child's health issues in the parent's health equation. The standard errors are computed with the delta method. The total indirect effect through the health channel is close to zero and statistically insignificant, with p-value = 0.4804 for mothers and 0.2066 for fathers.

All labor supply effects of long holidays are statistically insignificant at 5% level. Mothers' hours of remote work tend to be higher in occupations with more task freedom. They also increase with a higher spread of COVID-19. Single mothers tend to work more hours than non-single mothers. A child and home care helper outside of a household increases employment rate for mothers (but not fathers).

Table 6 also shows the estimated labor supply response to worsening children's health conditions. If children experience health issues, the childcare burden lies mostly on mothers. The labor supply of fathers barely responds to a child's illness. Russian mothers, on the other hand, when their child is sick, are more likely to leave employment and cut working hours. Our findings are in line with the existing research showing that mothers take on more housework than their spouses regardless of the circumstances (Bertrand et al., 2015; Blau and Kahn, 2007) and that mothers' labor supply is affected the most in the case of a health shock within the family (Eriksen et al., 2021; Jeon and Pohl, 2017).

Figures 7-10 picture the effects of school closures on parental health and labor supply depending on the level of COVID-19 exposure. While the individual fixed effects model reveals that school closures decrease the prevalence of health problems among children at the highest COVID-19 rates, this same model does not uncover any statistically significant effects of school closures on the prevalence of health problems among parents. A model with region and year-fixed effects shows the health benefits of school closures only for mothers and only at the highest levels of COVID-19 spread. As for labor supply, both models indicate that mothers worked from home more hours in response to school closures when COVID-19 cases were increasing rapidly, whereas changes in the labor supply behavior of fathers are less evident.

6 Discussion and Conclusion

We started this paper by asking, do the benefits of school closure outweigh the cost. Using the Russian example, we can see that the evaluation of perceived benefits and costs of this policy has changed over the course of the pandemic. By the time of the second COVID-19 wave in the Fall of 2020, regional authorities accumulated the first knowledge about the benefits and costs of school closure from the lockdown experience in the Spring of 2020. Despite all the evident costs of school closures, 64 out of 83 Russian regions decided to shut down schools again in the Fall of 2020 when

COVID-19 cases and deaths started climbing around October. However, when a new, more massive coronavirus wave hit one year later, the assessment of the benefits and costs of school closure changed. 23 regions opted not to go back to this policy despite COVID-19 cases increasing in record numbers. At the same time, authorities of 6 regions that did not implement a school closure policy in Fall 2020 reversed their decision one year later. 41 regions, or almost half of the Russian regions, re-instated school closure for the third time in an attempt to mitigate the spread of the COVID-19 infection, although the length of school closure was considerably shortened this time around. Over the course of the pandemic, a more critical and nuanced approach replaced the initial total shutdown of schools. Yet, the policy was not fully dismissed, as decision-makers recognized some important benefits despite insurmountable socio-economic costs.

In this study, we turn to the micro-level data to see if we can uncover some benefits and some costs of school closure for families during the pandemic. While most of the current literature on school closure focuses on learning losses and negative consequences of this policy for the labor market, the health effects are often overlooked, with the exception of mental health outcomes. We find a substantial and statistically significant decrease in the probability of children experiencing flu-like symptoms and having other health issues during pandemic-related school closure. We also find that parents indirectly benefit from school closure via lowered child-to-parent contagion. Furthermore, the higher the rate of COVID-19 spread, the larger the illness-reducing indirect effect of school closure on parents. At the same time, school closure is likely to have serious mental health consequences for both children and parents; some of these consequences are documented in recent studies (Lee, 2020; Li et al., 2022; Yamamura and Tsustsui, 2021). Our estimates show that longer school closures lead to a higher incidence of depression for both parents. Additional childcare responsibilities and disruptions in daily family life might have caused anxiety and depression, which may have triggered other health problems. At the highest rates of COVID-19 spread, the positive direct effect of school closure on parent's illness cancels out the negative indirect effect. We recognize that our calculations of direct and indirect effects do not account for the most important potential health benefit of school closure, which is the value of a saved life. Further research on a much bigger population sample than we have would be necessary to estimate how many lives were saved from school closure or any other COVID-19 restrictive policy.

Contrary to many studies from the U.S. and other countries, we find little to no change in the labor market in response to school closure.[17] Russian mothers did not quit employment, nor did they reduce their hours of work. Instead, they were able to find ways to balance work and caregiving. One such way is by working from home. We estimate that mothers increase the probability of remote work by approximately 5 percentage points and the duration of working from home by 8 hours per month in response to closing schools for 10 business days. The absence of a labor supply response does not imply that school closure was not costly for businesses and families. Among RLMS respondents who worked from home in 2020, 32 percent report lower productivity of distance work compared to their usual workplace, while only 12 percent answer that working from home increases their efficiency; 66 percent say that working from home hinders their family life. Since mothers take on most of the responsibility for childcare and household chores in Russia, the gender inequality in childcare duties has likely widened during school closure; this fact has also been documented in other countries (see e.g., Adams-Prassl et al., 2020, Alon et al., 2020, Deryugina et al., 2021). Several studies have raised the issue of learning loss from virtual schooling. They find that school closures have a large, persistent, and unequal effect on human capital (e.g., Agostinelli et al., 2022; Blanden et al, 2022; Donnelly and Patrinos, 2021; Goldhaber et al., 2023; Grewenig et al., 2021). This is probably true for Russia as well. According to the RLMS-HSE data, 61 percent of students who studied virtually in 2020 say that the quality of their education suffered. The adverse effects of learning loss, as well as mental health consequences, are likely to last for years to come.

Given what we know about the adverse effects of school closure, a bigger question is whether school closure should remain in the policy toolkit if, or likely when, a new pandemic arrives. Understanding the health benefits is the first step in answering this question. Further research is needed on bigger samples in different countries to assess how successful school closure is in saving lives and protecting health during pandemic conditions and whether these health benefits outweigh all related costs.

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8 Tables and Figures

Table 1: Definition of Variables

Variable	Vector	Definition
		Individual characteristics
Employed	L^P_{it}	=1 if worked for pay or profit at primary or secondary jobs in the last 30 days; =0 if did not work in the last 30 days (including job holders on a long-term leave)
Total hours of work	L^P_{it}	Hours worked at primary and secondary jobs in the last 30 days; includes hours worked from home
Hours at the primary job	L^P_{it}	Hours worked at a primary job in the last 30 days; includes hours worked from home
Work from home	L^P_{it}	=1 if worked from home at primary job in the last 30 days; =0 if worked at primary job but not from home in the last 30 days; no information on work from home at secondary job
Hours worked from home	L^P_{it}	Hours worked from home at a primary job in the last 30d. Set to zero if worked at the primary job but not from home. When used in logs, MaCurdy and Pencavel (1986) transformation is applied, log (hours+1)
Parent's health issues	H^P_{it}	=1 if the parent had any health issues in the last 30 days (parent-level analysis)
Any parent's health issues	$\widetilde{H}^P_{kt}$	=1 if any parent had health issues in the last 30 days (child-level analysis)
Child's health issues	H^C_{kt}	=1 if the child had health issues in the last 30 days (child-level analysis)
Any child health issues	$\widetilde{H}^C_{it}$	=1 if any child under age 15 had health issues in the last 30 days (parent-level analysis)
Child's flu-like symptoms	H^C_{kt}	=1 if the child had flu-like symptoms in the last 7 days. Symptoms include sore throat, cold and runny nose, cough, and earache.
Parent's age	X_{it}	3 categories: 18-34, 35-44, 45-60
Level of education	X_{it}	4 categories for parent's education: basic general (about 9 years), secondary general (11-12 years), secondary professional (12-13 years), tertiary professional or above (15+ years)
Married	X_{it}	=1 if a parent is married or lives together with a partner; =0 if not
Russian	X_{it}	=1 if parent is Russian; =0 if not
Foreign born	X_{it}	=1 if parent is born outside of Russia; =0 if not
Place of residence	X_{it}	3 categories: regional capital, other urban settlement, and rural area

Child's age	X_{kt}, X_{it}	Age of the child (child-level analysis); the age of the youngest school-age child in grades 1-8 (parent-level analysis)
Government assistance	X_{kt}, X_{it}	=1 if parents received government assistance; =0 if not
Child benefits	X_{kt}, X_{it}	=1 if parents received child benefits; =0 if not
Child's grade level	…	Grade level the child attends. The variable is used for linking the RLMS-HSE with grade-level policies. It is taken from the direct survey question.
Older caregiver	Z_{it}^{L}	=1 if there is an older household member other than parents, age 55-80, who is not disabled and not in bad health; =0 if none
Childcare by outside helper	Z_{it}^{L}	=1 if there is a person outside of the household who is helping parents with childcare; =0 if none
Industry	Z_{it}^{L}	10 categories: agriculture; mining and manufacturing; housing and utilities; construction; transportation and communication; trade and consumer services; health care and social assistance; education, science, culture; public administration; other/unknown
Indoor occupation	Z_{it}^{L}	Standardized score for a 4-digit occupation. Indicates the extent to which a typical job in a given occupation requires working indoors in environmentally controlled conditions. Source: O*NET occupational database using the crosswalk to the 4-digit ISCO-08 (International Standard Classification of Occupations) codes
Unstructured job	Z_{it}^{L}	Standardized score for a 4-digit occupation. Indicates the extent to which a typical job in a given occupation is unstructured for the worker, that is, allows the worker to determine tasks, priorities, and goals. Source: O*NET as above
Pre-pandemic chronic conditions	Z_{k}^{C}, Z_{i}^{P}	=1 if a child or parent had chronic illnesses of heart, lung, kidney, stomach, spine, or urogenital system, cancer, or diabetes by 2019
	Schooling Policy Tracker	
School closure	S_{it}	Number of days when schools were closed for in-person learning due to COVID-related reasons as the share of business days in the last 30 days. Varies by region, grade level, and date of interview
School break	X_{it}	Length of school breaks as the share of business days in the last 30 days. Varies by region, grade level, and date of interview
Long holidays	X_{it}	=1 if federal or regional holidays lasted for more than one working day in the last 30 days. Varies by region and date of interview
	Regional characteristics	
Workplace closure	X_{it}	Number of non-working days due to COVID-related reasons in the last 30 days in tens of days. Non-working days are declared by either federal or regional governments as paid days off during the high spread of coronavirus. With the exception of essential businesses, all enterprises are closed during non-working days. Varies by region and date of interview
Self-isolation policy	X_{it}	Number of days when people were recommended or mandated to self-isolate due to COVID-related reasons in the last 30 days in tens of days.

		Varies by region and date of interview
Social distancing policy	X_{it}	Number of days when people were recommended or mandated to practice social distancing due to COVID-related reasons in the last 30 days in tens of days. Varies by region and date of interview
Unemployment rate, %	X_{it}	Monthly unemployment rate in percent. Varies by region and month of interview. International Labor Organization methodology. Rosstat, https://rosstat.gov.ru/folder/210/document/13211
COVID-19 spread	X_{it}	New confirmed COVID-19 cases per 100 people in the last 30 days multiplied by the region-specific discrepancy factor. The discrepancy factor is the ratio of the annual COVID-19 morbidity level to the annual sum of daily coronavirus cases. Sources: Yandex Coronavirus Database, Rosstat Regions of Russia. Varies by region and interview date

Table 2: Summary Statistics

	2017-2019			2020-2021				Unconditional DID Effect	
					Ever treated		*p*-value		
	Never treated	Ever treated	*p*-value	Never treated	Not treated	Treated	(for treated vs. never treated)	Absolute value	Percent change
The parent has a health problem	.22	.22	.96	.18	.2	.21	.05	0.03	14%
Any child has a health problem	.38	.44	<0.01***	.33	.32	.34	.63	-0.05	-11%
Any child has flu symptoms	.29	.35	<0.01***	.25	.27	.28	.05	-0.03	-9%
Parent is depressed	.08	.07	.21	.06	.05	.07	.74	0.02	29%
Employed	.77	.79	.1	.76	.79	.8	<0.01***	0.02	3%
Total hours of work	183.94	184.21	.86	182.36	183.58	181.66	.72	-0.97	-1%
	(52.64)	(49.63)		(50.65)	(49.92)	(52.21)			
Work from home	.08	.1	.01	.08	.12	.13	<0.01***	0.03	30%
Hours worked from home	33.71	34.47	.87	58.43	71.55	60.25	.81	1.06	3%
(If worked from home)	(48.74)	(39.4)		(70.93)	(93.5)	(61.02)			
Days of COVID-19-related	0	0		0	0	5.23			
school closures						(3.88)			
Days of school breaks	1.79	2.43	<0.01***	2.02	1.81	2.92			
	(2.28)	(2.37)		(3.18)	(2.77)	(2.08)			
Age	38.17	37.24	<0.01***	38.69	38.55	38.7			
	(6.15)	(5.85)		(6.11)	(5.8)	(5.92)			
College	.36	.38	.03	.38	.39	.41			
Poverty rate, %	12.96	12.84	.25	11.95	11.99	11.82			
	(4.1)	(3.89)		(4)	(3.63)	(3.94)			

Unemployment rate, %	4.85	4.54	<0.01***	5.03	5.29	5.07
	(1.81)	(1.8)		(2)	(1.93)	(2.13)
COVID-19 spread	0	0		.56	.7	.83
				(.37)	(.43)	(.43)
N observations	5637	2096		3218	734	1281

Notes: The table reports the mean and standard deviation (in parentheses) of parents' characteristics by treatment status before and after the start of the COVID-19 pandemic. After the start of the pandemic, three groups of parents are considered, namely, never treated parents, those who have ever been treated but not treated in the last 30 days before the observation and those who are treated during the last 30 days before the observation. Standard deviations for binary variables are not shown. The sample consists of parents of school age children in grades 1 to 8 who are between 18 and 60 years old themselves and who participated at least twice. The description of variables can be found in Table 1. Total work hours are averaged over the sample of employed individuals and hours worked from home are averaged over the sample of individuals who worked at home at least one hour. Unconditional difference in differences effects of school closures is calculated as the difference in average change over time between never treated and treated groups (before 2020 we do not have a treated group, but only ever treated group). Percent change is calculated relative to average values for ever treated before 2020. P-values are calculated based on t-tests for mean differences between treated and never treated in 2017-2019 and for mean differences between recently treated and never treated in 2020-2021. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Distribution of Business Days by Schooling Mode

	2019 m9	2019 m10	2019 m11	2019 m12	2020 m9	2020 m10	2020 m11	2020 m12	2021 m9	2021 m10	2021 m11	2021 m12
In-person days, %	100.0	83.6	94.4	90.9	99.9	78.2	68.3	75.3	98.5	85.0	78.7	88.4
School closings, %	0.0	0.0	0.0	0.0	0.0	5.3	25.6	8.1	1.1	9.1	9.0	2.8
School breaks, %	0.0	16.4	5.6	9.1	0.0	16.5	6.1	16.6	0.0	6.0	12.2	8.7
Other, %	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.4	0.0	0.2	0.1
Business days	21.0	23.0	20.0	22.0	22.0	22.0	20.0	23.0	21.9	21.0	20.0	22.0

Notes: Table shows the percentage share of business days during which schools were in-person, closed for COVID-19 reasons, closed for fall break, and closed for other unrelated to COVID reasons. The shares are simple averages across 32 RLMS regions and school grades 1 to 8.

Table 4: Effect of School Closure on Child's Health

Estimation methods	Region +Year FEs			Individual + Year FEs		
Variables	Health Problems	Flu-like Symptoms	Upper Respiratory Tract Disease	Health Problems	Flu-like Symptoms	Upper Respiratory Tract Disease
School closure	-0.053**	-0.058***	-0.026***	-0.068***	-0.033	-0.018
	(0.024)	(0.016)	(0.009)	(0.025)	(0.025)	(0.011)
By COVID-19-cases quintile:						

Lowest	0.006	0.033	0.024	-0.049	0.061	0.015
	(0.061)	(0.043)	(0.034)	(0.063)	(0.067)	(0.029)
2nd quintile	-0.008	0.002	0.003	-0.046	0.024	0.003
	(0.044)	(0.030)	(0.023)	(0.044)	(0.045)	(0.020)
3rd quintile	-0.027	-0.037*	-0.022*	-0.045	-0.020	-0.011
	(0.026)	(0.020)	(0.013)	(0.028)	(0.028)	(0.013)
4th quintile	-0.051**	-0.080***	-0.045***	-0.050	-0.067*	-0.025*
	(0.020)	(0.023)	(0.015)	(0.033)	(0.037)	(0.015)
Highest	-0.094***	-0.116***	-0.037**	-0.106**	-0.083**	-0.025
	(0.023)	(0.027)	(0.015)	(0.042)	(0.039)	(0.019)
School break	-0.032	-0.029	-0.001	-0.033	-0.040*	-0.011
	(0.019)	(0.020)	(0.011)	(0.021)	(0.021)	(0.010)
Long holidays	-0.039*	-0.024	-0.020**	-0.018	0.013	0.000
	(0.021)	(0.023)	(0.010)	(0.028)	(0.028)	(0.011)
Child's age	-0.011***	-0.011***	-0.003	-0.007**	-0.007**	0.001
	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)
COVID-19 cases	-0.003	-0.006	0.000	0.038	-0.007	-0.013
	(0.023)	(0.040)	(0.022)	(0.034)	(0.033)	(0.016)
Parents' chronic diseases before	0.067***	0.060***	0.058***	…	…	…
the pandemic	(0.016)	(0.013)	(0.013)			
Children's chronic diseases before	0.146***	0.102***	0.057***	…	…	…
the pandemic	(0.016)	(0.022)	(0.019)			
Observations	9,241	8,441	9,228	8,743	7,956	8,730
R-squared	0.069	0.056	0.076	0.385	0.384	0.551

Notes: Table presents estimates of Equations (3) and (4). We only show estimates that are cited in the text; full results can be found in Appendix 2, Table W2. Sample includes children in grades 1-8 under age 15. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. Omitted (base) categories are age 18-34 for parent's age, basic general for parent's education. Parent's age and education are for mothers. If the mother is absent, then father's characteristics are used. The table also reports the average marginal effect of school closure by COVID-19 level of exposure. The effect is calculated based on Equations (3) and (4) with an added interaction term between school closure and COVID-19 spread.

Table 5: Direct, Indirect, and Total Effects of School Closure on Parent's Health

Estimation methods	Region + Year FE		Individual + Year FE	
Variables	Mothers	Fathers	Mothers	Fathers
		Effects of School Closure		
Direct effect	0.038	0.049*	0.034	0.045
	(0.037)	(0.026)	(0.030)	(0.032)
By COVID-19-cases quintile:				

Lowest	0.091**	0.075**	0.062	0.092
	(0.044)	(0.037)	(0.065)	(0.067)
2nd quintile	0.074*	0.066**	0.053	0.075
	(0.039)	(0.032)	(0.056)	(0.054)
3rd quintile	0.049	0.054**	0.041	0.051
	(0.032)	(0.027)	(0.047)	(0.044)
4th quintile	0.005	0.032	0.020	0.009
	(0.025)	(0.027)	(0.045)	(0.054)
Highest	-0.303***	-0.120	-0.130	-0.284
	(0.106)	(0.141)	(0.228)	(0.333)
Indirect effect	-0.007**	-0.005**	-0.004	-0.003
	(0.003)	(0.002)	(0.005)	(0.004)
By COVID-19-cases quintile:				
Lowest	-0.003	-0.002	-0.002	-0.001
	(0.004)	(0.003)	(0.003)	(0.002)
2nd quintile	-0.004	-0.003	-0.003	-0.002
	(0.004)	(0.002)	(0.003)	(0.002)
3rd quintile	-0.006*	-0.004**	-0.003	-0.002
	(0.003)	(0.002)	(0.003)	(0.002)
4th quintile	-0.009***	-0.006***	-0.005*	-0.003
	(0.002)	(0.001)	(0.003)	(0.003)
Highest	-0.031***	-0.020***	-0.017	-0.012
	(0.010)	(0.007)	(0.011)	(0.009)
Total effect	0.023	0.044	0.028	0.041
	(0.037)	(0.027)	(0.067)	(0.053)
By COVID-19-cases quintile:				
Lowest	0.089*	0.073**	0.060	0.090
	(0.046)	(0.037)	(0.065)	(0.066)
2nd quintile	0.070*	0.064**	0.051	0.073
	(0.041)	(0.032)	(0.057)	(0.054)
3rd quintile	0.043	0.050*	0.038	0.049
	(0.034)	(0.027)	(0.048)	(0.044)
4th quintile	-0.004	0.026	0.015	0.006
	(0.027)	(0.027)	(0.046)	(0.054)

Highest	-0.335***	-0.141	-0.147	-0.295
	(0.112)	(0.141)	(0.230)	(0.333)
	Effects of Children's Health Issues			
Any child's health issues	0.138***	0.090***	0.064***	0.061***
	(0.012)	(0.012)	(0.014)	(0.015)
Observations	7,533	5,918	6,993	5,459

Notes: The direct effects of school closure and child's health are estimated using Equations (5) and (6). We only show estimates that are cited in the text; full results can be found in Appendix 2, Table W3. The dependent variable is whether parents had health issues in the last 30 days. Sample includes parents of children in grades 1-8 under age 15. The table reports the average marginal effect of school closure by COVID-19 level of exposure. The effect is calculated based on Equations (3) and (4) with an added interaction term between school closure and COVID-19 spread. The indirect effect is the estimated coefficient on school closure in the child's health equation (in Table 4) multiplied by the corresponding coefficient on child's health issues in parent's health equation. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. Standard errors for average indirect and total effects are computed using the Delta method.

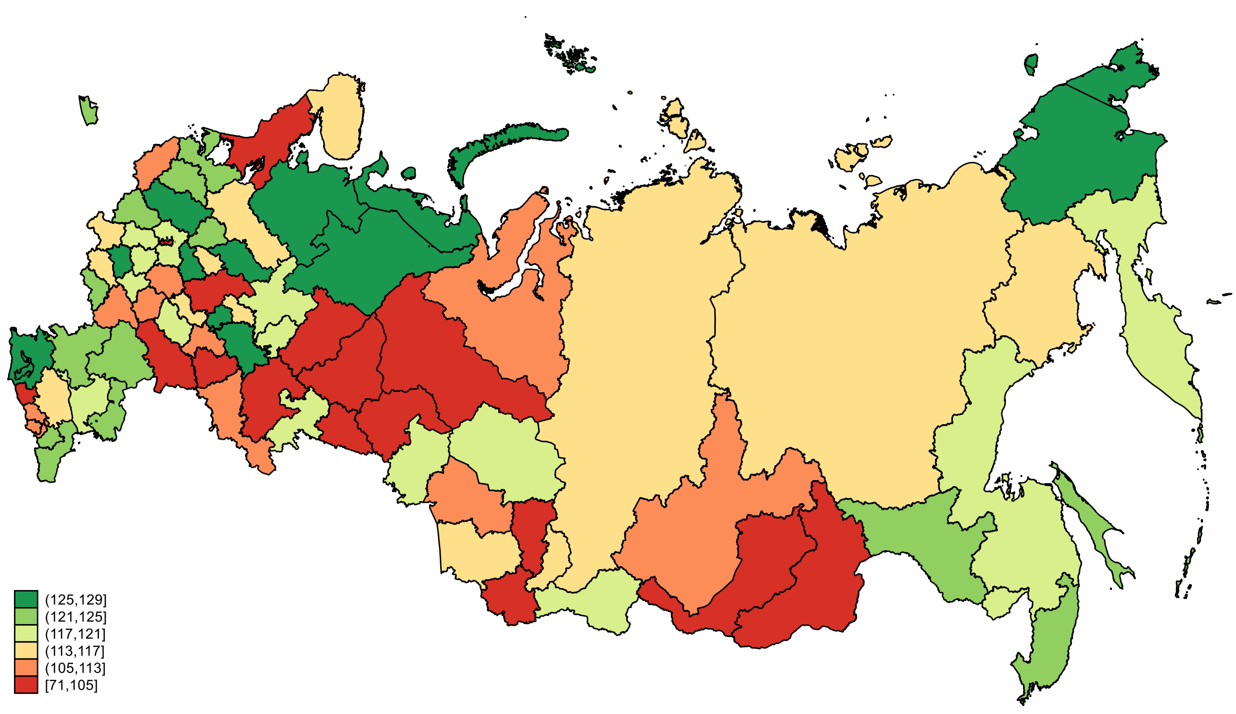
Table 6: Effect of School Closures on Parental Labor Supply and Health Problems

	Health problems		Employment		Log total hours		Working from home		Hours working from home	
	Mothers	Fathers	Mothers	Fathers	Mothers	Fathers	Mothers	Fathers	Mothers	Fathers
	Region + Year FE									
School closure	0.038	0.049*	-0.040	-0.019	0.025	-0.016	0.051***	0.013	0.219***	0.024
	(0.037)	(0.026)	(0.027)	(0.019)	(0.016)	(0.022)	(0.018)	(0.013)	(0.059)	(0.044)
School break	-0.006	0.023	0.013	-0.004	0.015	0.017	0.027*	-0.002	0.131**	0.001
	(0.019)	(0.017)	(0.018)	(0.019)	(0.015)	(0.017)	(0.015)	(0.009)	(0.050)	(0.024)
Long holidays	0.031	0.020	-0.042*	-0.011	-0.032	-0.012	0.032	-0.011	0.093	-0.028
	(0.023)	(0.017)	(0.024)	(0.024)	(0.025)	(0.018)	(0.023)	(0.011)	(0.066)	(0.025)
Any child's health issues	0.138***	0.090***	-0.041***	0.001	-0.017*	-0.003	0.022**	0.004	0.062**	0.007
	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)	(0.008)	(0.010)	(0.005)	(0.028)	(0.013)
Parent's prior chronic illnesses	0.137***	0.136***	-0.012	-0.024	0.013	0.005	0.001	0.006	0.017	0.030
	(0.015)	(0.019)	(0.014)	(0.016)	(0.014)	(0.009)	(0.011)	(0.007)	(0.034)	(0.021)
Childcare by outside helper	0.007	-0.002	0.021*	0.014	-0.015	-0.003	0.002	0.009	-0.030	0.012
	(0.011)	(0.014)	(0.012)	(0.013)	(0.012)	(0.009)	(0.012)	(0.006)	(0.037)	(0.015)
Indoor occupation	…	…	…	…	0.005	0.002	0.011	0.012***	0.035	0.020**
					(0.010)	(0.006)	(0.009)	(0.004)	(0.023)	(0.008)
Unstructured job	…	…	…	…	0.001	0.003	0.030***	0.009	0.088***	0.020
					(0.006)	(0.006)	(0.006)	(0.007)	(0.018)	(0.015)
COVID-19 spread	-0.027	-0.034	0.042	-0.033	0.053***	-0.041	0.070***	0.045**	0.319***	0.125***
	(0.025)	(0.030)	(0.028)	(0.025)	(0.012)	(0.027)	(0.022)	(0.019)	(0.086)	(0.042)
Observations	7,504	5,894	7,512	5,901	5,092	4,691	5,253	5,008	5,208	4,972
R-squared overall	0.102	0.075	0.162	0.213	0.067	0.086	0.144	0.090	0.150	0.091
	Individual + Year FE									
School closure	0.033	0.044	-0.022	-0.007	0.016	-0.001	0.036*	0.016	0.190***	0.011
	(0.030)	(0.032)	(0.022)	(0.023)	(0.021)	(0.023)	(0.021)	(0.020)	(0.070)	(0.042)

School break	-0.022	0.004	-0.000	-0.013	-0.000	0.026*	0.004	0.004	0.026	0.001
	(0.021)	(0.022)	(0.017)	(0.017)	(0.018)	(0.015)	(0.016)	(0.011)	(0.043)	(0.025)
Long holidays	0.023	0.005	-0.042*	0.006	-0.008	-0.034*	0.021	-0.019	0.080	-0.033
	(0.029)	(0.031)	(0.025)	(0.022)	(0.028)	(0.020)	(0.024)	(0.014)	(0.083)	(0.035)
Any child's health issues	0.062***	0.042***	-0.018*	-0.009	-0.018*	-0.015*	0.004	0.004	-0.005	0.011
	(0.014)	(0.014)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.007)	(0.028)	(0.016)
Childcare by outside helper	-0.004	0.001	0.031**	-0.000	0.011	0.005	-0.013	0.010	-0.064*	0.017
	(0.015)	(0.015)	(0.013)	(0.010)	(0.013)	(0.010)	(0.011)	(0.009)	(0.035)	(0.018)
Indoor occupation	…	…	…	…	-0.004	0.001	0.031**	-0.000	0.011	0.005
					(0.015)	(0.015)	(0.013)	(0.010)	(0.013)	(0.010)
Unstructured job	…	…	…	…	-0.004	0.001	0.031**	-0.000	0.011	0.005
					(0.015)	(0.015)	(0.013)	(0.010)	(0.013)	(0.010)
COVID-19 spread	-0.022	-0.062*	0.021	-0.031	0.030	-0.030	0.039	0.039	0.203*	0.114
	(0.041)	(0.036)	(0.030)	(0.025)	(0.027)	(0.027)	(0.033)	(0.029)	(0.119)	(0.082)
Observations	6,993	5,460	7,004	5,468	4,575	4,236	4,740	4,562	4,701	4,523
R-squared overall	0.447	0.447	0.697	0.716	0.567	0.602	0.663	0.597	0.684	0.608
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

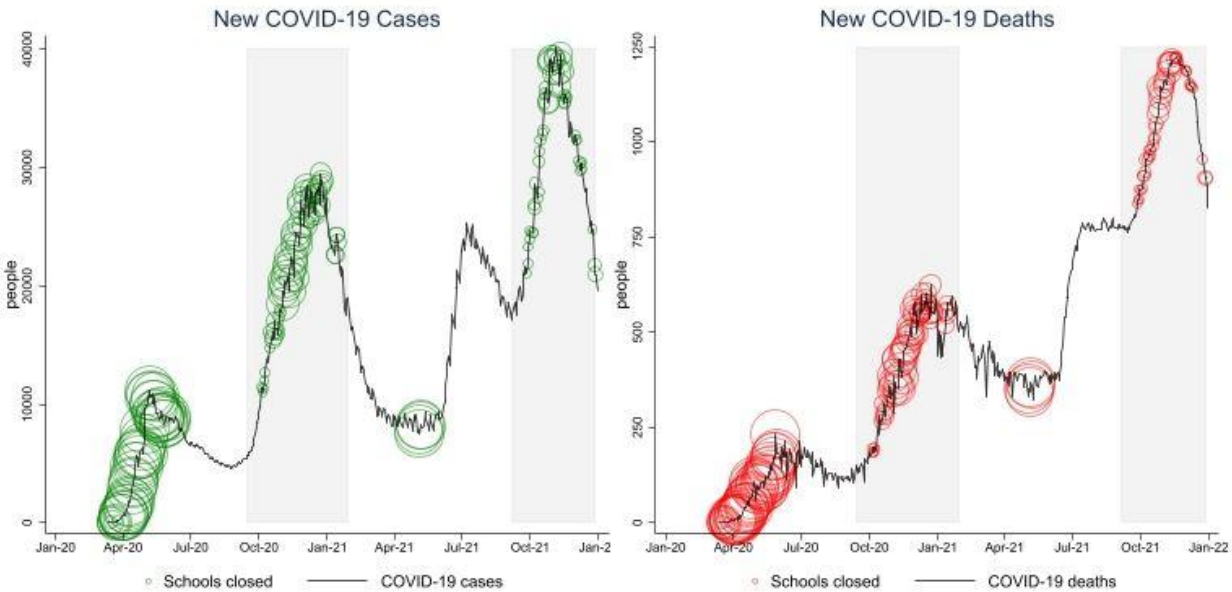
Notes: Table presents estimates of Equation (7) and (8). We only show estimates that are cited in the text; full results can be found in Appendix 2, Table W4. Sample includes parents with children in grades 1-8 under age 15. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: In-Person School Days, 2020



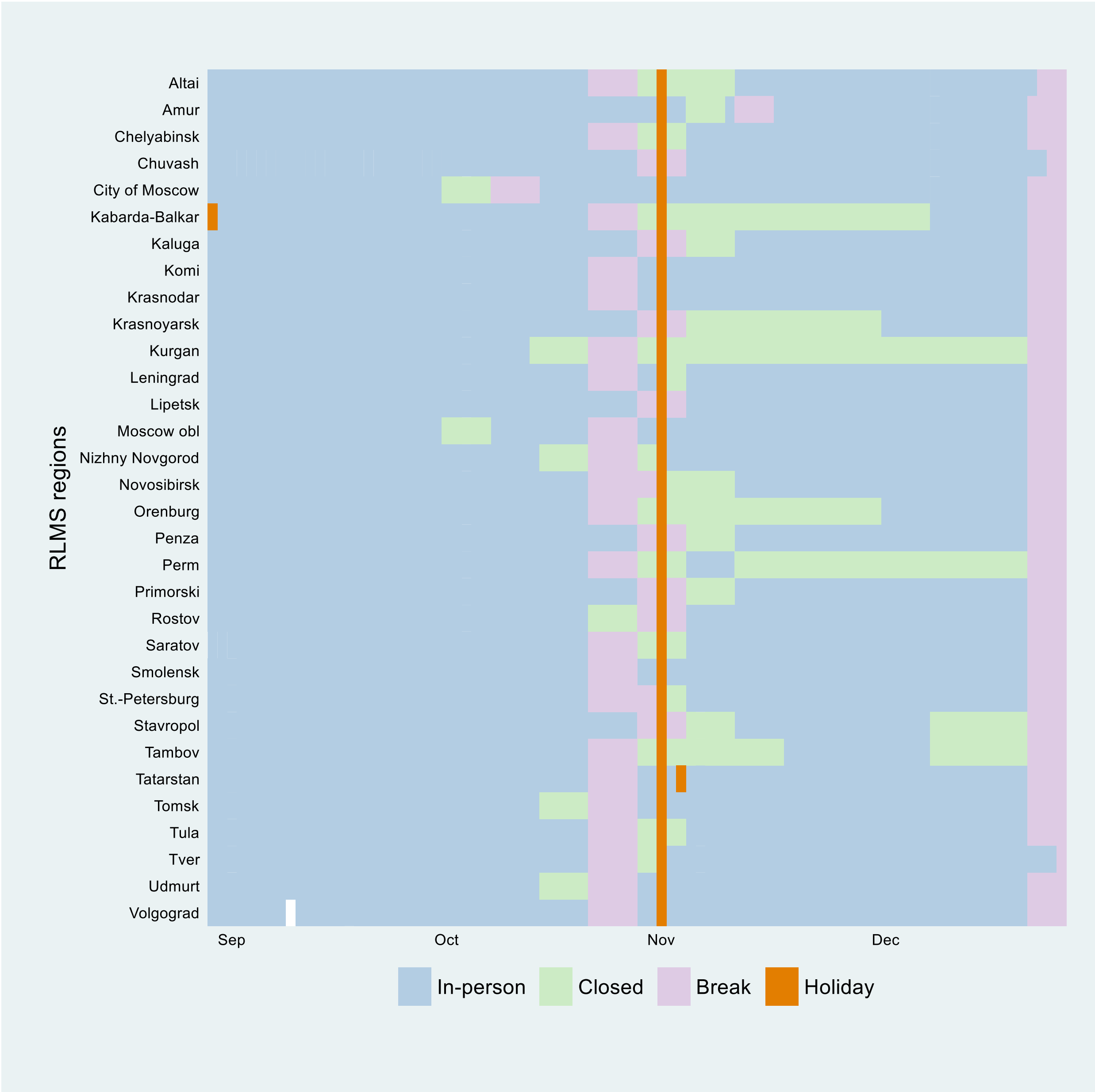
Notes: The map depicts the average number of in-person school days in 2020 for school grades 1-8.

Figure 2: School Closings and the Spread of COVID-19



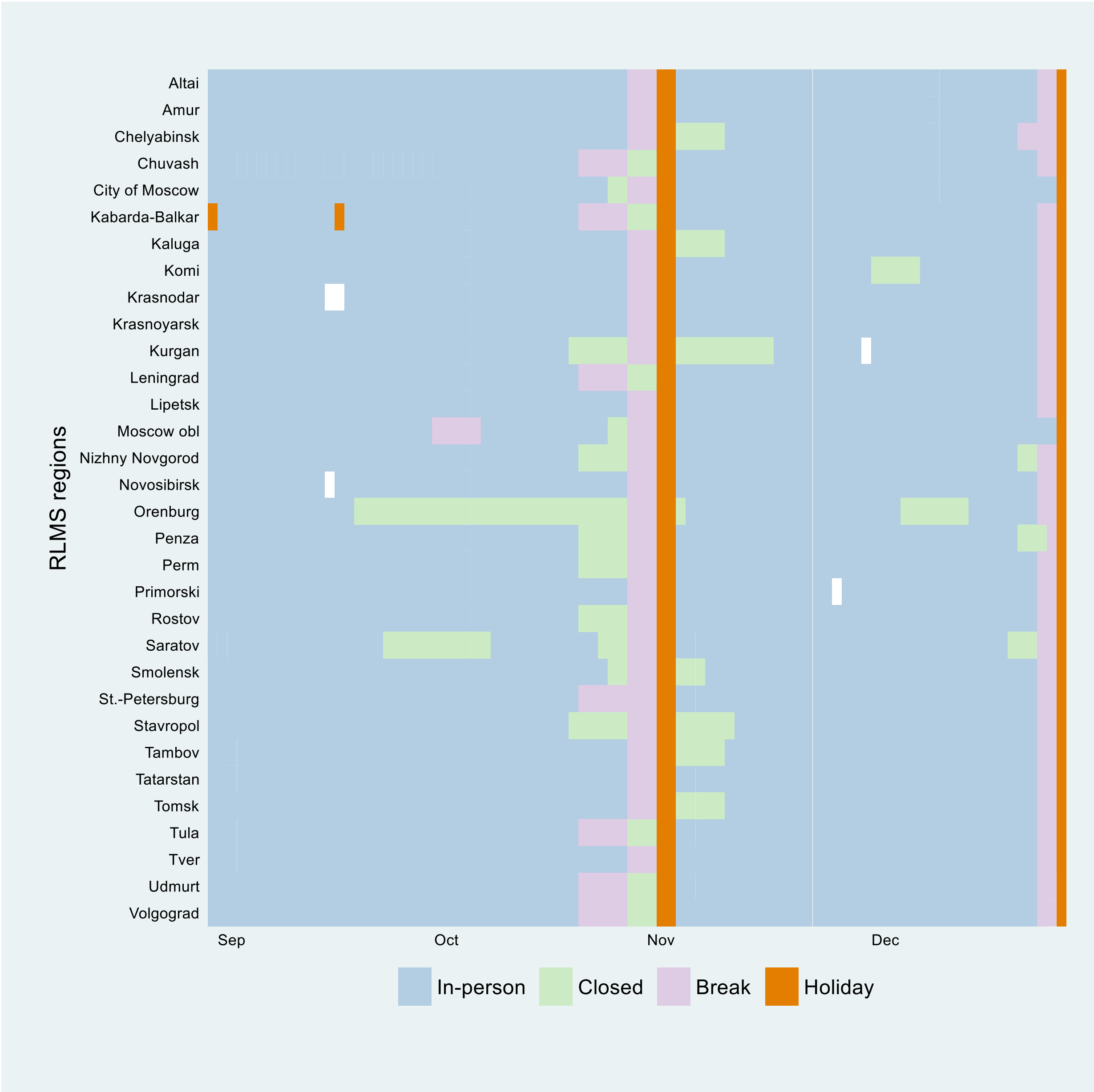
Notes: Figure plots the number of daily confirmed COVID-19 cases and deaths in Russia. The size of the hollow marker is proportional to the number of Russian regions (max 83) where schools have been closed due to COVID-related reasons. Shaded areas show periods when Russian Longitudinal Monitoring Survey interviews were conducted.

Figure 3: Timeline of School Closings, Fall 2020



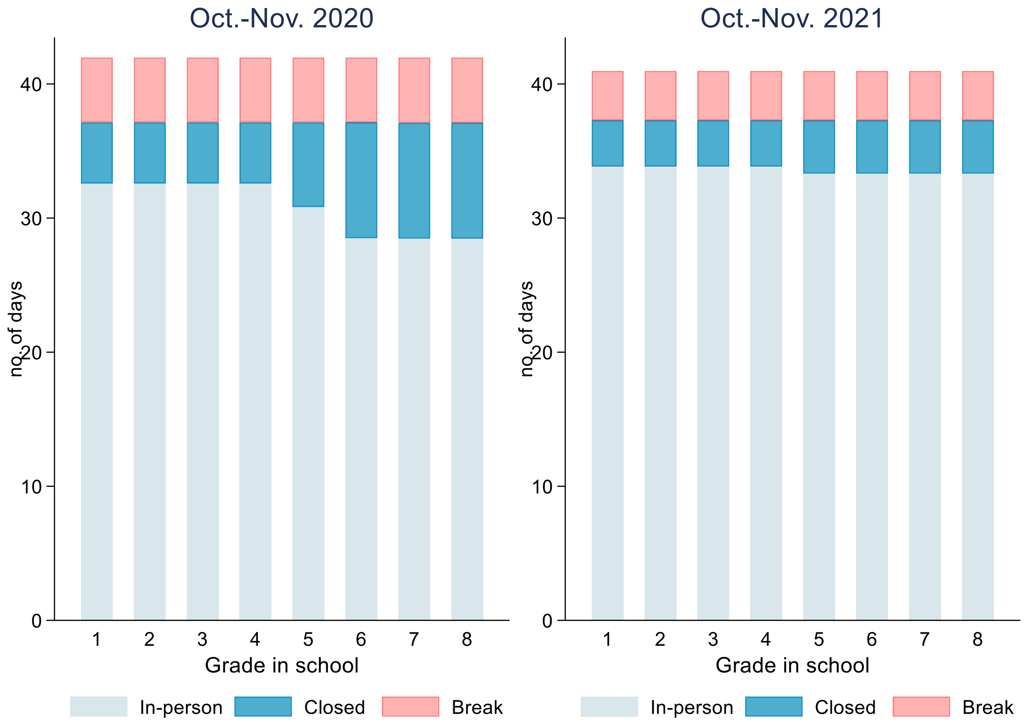
Notes: Figure presents the timeline of schooling modes for 5th graders in 32 RLMS regions beginning September 1, 2020, and ending December 31, 2020. Weekends are excluded from the timeline. White cells show days when schools are closed for reasons unrelated to COVID (voting, security, or inclement weather).

Figure 4: Timeline of School Closings, Fall 2021



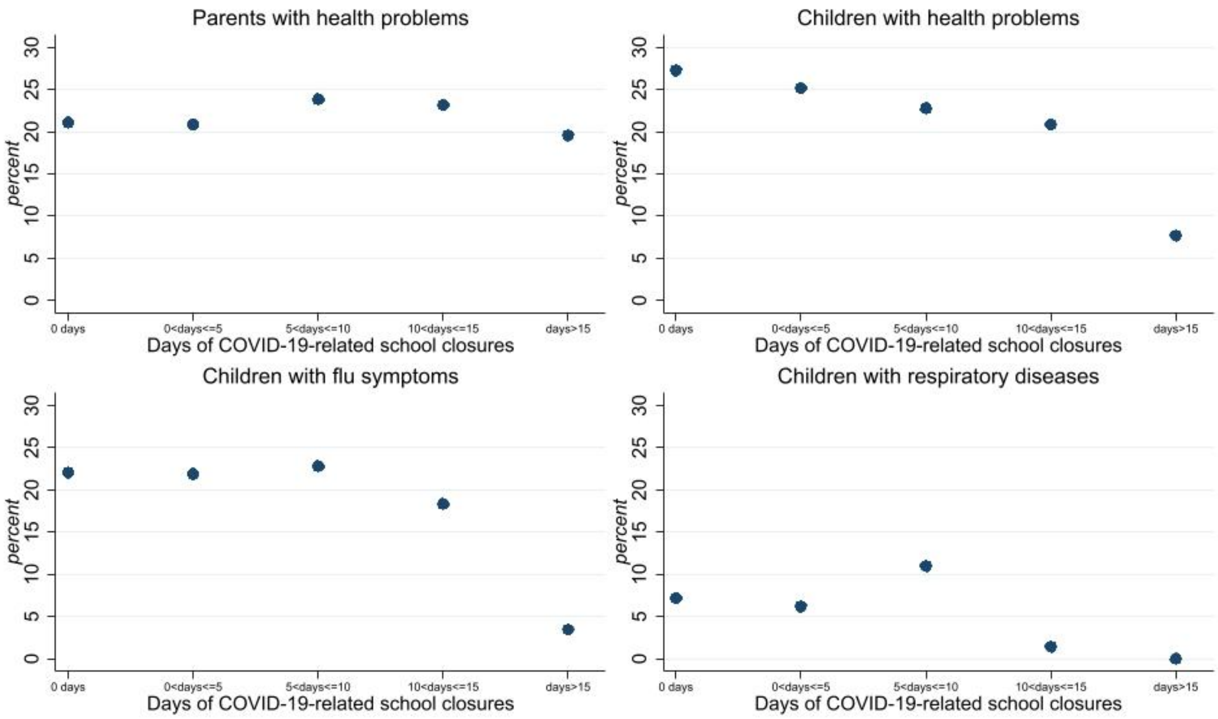
Notes: Figure presents the timeline of schooling modes for 5th graders in 32 RLMS regions beginning September 1, 2021, and ending December 31, 2021. Weekends are excluded from the timeline. White cells show days when schools are closed for reasons unrelated to COVID (voting, security, or inclement weather).

Figure 5: Distribution of Business Days by Grade and Schooling Mode



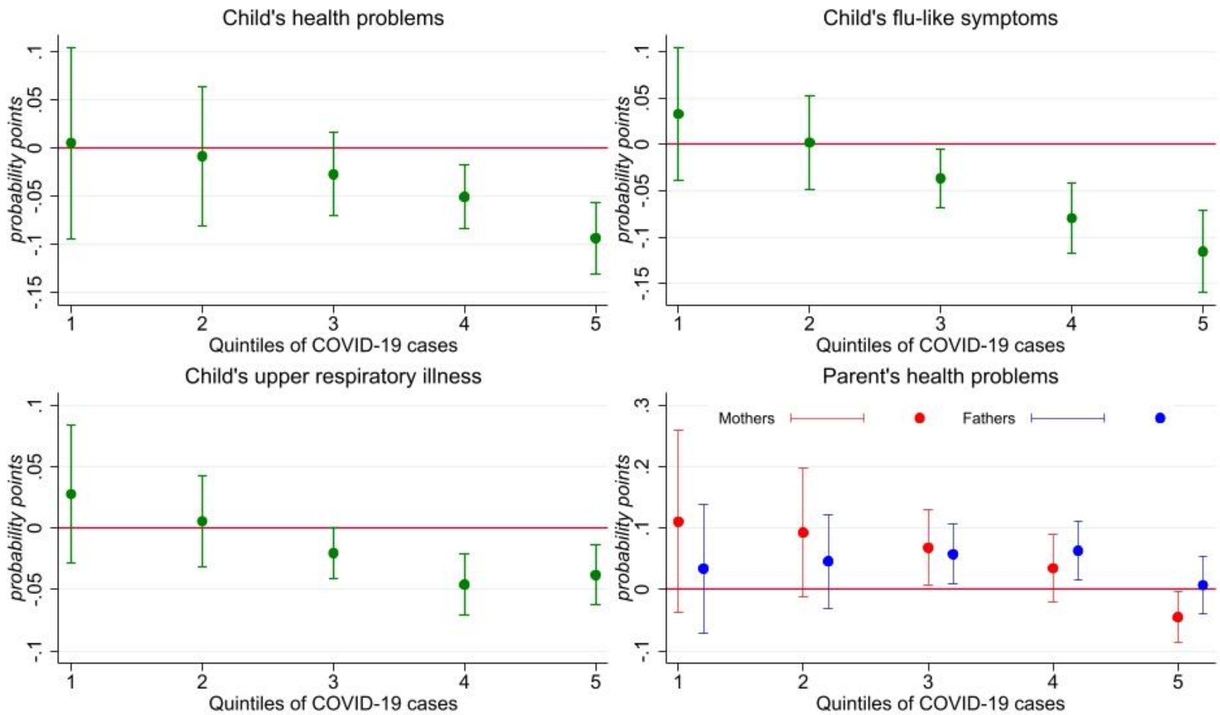
Notes: Figure plots the average number of business days during which schools were in-person, closed for COVID-19 reasons, or closed for a fall break. The average is calculated across 32 RLMS regions for October-November time periods of each year.

Figure 6: School Closures and the Prevalence of Health Issues, Flu Symptoms, and Respiratory Diseases



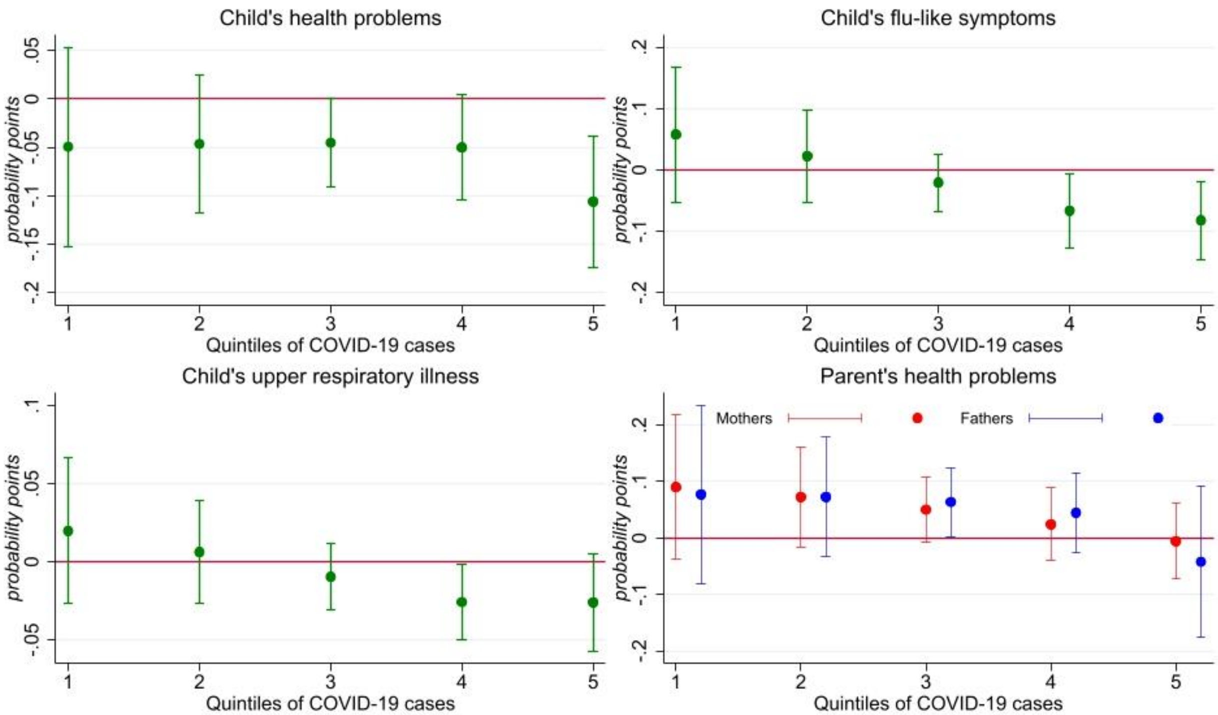
Notes: Figure shows an unconditional relationship between the shares of parents and children who have health issues, flu symptoms, or depression and the number of days of COVID-19-related school closures.

Figure 7: The Health Effects of School Closures by the Level of COVID-19 Exposure. Region and Year Fixed Effects Estimates



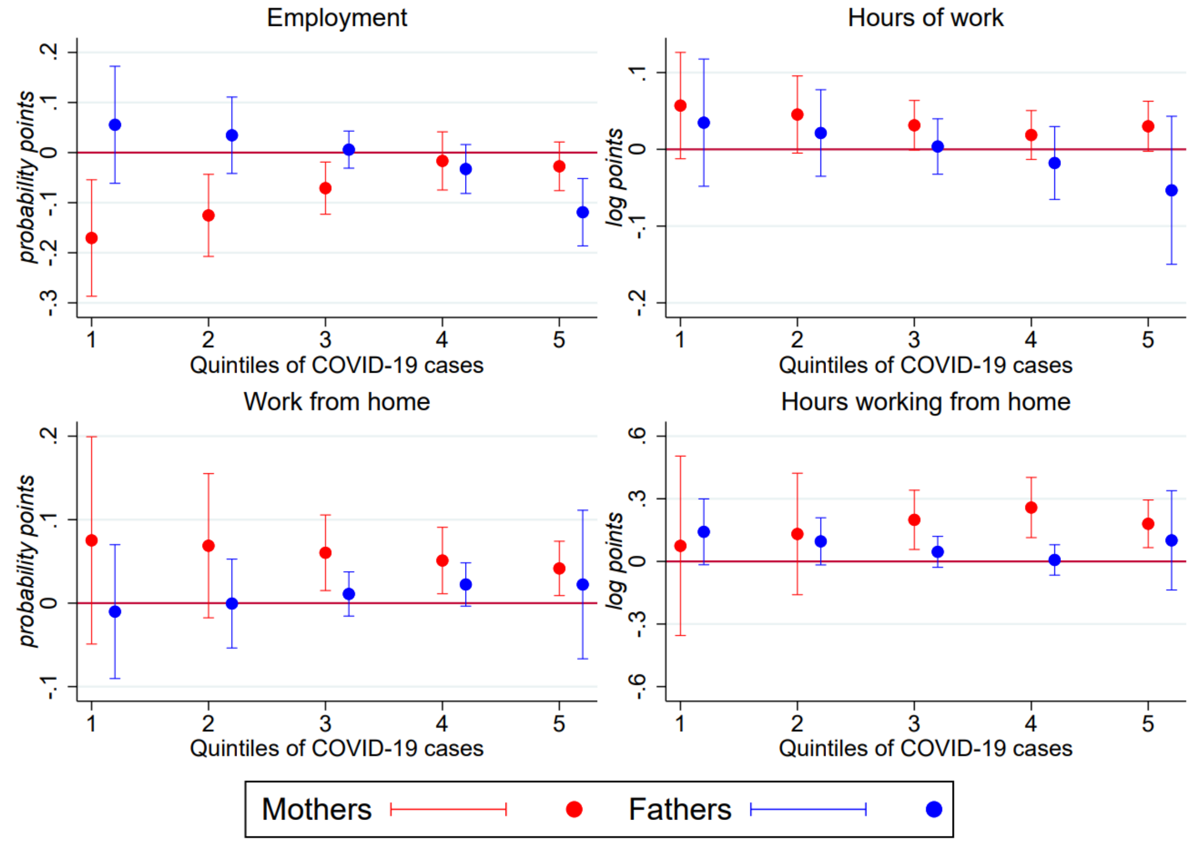
Notes: Figure shows a relationship between the average marginal effects of school closures on parental health problems, children's health problems, flu-like symptoms, upper respiratory illnesses, and different levels of COVID-19 exposure. AME corresponding to each quintile *k* is computed based on all observations between a quintile *k-1* and a quintile *k* using region and year fixed effects models. Error bands represent 90 percent confidence intervals.

Figure 8: The Health Effects of School Closures by the Level of COVID-19 Exposure. Individual and Year Fixed Effects Estimates



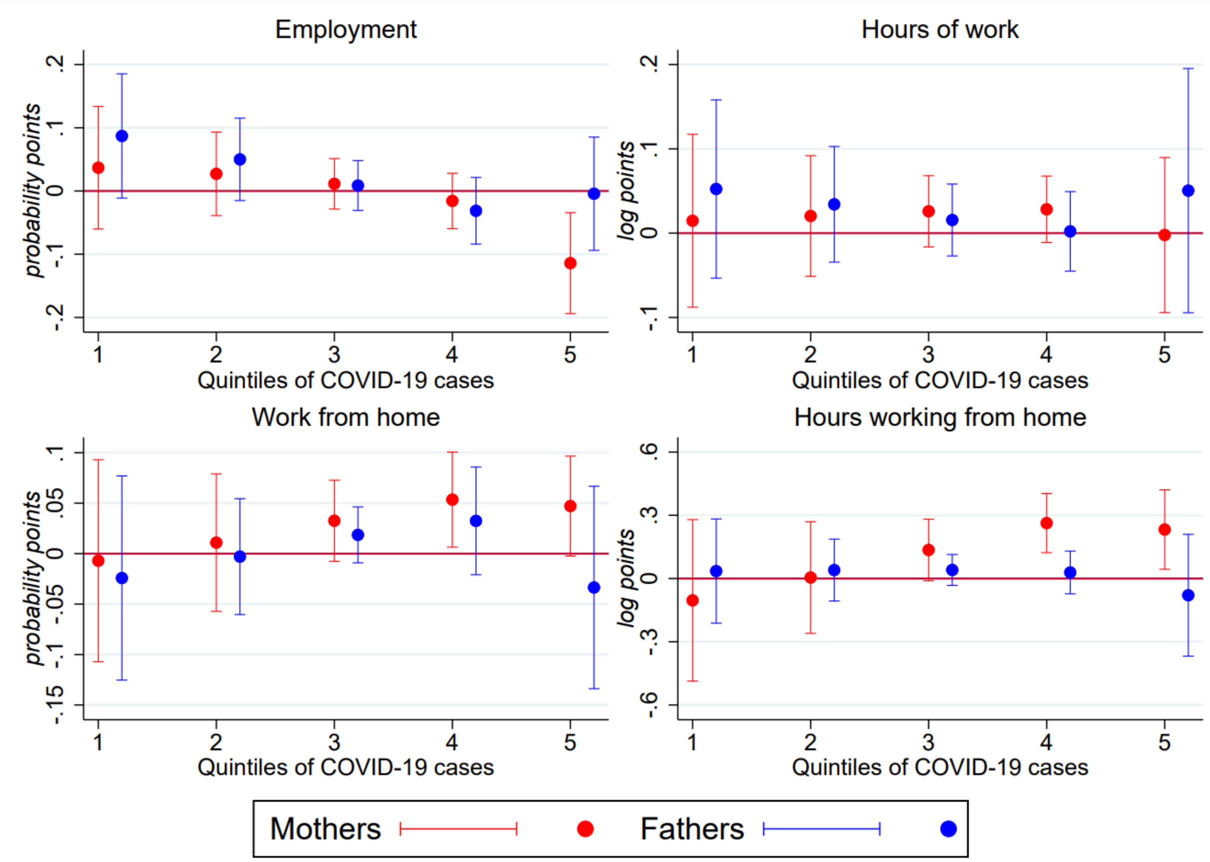
Notes: Figure shows a relationship between the average marginal effects (AME) of school closures on parental health problems, children's health problems, flu-like symptoms, upper respiratory illnesses, and different levels of COVID-19 exposure. AME corresponding to each quintile *k* is computed based on all observations between a quintile *k-1* and a quintile *k* using individual and year fixed effects models. Error bands represent 90 percent confidence intervals.

Figure 9: The Health Effects of School Closures by the Level of COVID-19 Exposure. Region and Year Fixed Effects Estimates



Notes: Figure shows a relationship between the average marginal effects of school closures on parental labor supply and different levels of COVID-19 exposure. AME corresponding to each quintile *k* is computed based on all observations between a quintile *k-1* and a quintile *k* using region and year fixed effects models. Error bands represent 90 percent confidence intervals.

Figure 10: The Health Effects of School Closures by the Level of COVID-19 Exposure. Individual and Year Fixed Effects Estimates



Notes: Figure shows a relationship between the average marginal effects of school closures on parental labor supply and different levels of COVID-19 exposure. AME corresponding to each quintile *k* is computed based on all observations between a quintile *k-1* and a quintile *k* using individual and year-fixed effects models. Error bands represent 90 percent confidence intervals.

9 Appendix 1: Theoretical Framework

See separate attachment.

10 Appendix 2: Additional Tables and Figures

See separate attachment.

11 Appendix 3: Effect of School Closure on Depression

See separate attachment.

12 Appendix 4: Why Are Hours of Work Not Responsive?

See separate attachment

Appendix to
"School Closure during the COVID-19 Pandemic: The Health-Employment Tradeoff"

Appendix 1: Theoretical Framework

In this section, we develop a static model of parents' time use which motivates our empirical research. The model is based on a set of assumptions which enable us to derive the closed-form solution. Assuming a one-child family, parents' utility, u, is a function of composite household consumption, c, parents' hours of leisure, l^P, and a child's quality, q. We also introduce a utility loss from the time when parents are sick, b^P. Under the assumption of the Cobb-Douglas form of utility,

$$u = \delta_1 \ln(c) + \delta_2 \ln(l^P) + \delta_3 ln(q) - \delta_4 ln(b^P), \tag{W1}$$

where $\delta_1 > 0$, $\delta_2 > 0, \delta_3 > 0$ and $\delta_4 > 0$. Parents work t hours earning w dollars per hour. We assume that parents can allocate earned income only towards composite household consumption, c. Therefore, parents' budget constraint is $c = wt.$ A child's quality, q, is given by $A \cdot I$, the productivity parameter multiplied by the net time investment to children:

$$q = A \cdot I = A(s + \pi\tau - b^C), \qquad A > 0, \qquad \pi > 0, \tag{W2}$$

where the net time investment to children, I, is equal to time at school, s, plus the time parents invest into education of their children, τ, times the substitutability parameter between teacher's and parent's time, π, minus the amount of time a child is ill, b^C. The more time children spend at school during the pandemic, the higher is the likelihood of being infected, and, therefore, the more time parents spend taking care of their ill child. We assume that the time parents spend with a sick child linearly depends on s, $b^C = \zeta \cdot s$, where ζ is the rate of disease spread, $\zeta \geq 0$; ζ is non-negative and increasing with the severity of the pandemic. We also assume that the time parents are being sick depends on the school length indirectly through within-family contagion from child to parent, which is assumed to be non-negative, $b^P = \lambda^{C \to P} b^C$, $\lambda^{C \to P} \geq 0$. For simplicity of presentation, we omit the potential direct effect of school closure on parents' mental health issues.

In total, parents have 480 hours per month to allocate between work, t, leisure, l^P, time invested into a child's education, τ, time caring for a sick child, b^C, and time being sick themselves, b^P. Consequently, parents' time constraint is the following:

$$480 = l^P + t + \tau + b^C + b^P. \tag{W3}$$

Given the time a child attends school in-person, s, the wage rate, w, the productivity parameter of investment into children, A, the illness spread rate, ζ, and the child-to-parent contagion rate, $\lambda^{C\to P}$, parents optimally choose their working hours, t, and time spent with children, τ, to maximize their utility function (1) subject to the budget constraint, $c = wt$, a child's quality production function (2), and time constraint (3). Thus, the parents' problem can be presented in the following way:

$$\max_{t,\tau} \delta_1 \ln(t) + \delta_2 \ln(480 - t - \tau - \zeta s - \lambda^{C\to P}\zeta s) + \delta_3 ln(s - \zeta s + \pi\tau) + Const, \text{ where } Const = \delta_1 \ln(w) + \delta_3 \ln(A) - \delta_4 ln(\lambda^{C\to P}\zeta s). \tag{W4}$$

The solution to the utility maximization problem is provided in web Appendix 1. We derive the following relationship between hours of work and in-person time at school.

We derive model solutions using first order conditions with respect to $\boldsymbol{\tau}$ (5) and $\boldsymbol{t}$ (6):

$$-\frac{\delta_2}{\boldsymbol{l^P}} + \frac{\delta_3}{\boldsymbol{I}} = 0 \tag{W5}$$

$$-\frac{\delta_2}{\boldsymbol{l^P}} + \frac{\delta_1}{\boldsymbol{t}} = 0 \tag{W6}$$

We first substitute the time constraints and child investment for $\boldsymbol{l^P}$ and $\boldsymbol{I}$ into equation (5) and derive the expression for $\boldsymbol{\tau}$:

$$\delta_2(\boldsymbol{s} - \zeta \boldsymbol{s} + \pi\boldsymbol{\tau}) = \delta_3(480 - \boldsymbol{t} - \boldsymbol{\tau} - \zeta \boldsymbol{s} - \lambda^{C\to P}\zeta \boldsymbol{s})$$
$$\delta_2\pi\boldsymbol{\tau} + \delta_3\boldsymbol{\tau} = 480\delta_3 - \delta_2(1-\zeta)\boldsymbol{s} - \delta_3\zeta(1+\lambda^{C\to P})\boldsymbol{s} - \delta_3\boldsymbol{t}$$

$$\tau = \frac{480\delta_3}{(\delta_2\pi + \delta_3)} - \frac{\delta_2(1-\zeta) + \delta_3\zeta(1+\lambda^{C\to P})}{(\delta_2\pi + \delta_3)}\boldsymbol{s} - \frac{\delta_3}{(\delta_2\pi + \delta_3)}\boldsymbol{t} \tag{W7}$$

Then, combining the two first order conditions (W1) and (W2) and the expression for $\boldsymbol{\tau}$ (W7), we derive an expression for $\boldsymbol{t}$:

$$\delta_3 \boldsymbol{t} = \delta_1 \boldsymbol{I}$$

$$\boldsymbol{t} = \frac{\delta_1}{\delta_3}(\boldsymbol{s} - \zeta \boldsymbol{s} + \pi \boldsymbol{\tau}) = \frac{\delta_1(1-\zeta)}{\delta_3}\boldsymbol{s} + \frac{\delta_1}{\delta_3}\pi\boldsymbol{\tau}$$

$$\boldsymbol{t} = \frac{\delta_1(1-\zeta)}{\delta_3}\boldsymbol{s} + \frac{480\delta_1}{(\delta_2\pi + \delta_3)} - \frac{\delta_1\delta_2(1-\zeta) + \delta_1\delta_3\zeta(1+\lambda^{C\to P})}{(\delta_2\pi + \delta_3)\delta_3}\boldsymbol{s} - \frac{\delta_1}{(\delta_2\pi + \delta_3)}\boldsymbol{t}$$

$$\frac{\delta_1 + \delta_2 + \delta_3}{(\delta_2\pi + \delta_3)}\boldsymbol{t} = \frac{480\delta_1}{(\delta_2\pi + \delta_3)} + \frac{\delta_1(1-\zeta)}{\delta_3}\boldsymbol{s} - \frac{\delta_1\delta_2(1-\zeta) + \delta_1\delta_3\zeta(1+\lambda^{C\to P})}{(\delta_2\pi + \delta_3)\delta_3}\boldsymbol{s}$$

$$\frac{\delta_1 + \delta_2 + \delta_3}{(\delta_2\pi + \delta_3)}\boldsymbol{t} = \frac{480\delta_1}{(\delta_2\pi + \delta_3)} - \frac{(\delta_2 + \delta_3)\delta_1(1-\zeta) - \delta_1\delta_2(1-\zeta) - \delta_1\delta_3\zeta(1+\lambda^{C\to P})}{(\delta_2\pi + \delta_3)\delta_3}\boldsymbol{s}$$

$$\frac{\delta_1 + \delta_2 + \delta_3}{(\delta_2\pi + \delta_3)}\boldsymbol{t} = \frac{480\delta_1}{(\delta_2\pi + \delta_3)} + \frac{\delta_1(1-\zeta) - \delta_1\zeta(1+\lambda^{C\to P})}{(\delta_2\pi + \delta_3)}\boldsymbol{s}$$

$$\boldsymbol{t} = \frac{480\delta_1}{(\delta_1 + \delta_2 + \delta_3)} + \frac{\delta_1(1-\zeta) - \delta_1\zeta(1+\lambda^{C\to P})}{(\delta_1 + \delta_2 + \delta_3)}\boldsymbol{s}$$

$$\boldsymbol{t} = Const2 + \delta_1\frac{(1-\zeta) - \zeta(1+\lambda^{C\to P})}{(\delta_1 + \delta_2 + \delta_3)}\boldsymbol{s}$$

Alternative representation

$$t = Const2 + \delta_1\frac{1 - \zeta[2 + \lambda^{C\to P}]}{(\delta_1 + \delta_2 + \delta_3)}s \qquad \text{(W8)}$$

When the transmission of disease is zero or close to zero ($\zeta \to 0$), the effect of in-person school time on parents' labor supply is predicted to be positive, and this effect is increasing with higher preferences of parents towards work and consumption (δ_1). As the rate of disease transmission goes up, the effect of keeping schools open on working hours becomes smaller due to the increased likelihood of parents and children becoming ill and more time being taken from work. At higher values of the disease spread, the marginal effect of s on t switches to negative and decreases further with more contagion from children to parents.

The main takeaway from this model is that the pandemic-related school closure (i.e., reduction in s when ζ is non-zero) has a theoretically ambiguous effect on hours of work. The relationship between school closings and labor supply is predicted to be negative under non-pandemic conditions, but it becomes weaker (or switches the sign) with higher disease transmissibility. Thus, when assessing the effect of pandemic-related schooling disruptions on labor supply, the proper counterfactual policy should be school opening that provides the same level of protection against illness.

The introduction of the mental health channel into the model does not change model predictions, but it would mitigate the negative indirect effect of school closure on parent's illness. If longer school closures trigger various health issues by elevating parent's stress level, then the overall policy effect on parent's health becomes theoretically ambiguous.[1] It would be interesting to test this effect empirically. The model can be further developed to accommodate the possibility of working from home by splitting the total hours by place of work. In this case, the model would predict the re-allocation of hours towards work from home in response to school closures, provided that such re-allocation is feasible for the type of job the parent holds. We leave these and other important considerations for the empirical analysis.

Conclusions:

1. The effect of in-person school time on labor supply is unambiguously positive when disease spread, ζ, is zero or close to zero:
$$\left.\frac{dt}{ds}\right|_{\zeta=0} = \frac{\delta_1}{(\delta_1 + \delta_2 + \delta_3)}$$
2. When the spread goes up, the effect of opened schools on labor supply becomes smaller and can become negative if the spread is high enough.
3. When the disease spread is non-zero, we also see that the responsiveness of labor supply to open schooling is diminishing with higher contagion from children to parent (and the likelihood of parents being sick) and with higher preferences towards work and consumption.

[1] Suppose $b^P = \lambda^{C\to P}\zeta s - ms$, where m is the effect of school length on the time associated with parents' illness through the mental health channel, $m \geq 0, \lambda^{C\to P} \geq 0, \zeta \geq 0$. Then, the equation for hours of work becomes:
$$t = Const3 + \delta_1 \frac{1 - \zeta[2 + \lambda^{C\to P}] + m}{(\delta_1 + \delta_2 + \delta_3)} s$$

The model is based on theoretical assumptions, some of which can be tested empirically:

1. Keeping schools opened under the pandemic increases the likelihood of children getting infection and becoming ill, $b^C = \zeta \cdot s$ when $\zeta > 0$
2. The effect of school closure on child's illness is larger (more negative) at the higher rates of coronavirus spread, ζ.
3. The indirect contagion effect of in-person schools on parent's illness is positive $b^P = \lambda^{C \to P} \cdot \zeta \cdot s$, $\lambda^{C \to P} \geq 0$
4. The indirect effect of school closure on parent's illness is larger (more negative) at the higher rates of coronavirus spread, ζ.
5. The direct effect of school closure on a parent's illness could be positive.
6. The illness rate is likely to go down when schools are closed for pandemic-related reasons than when schools are closed for other reasons (e.g., school breaks).

Appendix 2: Additional Tables and Figures

Table W1: Additional Summary Statistics

Variables	Mothers' Sample	Fathers' Sample	Variables	Children' Sample
		A. Variables used in health models		
Any child's health problems	.404	.407	Child's health problems	.269
Parent's health issues	.235	.18	Any parent's health issues	.237
Parent's age			Parent's age	
18-34	.348	.239	18-34	.35
35-44	.539	.556	35-44	.543
45-60	.113	.205	45-60	.107
Parent's education			Parent's education	
Basic general	.093	.133	Basic general	0.107
Secondary general	.259	.364	Secondary general	0.269
Secondary professional	.22	.208	Secondary professional	.21
Tertiary	.428	.295	Tertiary	.412
Married parent	.837	.986	Married parent	.834
Place of residence			Place of residence	
Regional capital	.389	.38	Regional capital	.377
Other urban settlement	.354	.355	Other urban settlement	.345
Rural area	.257	.265	Rural area	.277
Child's age (youngest)	9.843	9.771	Child's age	10.174
	2.284	2.256		2.268
Pre-pandemic serious illness	.696	.683	Pre-pandemic serious illness	.692
N (parent's health model)	7,571	5,941	N (child's health model)	9,279

	B. Variables used in other models			
Indoor occupation	.196	-.797	Child's flu-like symptoms	.22
Unstructured job	.127	-.202	Child's absent for illness	.071
Older caregiver	.16	.141	Non-HH member cared for child	.164
Depression	.086	.05	A relative cared for child	.089

Notes: This table reports summary statistics for individual and household characteristics in 2017-2021. The samples in Panel A are from the estimated equations in Tables 4 (W2), 5 and 6 (W3). Summary statistics in Panel B are from the largest estimation sample where each variable was used. The description of variables can be found in Table 1. In children's sample, parent's age and education are for mothers; if the mother is absent, then father's characteristics are used.

Table W2: Child's Health Equations

	Region +Year FEs			Individual + Year FEs		
	Health Problems	Flu-like Symptoms	Upper Respiratory Tract Disease	Health Problems	Flu-like Symptoms	Upper Respiratory Tract Disease
School closure	-0.053**	-0.058***	-0.026***	-0.068***	-0.033	-0.018
	(0.024)	(0.016)	(0.009)	(0.025)	(0.025)	(0.011)
School break	-0.032	-0.029	-0.001	-0.033	-0.040*	-0.011
	(0.019)	(0.020)	(0.011)	(0.021)	(0.021)	(0.010)
Long holidays	-0.039*	-0.024	-0.020**	-0.018	0.013	0.000
	(0.021)	(0.023)	(0.010)	(0.028)	(0.028)	(0.011)
Workplace closure	0.053	0.065	-0.012	0.014	0.037	0.013
	(0.054)	(0.060)	(0.031)	(0.081)	(0.074)	(0.030)
Self-isolation policy	0.019**	0.005	0.004	0.004	-0.002	-0.001
	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)	(0.004)
Social distancing policy	-0.008	-0.005	0.004	-0.008	-0.001	0.003
	(0.010)	(0.007)	(0.003)	(0.009)	(0.008)	(0.004)
Child's age	-0.011***	-0.011***	-0.003	-0.007**	-0.007**	0.001
	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)
Parent's age						
35-44	0.001	0.001	0.003	0.017	0.031	0.011
	(0.015)	(0.014)	(0.009)	(0.023)	(0.023)	(0.011)
45-60	-0.006	0.012	0.002	0.045	0.046	0.044**
	(0.019)	(0.022)	(0.016)	(0.041)	(0.045)	(0.020)
Parent's education						
Secondary general	-0.012	-0.025	0.048***	-0.030	-0.027	0.005
	(0.020)	(0.018)	(0.015)	(0.048)	(0.049)	(0.024)
Secondary professional	-0.008	-0.028	0.028**	-0.111*	-0.001	-0.012
	(0.019)	(0.018)	(0.010)	(0.063)	(0.060)	(0.029)
Tertiary	-0.002	-0.017	0.048***	-0.211**	-0.029	-0.044
	(0.021)	(0.020)	(0.011)	(0.087)	(0.073)	(0.037)
Married parent	0.007	0.019*	-0.003	-0.014	0.061*	-0.021
	(0.016)	(0.011)	(0.009)	(0.032)	(0.034)	(0.017)
Older caregiver	0.001	0.012	0.013	-0.024	0.019	-0.005
	(0.020)	(0.018)	(0.016)	(0.035)	(0.038)	(0.018)
Childcare from outside helper	0.023	0.005	0.003	-0.002	-0.019	0.011
	(0.014)	(0.012)	(0.009)	(0.014)	(0.015)	(0.007)
Received government assistance	0.041*	0.025	0.007	0.013	0.000	0.013
	(0.021)	(0.023)	(0.012)	(0.023)	(0.023)	(0.010)

Received children's benefits	0.001	0.003	0.013	-0.017	0.012	0.008
	(0.014)	(0.014)	(0.010)	(0.015)	(0.015)	(0.009)
Unemployment rate	0.012	-0.002	-0.007	0.010	-0.003	-0.005
	(0.010)	(0.007)	(0.005)	(0.008)	(0.007)	(0.003)
COVID-19 spread	-0.003	-0.006	0.000	0.038	-0.007	-0.013
	(0.023)	(0.040)	(0.022)	(0.034)	(0.033)	(0.016)
Pre-pandemic serious illness	0.067***	0.060***	0.058***	…	…	…
of a parent	(0.016)	(0.013)	(0.013)			
Pre-pandemic serious illness	0.146***	0.102***	0.057***	…	…	…
of a child	(0.016)	(0.022)	(0.019)			
Russian	0.002	0.032*	-0.004	…	…	…
	(0.025)	(0.016)	(0.017)			
Born abroad	0.007	0.028	0.002	…	…	…
	(0.019)	(0.023)	(0.018)			
Observations	9,241	8,441	9,228	8,743	7,956	8,730
R squared overall	0.069	0.056	0.076	0.385	0.384	0.551

Notes: Table presents estimates of Equations (3) and (4). Sample includes children in grades 1-8 under age 15. The description of variables can be found in Table 1. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. Omitted (base) categories are age 18-34 for parent's age, basic general for parent's education. Parent's age and education are for mothers. If the mother is absent, then father's characteristics are used.

Table W4: Effect of School Closures on Parental Labor Supply and Health Problems

Variables	Health Problems		Employed		Log total hours		Work from home		Hours working from	
	Mothers	Fathers	Mothers	Fathers	Mothers	Fathers	Mothers	Fathers	Mothers	Fathers
	Region + Year FE									
School closure	0.038	0.049*	-0.040	-0.019	0.025	-0.016	0.051***	0.013	0.219***	0.024
	(0.037)	(0.026)	(0.027)	(0.019)	(0.016)	(0.022)	(0.018)	(0.013)	(0.059)	(0.044)
School break	-0.006	0.023	0.013	-0.004	0.015	0.017	0.027*	-0.002	0.131**	0.001
	(0.019)	(0.017)	(0.018)	(0.019)	(0.015)	(0.017)	(0.015)	(0.009)	(0.050)	(0.024)
Long holidays	0.031	0.020	-0.042*	-0.011	-0.032	-0.012	0.032	-0.011	0.093	-0.028
	(0.023)	(0.017)	(0.024)	(0.024)	(0.025)	(0.018)	(0.023)	(0.011)	(0.066)	(0.025)
Workplace closure	-0.079	-0.058	0.088	0.009	0.019	-0.005	-0.140**	0.010	-0.438**	0.041
	(0.076)	(0.040)	(0.092)	(0.054)	(0.053)	(0.047)	(0.065)	(0.049)	(0.185)	(0.107)
Self-isolation policy	0.028***	0.015**	0.005	-0.005	-0.005	0.003	0.009*	0.001	0.025*	0.002
	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)	(0.004)	(0.005)	(0.004)	(0.014)	(0.010)
Social distancing policy	-0.005	-0.003	-0.002	0.011*	-0.007	-0.012***	-0.001	0.001	0.017	-0.005
	(0.009)	(0.008)	(0.008)	(0.005)	(0.008)	(0.004)	(0.006)	(0.004)	(0.020)	(0.011)
Age of youngest child	0.005**	0.003	0.006*	0.001	0.000	0.002	-0.003	-0.000	-0.009	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)
Parent's age										
30-44	0.006	0.017	0.063***	-0.010	0.008	-0.006	0.017	0.003	0.028	0.003
	(0.008)	(0.016)	(0.014)	(0.012)	(0.009)	(0.012)	(0.010)	(0.007)	(0.027)	(0.014)
45-60	0.005	0.041**	0.026	-0.064***	0.015	-0.002	0.031*	-0.002	0.067	0.002
	(0.018)	(0.018)	(0.028)	(0.021)	(0.017)	(0.017)	(0.018)	(0.011)	(0.055)	(0.019)
Parent's education										
Secondary general	0.004	0.014	0.105***	0.069**	-0.001	-0.020	-0.003	0.010**	-0.014	0.010
	(0.022)	(0.015)	(0.035)	(0.026)	(0.027)	(0.019)	(0.012)	(0.004)	(0.025)	(0.008)
Secondary professional	0.030	0.027	0.116***	0.104***	-0.015	-0.039**	0.008	0.014	0.035	0.026
	(0.026)	(0.018)	(0.038)	(0.031)	(0.029)	(0.019)	(0.014)	(0.008)	(0.029)	(0.015)

Tertiary	0.017	0.019	0.166***	0.130***	-0.014	-0.063**	0.105***	0.063***	0.298***	0.135***
	(0.024)	(0.019)	(0.032)	(0.027)	(0.028)	(0.025)	(0.014)	(0.013)	(0.043)	(0.032)
Married parent	-0.019	0.003	-0.127***	0.137***	-0.053***	0.036	-0.015	-0.004	-0.047	-0.069
	(0.016)	(0.034)	(0.019)	(0.036)	(0.008)	(0.052)	(0.011)	(0.031)	(0.033)	(0.100)
Older caregiver	-0.032*	-0.009	-0.012	0.050***	0.011	-0.014	0.022	0.002	0.049	-0.004
	(0.016)	(0.023)	(0.013)	(0.016)	(0.014)	(0.016)	(0.018)	(0.010)	(0.055)	(0.019)
Childcare from outside	0.007	-0.002	0.021*	0.014	-0.015	-0.003	0.002	0.009	-0.030	0.012
helper	(0.011)	(0.014)	(0.012)	(0.013)	(0.012)	(0.009)	(0.012)	(0.006)	(0.037)	(0.015)
Received government	0.056***	0.051***	-0.107***	-0.110***	-0.008	0.012	-0.039***	-0.002	-0.113***	-0.013
assistance	(0.015)	(0.017)	(0.023)	(0.020)	(0.023)	(0.019)	(0.012)	(0.014)	(0.036)	(0.034)
Received children's	-0.019	0.022*	-0.211***	-0.043***	-0.044**	-0.005	-0.026***	-0.011**	-0.056**	-0.016
benefits	(0.012)	(0.011)	(0.021)	(0.015)	(0.017)	(0.009)	(0.008)	(0.005)	(0.025)	(0.010)
Unemployment rate	-0.009	0.006	-0.009	-0.015**	-0.001	-0.003	-0.004	0.002	0.029	0.005
	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.004)	(0.018)	(0.009)
COVID-19 spread	-0.027	-0.034	0.042	-0.033	0.053***	-0.041	0.070***	0.045**	0.319***	0.125***
	(0.025)	(0.030)	(0.028)	(0.025)	(0.012)	(0.027)	(0.022)	(0.019)	(0.086)	(0.042)
Pre-pandemic serious illness	0.138***	0.090***	-0.041***	0.001	-0.017*	-0.003	0.022**	0.004	0.062**	0.007
of any child	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)	(0.008)	(0.010)	(0.005)	(0.028)	(0.013)
Pre-pandemic serious illness	0.137***	0.136***	-0.012	-0.024	0.013	0.005	0.001	0.006	0.017	0.030
of a parent	(0.015)	(0.019)	(0.014)	(0.016)	(0.014)	(0.009)	(0.011)	(0.007)	(0.034)	(0.021)
Russian	0.031	-0.000	0.028	0.048**	0.015	-0.028	0.028	0.011	0.106*	0.008
	(0.020)	(0.019)	(0.034)	(0.018)	(0.021)	(0.020)	(0.018)	(0.009)	(0.054)	(0.020)
Born abroad	0.006	-0.020	-0.022	-0.011	0.047**	0.028*	-0.015	-0.025**	-0.019	-0.065***
	(0.025)	(0.018)	(0.033)	(0.022)	(0.022)	(0.015)	(0.019)	(0.011)	(0.060)	(0.021)
Indoor occupation	…	…	…	…	0.005	0.002	0.011	0.012***	0.035	0.020**
					(0.010)	(0.006)	(0.009)	(0.004)	(0.023)	(0.008)
Unstructured job	…	…	…	…	0.001	0.003	0.030***	0.009	0.088***	0.020
					(0.006)	(0.006)	(0.006)	(0.007)	(0.018)	(0.015)
Industry										
Mining & manufacturing	…	…	…	…	0.012	-0.068*	-0.022	-0.004	-0.045	-0.013
					(0.030)	(0.040)	(0.019)	(0.010)	(0.046)	(0.022)
Housing & utilities	…	…	…	…	-0.088*	-0.128***	-0.082***	-0.004	-0.224**	-0.020
					(0.047)	(0.045)	(0.028)	(0.012)	(0.091)	(0.027)
Construction	…	…	…	…	-0.046	-0.041	0.045	0.017	0.074	0.022
					(0.044)	(0.040)	(0.042)	(0.013)	(0.088)	(0.029)
Transportation &	…	…	…	…	-0.046	-0.019	-0.028	0.004	-0.073	-0.002
communication					(0.033)	(0.042)	(0.019)	(0.011)	(0.054)	(0.025)
Trade & consumer services	…	…	…	…	0.012	-0.048	0.003	0.032**	-0.005	0.033
					(0.033)	(0.046)	(0.019)	(0.015)	(0.048)	(0.031)
Health care & social	…	…	…	…	-0.041	-0.073	-0.019	-0.018	-0.072	-0.019
assistance					(0.035)	(0.051)	(0.019)	(0.016)	(0.048)	(0.040)
Education, science, culture	…	…	…	…	-0.074**	-0.137**	0.130***	0.088**	0.366***	0.255**
					(0.031)	(0.051)	(0.024)	(0.040)	(0.076)	(0.124)
Public administration	…	…	…	…	-0.007	0.002	-0.041**	-0.029**	-0.133**	-0.062**
					(0.035)	(0.046)	(0.020)	(0.011)	(0.051)	(0.025)
Other/unknown	…	…	…	…	-0.055	-0.089**	0.067**	0.069**	0.201**	0.094
					(0.040)	(0.042)	(0.027)	(0.030)	(0.083)	(0.059)
Observations	7,504	5,894	7,512	5,901	5,092	4,691	5,253	5,008	5,208	4,972

R squared overall	0.102	0.075	0.162	0.213	0.067	0.086	0.144	0.090	0.150	0.091
					Individual + Year FE					
School closure	0.033	0.044	-0.022	-0.007	0.016	-0.001	0.036*	0.016	0.190***	0.011
	(0.030)	(0.032)	(0.022)	(0.023)	(0.021)	(0.023)	(0.021)	(0.020)	(0.070)	(0.042)
School break	-0.022	0.004	-0.000	-0.013	-0.000	0.026*	0.004	0.004	0.026	0.001
	(0.021)	(0.022)	(0.017)	(0.017)	(0.018)	(0.015)	(0.016)	(0.011)	(0.043)	(0.025)
Long holidays	0.023	0.005	-0.042*	0.006	-0.008	-0.034*	0.021	-0.019	0.080	-0.033
	(0.029)	(0.031)	(0.025)	(0.022)	(0.028)	(0.020)	(0.024)	(0.014)	(0.083)	(0.035)
Workplace closure	-0.101	-0.094	0.040	-0.026	-0.036	0.023	-0.156**	0.018	-0.431**	0.003
	(0.079)	(0.071)	(0.071)	(0.050)	(0.064)	(0.051)	(0.066)	(0.054)	(0.201)	(0.126)
Self-isolation policy	0.009	-0.005	0.011*	0.001	-0.009	-0.005	0.003	0.002	0.004	0.008
	(0.008)	(0.008)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.014)	(0.008)
Social distancing policy	0.000	-0.005	0.001	0.009	-0.008	-0.002	0.005	-0.001	0.015	-0.011
	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.004)	(0.017)	(0.008)
Age of youngest child	0.004	0.005	0.005	-0.004	0.005	0.001	-0.003	-0.001	-0.010	-0.006
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.008)	(0.004)
Parent's age										
30-44	0.019	0.013	0.042*	0.001	-0.001	0.032**	0.012	-0.023*	0.020	-0.045
	(0.023)	(0.024)	(0.023)	(0.019)	(0.016)	(0.015)	(0.016)	(0.013)	(0.045)	(0.029)
45-60	-0.055	-0.020	0.050	0.013	-0.041	0.041	0.016	-0.032	0.016	-0.079*
	(0.043)	(0.042)	(0.037)	(0.028)	(0.032)	(0.027)	(0.030)	(0.020)	(0.079)	(0.048)
Parent's education										
Secondary general	-0.010	-0.003	0.038	-0.010	-0.010	-0.013	0.002	0.015*	0.016	0.012
	(0.046)	(0.035)	(0.049)	(0.026)	(0.043)	(0.024)	(0.019)	(0.008)	(0.049)	(0.014)
Secondary professional	0.001	-0.106**	0.034	-0.022	-0.000	0.021	-0.004	-0.012	0.019	-0.021
	(0.059)	(0.050)	(0.054)	(0.032)	(0.054)	(0.030)	(0.023)	(0.023)	(0.059)	(0.045)
Tertiary	-0.047	-0.083	0.055	0.005	0.009	0.050	0.032	-0.001	0.099	0.059
	(0.078)	(0.065)	(0.064)	(0.053)	(0.060)	(0.046)	(0.035)	(0.033)	(0.121)	(0.079)
Married parent	0.014	0.010	-0.069**	0.038	-0.031	-0.079	-0.009	0.012	-0.015	0.014
	(0.038)	(0.063)	(0.033)	(0.073)	(0.034)	(0.085)	(0.019)	(0.024)	(0.055)	(0.042)
Older caregiver	-0.035	-0.055	-0.023	0.004	0.063**	-0.004	0.063**	-0.004	0.159*	-0.024
	(0.033)	(0.041)	(0.029)	(0.024)	(0.031)	(0.023)	(0.028)	(0.017)	(0.082)	(0.040)
Childcare from outside helper	-0.004	0.001	0.031**	-0.000	0.011	0.005	-0.013	0.010	-0.064*	0.017
	(0.015)	(0.015)	(0.013)	(0.010)	(0.013)	(0.010)	(0.011)	(0.009)	(0.035)	(0.018)
Received government assistance	0.036	0.029	-0.077***	-0.074***	-0.003	0.002	-0.017	-0.001	-0.040	0.004
	(0.023)	(0.023)	(0.021)	(0.020)	(0.019)	(0.016)	(0.014)	(0.012)	(0.042)	(0.027)
Received children's benefits	-0.017	-0.019	-0.136***	-0.022*	-0.036***	0.028***	-0.009	-0.000	-0.030	0.003
	(0.016)	(0.016)	(0.017)	(0.011)	(0.014)	(0.010)	(0.012)	(0.007)	(0.036)	(0.017)
Unemployment rate	-0.015*	0.002	-0.000	-0.005	-0.002	-0.002	-0.003	0.001	0.025	-0.003
	(0.008)	(0.008)	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.005)	(0.021)	(0.012)
COVID-19 spread	-0.022	-0.062*	0.021	-0.031	0.030	-0.030	0.039	0.039	0.203*	0.114
	(0.041)	(0.036)	(0.030)	(0.025)	(0.027)	(0.027)	(0.033)	(0.029)	(0.119)	(0.082)
Pre-pandemic serious illness of any child	0.062***	0.042***	-0.018*	-0.009	-0.018*	-0.015*	0.004	0.004	-0.005	0.011
	(0.014)	(0.014)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.007)	(0.028)	(0.016)
Indoor occupation	…	…	…	…	0.003	-0.012	0.002	0.000	0.044*	-0.007
					(0.019)	(0.010)	(0.011)	(0.004)	(0.027)	(0.011)
Unstructured job	…	…	…	…	0.001	-0.000	0.020**	-0.003	0.040*	-0.005
					(0.010)	(0.008)	(0.009)	(0.005)	(0.022)	(0.012)
Industry										
Mining &	…	…	…	…	-0.061	-0.024	-0.038	-0.007	-0.136*	0.002

manufacturing					(0.060)	(0.043)	(0.040)	(0.009)	(0.074)	(0.024)
Housing & utilities	…	…	…	…	-0.127**	-0.040	-0.026	0.003	-0.218	0.032
					(0.064)	(0.047)	(0.061)	(0.014)	(0.166)	(0.033)
Construction	…	…	…	…	-0.110	-0.030	-0.129**	0.006	-0.448***	0.015
					(0.081)	(0.045)	(0.064)	(0.008)	(0.138)	(0.021)
Transportation &	…	…	…	…	-0.078	0.033	-0.045	-0.025*	-0.151	-0.020
communication					(0.066)	(0.046)	(0.045)	(0.013)	(0.096)	(0.030)
Trade & consumer	…	…	…	…	-0.052	-0.043	-0.017	-0.011	-0.107	-0.023
services					(0.060)	(0.041)	(0.044)	(0.012)	(0.074)	(0.027)
Health care & social	…	…	…	…	-0.114	-0.070	-0.057	0.034	-0.173	0.074
assistance					(0.071)	(0.071)	(0.059)	(0.047)	(0.117)	(0.135)
Education, science,	…	…	…	…	-0.123*	-0.018	0.037	0.070**	0.040	0.155*
culture					(0.070)	(0.057)	(0.054)	(0.031)	(0.126)	(0.090)
Public administration	…	…	…	…	-0.093	0.006	-0.067	0.024	-0.219*	0.054
					(0.067)	(0.051)	(0.051)	(0.021)	(0.113)	(0.053)
Other/unknown	…	…	…	…	-0.161**	-0.068	0.037	0.001	0.111	-0.084
					(0.070)	(0.050)	(0.048)	(0.033)	(0.102)	(0.064)
Observations	6,993	5,460	7,004	5,468	4,575	4,236	4,740	4,562	4,701	4,523
R squared overall	0.447	0.447	0.697	0.716	0.567	0.602	0.663	0.597	0.684	0.608
Industry fixed effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents estimates of Equations (5) - (8). Sample includes parents with children in grades 1-8 under age 15. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. Omitted (base) categories are age 18-34 for parent's age, basic general for parent's education, regional center for place of residence, agriculture for industry. The negative effect of workplace closure on mother's remote work may seem counter intuitive. In most regions workplace closures lasted for a few days adjacent to holidays, and employers were mandated to provide all non-essential workers with days off.

Table W5: Falsification Test for the Effect of School Closure

Placebo groups/Outcomes	Grade 1	Grade 3	Grade 5	Grade 7	N
Females Without Kids					
Employed	0.026	0.026	0.049	0.002	3,615
	(0.057)	(0.057)	(0.037)	(0.032)	
Total hours of work, log	0.056	0.056	0.019	0.010	1,736
	(0.044)	(0.044)	(0.038)	(0.035)	
Hours at primary job, log	0.020	0.020	-0.021	-0.008	1,736
	(0.059)	(0.059)	(0.065)	(0.044)	
Work from home	0.077	0.077	0.049	0.006	1,911
	(0.122)	(0.122)	(0.067)	(0.049)	
Hours worked from home, log	0.293	0.293	0.132	0.088	1,859
	(0.244)	(0.244)	(0.145)	(0.100)	
Health issues	-0.048	-0.048	0.033	0.020	3,613
	(0.068)	(0.068)	(0.028)	(0.019)	
Males Without Kids					
Employed	0.046	0.046	-0.017	-0.043	4,367
	(0.061)	(0.061)	(0.035)	(0.040)	
Total hours of work, log	-0.076	-0.076	-0.000	-0.015	2,148
	(0.072)	(0.072)	(0.057)	(0.043)	
Hours at primary job, log	-0.086	-0.086	-0.001	-0.010	2,148

	(0.072)	(0.072)	(0.058)	(0.043)	
Work from home	-0.010	-0.010	-0.016	-0.040***	2,444
	(0.035)	(0.035)	(0.024)	(0.013)	
Hours worked from home, log	0.016	0.016	0.014	-0.023	2,411
	(0.043)	(0.043)	(0.028)	(0.017)	
Health issues	0.001	0.001	0.065	0.036	4,361
	(0.065)	(0.065)	(0.051)	(0.045)	
Mothers with Young Kids					
Employed	-0.116	-0.116	-0.081	-0.063	1,417
	(0.107)	(0.107)	(0.058)	(0.047)	
Total hours of work, log	-0.021	-0.021	-0.203	-0.211	566
	(0.155)	(0.155)	(0.199)	(0.129)	
Hours at primary job, log	-0.001	-0.001	-0.191	-0.183	564
	(0.124)	(0.124)	(0.196)	(0.117)	
Work from home	-0.044	-0.044	-0.003	0.005	612
	(0.127)	(0.127)	(0.074)	(0.073)	
Hours worked from home, log	0.075	0.075	-0.096	-0.129	600
	(0.365)	(0.365)	(0.223)	(0.284)	
Health issues	0.053	0.053	0.045	0.005	1,419
	(0.157)	(0.157)	(0.076)	(0.048)	
Fathers with Young Kids					
Employed	0.073	0.073	-0.039	-0.029	1,160
	(0.096)	(0.096)	(0.092)	(0.064)	
Total hours of work, log	0.032	0.032	0.003	-0.004	879
	(0.074)	(0.074)	(0.053)	(0.039)	
Hours at primary job, log	0.037	0.037	0.006	-0.003	879
	(0.073)	(0.073)	(0.052)	(0.039)	
Work from home	-0.052	-0.052	-0.111	-0.052	987
	(0.076)	(0.076)	(0.071)	(0.063)	
Hours worked from home, log	-0.139	-0.139	-0.253**	-0.086	965
	(0.153)	(0.153)	(0.128)	(0.134)	
Health issues	0.051	0.051	0.167	0.089	1,159
	(0.181)	(0.181)	(0.128)	(0.093)	

Notes: Table presents results of the falsification test by replicating Equations (7) and (8) for two placebo groups: (i) childless adults ("no kids") and (ii) parents with young kids under age 7 who do not go to school and who do not have siblings in school ("young kids"). Placebo groups are assumed to have a school-age child in one of the grade levels: 1, 3, 5, and 7 (columns). We assign counterfactual schooling policies to placebo groups based on the region of residence, date of interview, and a fake grade level. The table reports the estimated effect of school closure on the respective outcome variable indicated in the left column. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 3: The Effect of School Closure on Depression

Many studies show negative repercussions of the COVID-19 pandemic for mental health of children and adults (Brodeur et al., 2021; Cheng et al., 2021). Russia is no exception. In 2020, 28.7 percent of adult respondents in the RLMS-HSE noted an increased anxiety during the COVID-19 stay-at-home order and other restrictive measures. 9.8 percent reported elevated levels of depression.

Closing schools has also likely added stress to parents due to altered schedules and more responsibilities for childcare. Unfortunately, the RLMS-HSE survey has only one relevant mental health question which is repeated in every round, "Have you had a serious nervous disorder or depression in the last 12 months?"

The reference to the past 12 months prevents us from exploiting month-to-month variation in depression and schooling policies within a year. For that reason, we choose to report the results in Appendix instead of the main body of the paper. To address the data limitation, we calculate a number of closed school days and school beaks in the last 12 months and estimate the following models:

$$M_{it}^{P} = \gamma^{MR}\tilde{S}_{it} + \beta^{MHR}\widetilde{H}_{it}^{C} + \beta^{MXR}\tilde{X}_{it}^{PR} + \beta^{MZR}Z_{i,pre}^{P} + \theta_{t}^{MR} + \eta_{r}^{M} + \epsilon_{it}^{MR}, \tag{W9}$$

$$M_{it}^{P} = \gamma^{MF}\tilde{S}_{it} + \beta^{MHF}\widetilde{H}_{it}^{C} + \beta^{MXF}\tilde{X}_{it}^{PF} + \theta_{t}^{MF} + \alpha_{i}^{M} + \epsilon_{it}^{MR}, \tag{W10}$$

where M_{it}^{P} is a binary indicator for parents having psychological disorder or depression in the last 12 months, $\tilde{S}_{it}$ denotes cumulative measures of schooling disruptions over the 12-month period. The only differences between $\tilde{X}_{it}^{PR}$ and $\tilde{X}_{it}^{PF}$ and X_{it}^{PR} and X_{it}^{PF} is that former variables include the numbers of days of long holidays, workplace closures, self-isolation, and social distancing over the last 12-month period instead of last 30 days. For ease of interpretation, we count all days in the hundreds. Other variables are described in Sections 4 and 5. The estimated results below suggest that the longer schools remain closed, the more elevated parental stress is. The negative effect of school closure on mental health is statistically significant only for fathers. This is in line with our previous results on the positive effects of school closure on parental health problems. Our results imply that these positive effects of school closure on parental health problems can be explained by increased incidence of mental health issues.

Table W7: Equations for Parent's Depression

Estimation methods	Region + Year FE		Individual + Year FE	
Variables	Mothers	Fathers	Mothers	Fathers
School closure 12m	0.099	0.081**	0.074	0.060*
	(0.067)	(0.036)	(0.058)	(0.030)
School break 12m	-0.027	0.074*	0.139**	0.046*
	(0.090)	(0.042)	(0.064)	(0.027)
Long holidays 12m	0.369	-0.091	-0.816**	-0.263
	(0.486)	(0.117)	(0.352)	(0.157)
Workplace closure 12m	-0.058	-0.252**	-0.072	-0.115**
	(0.271)	(0.110)	(0.103)	(0.054)

Days of self-isolation 12 m	0.008	-0.003	0.008	0.004*
	(0.006)	(0.004)	(0.007)	(0.002)
Days of social distancing 12 m	-0.003	-0.002	-0.003	-0.001
	(0.005)	(0.002)	(0.006)	(0.002)
Any child had health issues last 30d	0.023**	-0.000	0.027**	0.003
	(0.011)	(0.003)	(0.011)	(0.003)
Age of youngest student	0.001	0.000	-0.077***	-0.012
	(0.002)	(0.001)	(0.018)	(0.008)
Parent's age				
35-44	0.012	-0.001	0.013*	-0.000
	(0.008)	(0.003)	(0.008)	(0.002)
45-60	0.001	0.018**	0.007	0.024***
	(0.013)	(0.007)	(0.015)	(0.009)
Parent's education				
Secondary general	0.009	-0.001	0.006	0.001
	(0.016)	(0.006)	(0.018)	(0.006)
Secondary professional	-0.014	0.000	-0.009	0.004
	(0.014)	(0.008)	(0.015)	(0.009)
Tertiary	-0.048***	-0.002	-0.043**	0.002
	(0.016)	(0.005)	(0.017)	(0.006)
Married parent	-0.048***	-0.152***	-0.052***	-0.152***
	(0.011)	(0.042)	(0.011)	(0.044)
Parent is Russian	-0.014	-0.031***		
	(0.021)	(0.010)		
Parent is an immigrant	0.008	-0.014***		
	(0.015)	(0.003)		
Parent's prior chronic illness	0.025**	0.027***		
	(0.009)	(0.009)		
Older caregiver in the household	-0.035***	0.001	-0.045***	-0.001
	(0.009)	(0.004)	(0.010)	(0.004)
Childcare help from outside of the household	0.002	0.005	0.011	0.008***
	(0.006)	(0.003)	(0.008)	(0.003)
Household receives government assistance	0.001	0.009	0.004	0.016*
	(0.015)	(0.007)	(0.016)	(0.008)
Household receives children's benefits	0.020	0.016**	0.013	0.012**
	(0.013)	(0.007)	(0.013)	(0.006)
Unemployment rate	0.008	0.002	0.004	0.001
	(0.007)	(0.006)	(0.004)	(0.001)
COVID-19 spread 12m	0.001	0.001	-0.004	-0.001*
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	7,632	5,805	7,632	5,805
R squared overall	0.054	0.105	0.023	0.045

Notes: Table presents estimates of equations for parent's depression. The dependent variable is whether parents had a serious nervous disorder or depression in the last 12 months. All estimations include year fixed effects. Whenever possible, variables are constructed for the 12-month period. The description of variables can be found in Table 1. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. Omitted (base) categories are age 18-34 for parent's age and basic secondary for parent's education.

Appendix 4: Why Are Hours of Work Not Responsive?

In this Appendix, we test two hypotheses for why we find no response in hours of work to school closure. We hypothesize that families may keep the same workload by arranging alternative childcare or by reallocating hours across time (e.g., working more hours during days when schools were open). The third hypothesis related to work from home is discussed in the main text. To test the first hypothesis, we consider two dependent variables for whether someone outside the household cared for child in the last 7 days ("outsider") and whether relatives outside the household cared for child in the last 7 days ("relatives"). The model is very similar to Equations (3) and (4) for child's health except that child' health issues are now added on the right-hand side of the equation as a regressor. In addition, we check if the effect of school closure and school breaks on alternative childcare arrangement varies by child's grade. The table below shows that the longer the regular school break, the more likely families of younger children in grades 1-4 are seeking outside help to care for their children. We do not observe a similar response with respect to the COVID-19 school closure. It might be the case that families were not able to make childcare arrangements because epidemiological school closures are typically announced on very short notice, or it might be the case that families were reluctant to invite outside caregivers out of concerns over infection. Therefore, we do not find support for the first hypothesis.

Table W8: Marginal Effects of School Closure and School Breaks on Outside Childcare

	Region +Year FEs		Individual + Year FEs	
	Outsiders	Relatives	Outsiders	Relatives
School closure				
Average effect	-0.004	0.007	-0.009	0.007
	(0.019)	(0.018)	(0.021)	(0.020)
Grade 1-4	-0.006	0.025	-0.046	-0.001
	(0.032)	(0.030)	(0.047)	(0.045)
Grade 5-8	-0.003	0.001	0.006	0.012
	(0.020)	(0.019)	(0.019)	(0.017)
School break				
Average effect	0.024	0.027	0.023	0.022
	(0.018)	(0.015)	(0.018)	(0.016)
Grade 1-4	0.053*	0.060***	0.053**	0.056**
	(0.027)	(0.021)	(0.026)	(0.023)
Grade 5-8	-0.008	-0.011	-0.010	-0.017
	(0.017)	(0.016)	(0.021)	(0.018)
N of observations	9,232	9,231	9,232	9,231

Notes: Table presents the average marginal effects (AMEs) of school closure and school breaks on childcare provided by non-household members. Estimation is done using the linear probability model. The model includes a child's health issues as a covariate. All other covariates are the same as in Equations (3) and (4) or Appendix Table W2. The AMEs by grade level are calculated from estimating the same model with an added interaction term between school closure/breaks and child's grade level. The sample includes children in grades 1-8 under age 15. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1.

The ability to shift working hours across days in a month is another possible explanation why parents are not reducing total working hours when schools are closed. If a parent's job allows for shifting hours between days, then we would expect parents to work more hours on the day when schools are not closed to compensate for the lost working time. To test this hypothesis, we create a new variable for "excess worktime" per day of work. We first divide total hours worked at primary job in the last 30 days by the number of business days worked in the last 30 days. This gives us the average actual hours worked per day in the last 30 days. Then, we subtract the average length of a normal workday. Thus, the difference shows excess hours worked per day in the last 30 days over the usual daily workload. We estimate the equation for excess hours using the same methods and the same set of covariates as it is specified in Equations (7) and (8). The results reported in Table W9 suggest that the longer schools remain closed, the longer parents stay at work per day compared to a typical workday. At the same time, there is a negative effect of school breaks on excess hours among fathers of older children. The results indicate that parents have flexibility in working hours, and they can work extra hours on the days when they have the opportunity to go to work. This supports our hypothesis that parents have the ability to shift their working hours across time in response to school closures.

Table W9: Marginal Effects of School Closure and School Breaks on Excess Hours per Day

	Region +Year FEs		Individual + Year FEs	
	Mothers	Fathers	Mothers	Fathers
School closure				
Average effect	0.208	0.099	0.126*	0.091
	(0.172)	(0.074)	(0.073)	(0.103)
Grade 1-4	0.347	0.032	0.139*	-0.006
	(0.249)	(0.068)	(0.081)	(0.109)
Grade 5-8	0.136*	0.159	0.115	0.179
	(0.075)	(0.106)	(0.091)	(0.152)
School break				
Average effect	-0.006	-0.026	-0.022	-0.045
	(0.101)	(0.046)	(0.057)	(0.071)
Grade 1-4	0.023	0.045	0.035	0.034
	(0.078)	(0.063)	(0.058)	(0.086)
Grade 5-8	-0.052	-0.144**	-0.103	-0.167*
	(0.079)	(0.063)	(0.107)	0.093
N of observations	5,074	4,634	4,533	4,173

Notes: Table presents the average marginal effects (AMEs) of school closure and school breaks on parent's excess hours per day. All covariates are the same as in Equations (7) and (8). The AMEs by grade level are calculated from estimating the same model with an added interaction term between school closure/breaks and child's grade level. Sample includes working parents with children in grades 1-8 under age 15. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1.

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