

School Closure during the COVID-19 Pandemic: The Health-Employment Tradeoff*

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ABSTRACT: Do the benefits of school closure outweigh the cost? This paper brings the notion of the benefit-cost tradeoff into the analysis 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 is undertaken using the Russian household survey linked with the grade-specific daily dataset on regional school closures and school breaks. We find that school closures (but not breaks) significantly decrease the probability of children experiencing flu-like symptoms and having other health issues. Parents indirectly benefit from school closure via reduced contagion. However, longer school closures cause more depression for both parents. Contrary to other accounts, we find little to no change in maternal labor supply but a significant increase in remote work by mothers. Other benefits and costs of school closure are also discussed.

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 has 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 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 hours of work, 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. What we try to achieve in this study is to bring the notion of 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 that has time-varying measures of parent's employment and hours, parent's health, and child's health. Studies focusing on 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 and deaths after schools re-open for in-person learning. These results are consistent with the

¹ Other costs also include learning losses (Agostinelli et al., 2022; Donnelly and Patrinos, 2021), mental health issues (Lee, 2020; Li et al., 2022; Yamamura and Tsustsui, 2021), etc.

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 to be an effective tool in delaying an epidemic peak and limiting the overall infection spread, especially if schools are closed at the start of the pandemic wave. Therefore, when childcare needs are not an issue, school closure may have a positive effect on labor supply during the pandemic by preventing a possible 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 labor market consequences of school closure. 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 cancelling in-person classes is mainly explained by the necessity to provide additional care for children staying at home. What is missing from the current economics literature is the analysis of the health channel through which school closing may influence employment outcomes as well as the micro-analysis of health consequences of this policy. 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, examining indirect child-to-parent contagion effects of school closure, and estimating the intra-family responses to school closure jointly for mothers, fathers, and children.

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).

We undertake this research using the Russia Longitudinal Monitoring Survey-Higher School of Economics (RLMS-HSE), a representative annual longitudinal survey of Russian households. The choice of country is partly owed to the high quality-data on school closure which is 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. Another important reason is 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 time period that matches the time frame of schooling restrictive policies. Above 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 the length of school closures.

Our data on school closure 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.

Another unique feature of our research design is the possibility to separate COVID-related school closures and 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 a epidemiological study, Garza et al. (2013) find that winter school breaks in Argentina noticeably

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).

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 break across regions and little variation over time may also explain this result.

We estimate that 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; the effect is statistically significant only for mothers in the joint intra-family model. We conjecture that the direct effect of school closure likely captures exacerbated mental health issues due to changed routines and additional stress in balancing work and family when schools are closed. Our estimates indicate a strong positive association between the length of school closure and depression for both parents, although the size of the depression effect for mothers is nearly twice as big as for fathers. Simultaneously, there is an illness-reducing indirect effect of school closure through lowered child-to-parent contagion. In the joint intra-family estimation, the average size of the negative indirect effect fully counterbalances the average size of the positive direct effect, thus, making the mean net effect of schooling restrictive measures on parent's illness close to zero. However, only the indirect effect (and not the direct effect) increases with the COVID-19 spread; hence, at higher rates of disease transmission (more than 1 additional case per 100 people over the 30-day period), epidemiological school closure becomes beneficial for parent's health regardless of associated mental health problems.

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 8.9 pp and hours of remote work rise by 22 per month in response to closing schools for 21 business

days. The likelihood and duration of mother's remote work also increase 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 job, cutting working hours, and working more from home. As a result, the indirect effect of school closure through lower children illness is found only among mothers. However, the magnitude of such 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.

The rest of the paper is structured as follows. Section 2 presents a simple model of parents' time use which incorporates the child's and parent's health. Section 3 describes our survey data and measures of schooling disruptions. In Sections 4 and 5, we estimate the effects of school closure on health and labor supply, respectively. We discuss several identification issues and present estimates of the joint intra-family model in Section 6 and make concluding remarks in Section 7.

2 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,

$$u = \delta_1 \ln(c) + \delta_2 \ln(l^P) + \delta_3 \ln(q) - \delta_4 \ln(b^P), \quad (1)$$

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:

$$q = A \cdot I = A(s + \tau - b^C), \quad A > 0, \quad \pi > 0, \quad (2)$$

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 , 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 at home. 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, $b^P = \lambda^{C \rightarrow P} b^C$, $\lambda^{C \rightarrow P} \geq 0$. At this stage, for simplicity of presentation, we omit the potential direct effect of school closure on parents' mental health issues that may also cause illness-related loss of time.

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:

$$480 = l^P + t + \tau + b^C + b^P. \quad (3)$$

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, $\lambda^{C \rightarrow P}$, 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:

$$\begin{aligned} \max_{t, \tau} & \delta_1 \ln(t) + \delta_2 \ln(480 - t - \tau - \zeta s - \lambda^{C \rightarrow P} \zeta s) + \delta_3 \ln(s - \zeta s + \tau) + \\ & Const, \text{ where } Const = \delta_1 \ln(w) + \delta_3 \ln(A) - \delta_4 \ln(\lambda^{C \rightarrow P} \zeta s). \end{aligned} \quad (4)$$

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.

$$t = Const2 + \delta_1 \frac{1 - \zeta[2 + \lambda^{C \rightarrow P}]}{(\delta_1 + \delta_2 + \delta_3)} s \quad (5)$$

When the transmission of disease is zero or close to zero ($\zeta \rightarrow 0$), 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 model is based on several theoretical assumptions, some of which can be tested empirically with proper data on health conditions of children and parents. Specifically, one can test the model's assumption of the negative association between school closings and the probability of children being sick. The model assumes this association to be stronger at the higher rates of coronavirus spread which can be tested empirically. The indirect child-to-parent contagion effect of school closure on parent's illness is also expected to be negative and stronger in a more severe pandemic environment.

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.⁴ It would be interesting to test this

⁴ Suppose $b^P = \lambda^{C \rightarrow P} \zeta s - ms$, where m is the effect of school length on the time associated with parents' illness through the mental health channel, $m \geq 0, \lambda^{C \rightarrow P} \geq 0, \zeta \geq 0$. Then, the equation for hours of work becomes:

$$t = Const3 + \delta_1 \frac{1 - \zeta[2 + \lambda^{C \rightarrow P}] + m}{(\delta_1 + \delta_2 + \delta_3)} s$$

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.

3 Data

3.1 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 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 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 2019-2021 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 subjects of the Russian Federation.⁵ 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 Fall 2020 and Fall 2021. Even though the data is missing 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

⁵ 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.

the complete lockdown period. Starting in Fall 2020, the isolation of net effects becomes feasible, as we discuss below. In descriptive analysis, we also use a retrospective module on COVID-19 referring to the onset of the COVID-19 pandemic in Spring 2020.

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 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. We exclude parents of pre-school children unless there is an older sibling who goes to school.⁶ 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.⁷ The child-based sample consists of all surveyed school-age children in 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 looked after the child in the past 7 days.

Table 1 shows the description of the variables, whereas Table 2 reports summary statistics of key variables. Additional tables describing the structure of the sample are provided in Appendix 2. We note that presented numbers in Table 2 are for the Fall of each year, thus, they exclude the period of the stay-at-home order in Spring 2020. A smaller percentage of mothers (70-73%) are employed than fathers (86-87%). Mothers' employment went down by 2.5 pp in Fall 2020 compared to Fall 2019 and increased back by 0.7 pp in 2021. Mothers also work fewer hours (175 in the 30-day period in 2019) than fathers (193 hours). Mothers' hours of work decreased by 3 hours per month in 2020 and by 2 hours more during the second pandemic year while fathers' hours of work barely changed. Mothers tend to work from home considerably more frequently than fathers do. The share of mothers who work from home increased from 0.12 to 0.14 in 2020 and decreased to 0.13 in 2021. Only 6 to 7 percent of fathers worked from home during the pandemic. In 2020, average hours worked from home in a 30-day period increased from 37 hours to 50 hours for mothers and from 33 hours to 68 hours for fathers. In 2021, both mothers and fathers worked from home approximately 60 hours, on average. Interestingly, the share of fathers who reported health problems decreased in 2020, from 0.18

⁶ 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.

⁷ This is done to avoid multiple observations per parent-year. The youngest child is likely to require more efforts on childcare arrangement when schools are closed and more parental time when the child gets sick.

to 0.15, and increased back to 0.18 in 2021. This share for mothers was about 0.21-0.22. Not only fathers have had less health problems in 2020 than in pre-pandemic 2019, but also children. The proportion of parents with any child under age 15 experiencing health issues in the last 30 days dropped from 0.37 in 2019 to 0.30 in 2020 and increased back to 0.37 in 2021. At the regional level, unemployment rate increased from 4.5 percent to 6 percent in 2020 but decreased to 4.2 percent in 2021, and the average number of new confirmed COVID-19 cases over the last 30 days was 1 per 100 people in 2021, which is more than twice as big as that was in 2020.

3.2 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.⁸ In turn, each business day is further classified into four categories depending on whether a typical 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 cancelled for non-COVID reasons such as inclement weather, security threats, voting, etc.⁹ 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

⁸ 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.

⁹ 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.

contagion effect, the key distinction here is between in-person school attendance vs. staying at home.

Main decisions regarding the school closure in Russia are made by regional authorities, causing substantial regional variation in schooling policies. The country map in Figure 1 shows 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 (Southeast Siberia) to 129 days in Chuvash Republic (in the Volga Upland); in comparison, there are about 170 in-person school days in a normal year. 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 that shows the relative number of regions which 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.

To visualize the sequence of schooling restrictive measures, we create their timeline for each RLMS region and every grade level. An example of 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.¹⁰ 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 the COVID-19 being more widespread. Typical arguments against school closure came down to the high cost to the economy of past restrictive

¹⁰ 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.

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 Fall 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 and also 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 exploit intertemporal within-round variation in schooling disruptions. Specifically, we aggregate daily data on schooling policies to match 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 interview, we construct schooling policies for the same time 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 the same interval, where business days are defined as 30 minus weekends minus federal holidays and minus 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 interview, region of residence, and the grade level of child.

3.3 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.¹¹

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 стопкоронавирус.рф. Although this data source is widely used by reputable data aggregators such as World Health Organization, the Coronavirus Resource Center at John 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.¹² 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

¹¹ 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.

¹² 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 publishes 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 exceeds the total number of confirmed COVID-19 cases from daily reports, which is equal to 50.7 cases per 1,000 population in 2021.

cycle. To deal with undercounting, we multiply the number of new coronavirus cases over the 30-day period by the region-specific discrepancy factor (i.e., the ratio of annual regional statistics between the two data sources). We acknowledge that our measure of the COVID-19 spread is likely to be noisy and has to be interpreted with caution.

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. In the next two sections, we use this dataset to estimate the effects of school closure on health and labor supply.

4 Health Effects of School Closure

Policy makers 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. Our goal here is more 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 coronavirus infection, the main dependent variable we use for both children and parents is the answer to the survey question whether an individual experienced any health issues 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.¹³ Two additional variables are available to measure child’s illness – missing any school day due to illness in the last 30 days and having flu-like symptoms in the last 7 days. We consider these variables in the robustness analysis.

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_{it} , parents’ health, $\tilde{H}_{kt}^P$, control variables, X_{it} , pre-pandemic health, $Z_{k,pre}^C$,

¹³ 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.

year fixed effects, θ_t , region fixed effects, η_r , and time invariant individual heterogeneity, μ_k^C , as shown in Equation (6).

$$H_{kt}^C = f^C(S_{kt}, \tilde{H}_{kt}^P, X_{kt}, Z_{k,pre}^C, \theta_t, \eta_r) + \mu_k^C + \epsilon_{kt}^C. \quad (6)$$

The key independent variable, S_{kt} , is the number of days of COVID-related school closings as the share of business days in the last 30 days. It varies by region, child's grade level, and the time of survey interview. $\tilde{H}_{it}^P$ is a binary variable indicating if any parent living with a child had health issues in the last 30 days. We expect a strong dependence of a child's illness on parent's health conditions due to genetic factors, exposure to similar health hazards (e.g., poor nutrition), and within-family contagion. $Z_{k,pre}^C$ denotes whether a child acquired any serious illness by 2018 such as infarction, stroke, cancer, diabetes as well as chronic diseases of the heart, lung, kidney, stomach, spine, and urogenital system. A dummy variable for non-participants in the 2018 survey is also added (about 12 percent). The rationale for the $Z_{k,pre}^C$ variables is to control for initial conditions related to health prior to the pandemic and before our sample period.

The X_{kt} vector has a multitude of control variables. Three variables account for other reasons why schools may not be working, 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 interview date. These variables are necessary to isolate the health effect of COVID-19 school closure from the influence of the business shutdown and other non-school days. The X_{kt} also includes demographic characteristics such as child's age, mother's age, mother's level of education, living with a single parent, and the place of residence (large city/regional center, other urban settlement, or rural area). If the mother is absent, then father's age and education are used for less than 2 percent of children. Lastly, we control for the regional number of new confirmed COVID-19 cases in the last 30 days adjusted for undercounting and monthly unemployment rate as a proxy for current regional economic conditions.

The error term is decomposed into the child-specific random effect (RE) μ_k^C , an idiosyncratic observation-level error ϵ_{kt}^C , and fixed effects for time and location. μ_k^C is a latent child-level component

which is assumed to be independently and normally distributed. ϵ_{kt}^C also follows normal distribution. It is assumed to be independently distributed across clusters. 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.

The equation for parent's illness has a similar structure:

$$H_{it}^P = f^P(S_{it}, \tilde{H}_{it}^C, X_{it}, Z_{i,pre}^P, \theta_t, \eta_r) + \mu_i^P + \epsilon_{it}^P, \quad (7)$$

where μ_i^P denotes a parent-specific random component of the error term. The differences 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 $\tilde{H}_{it}^C$ which indicates health issues for any child under age 15 in the last 30 days. Equation (7) is estimated separately for mother and fathers. Pre-pandemic conditions in $Z_{i,pre}^P$ as well as age and education in X_{it} are chosen for the corresponding parent.

Table 4 shows the key parameter estimates of Equations (6) 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 school closure for 21 business days during the pandemic reduces the probability of children's health problems by 13 pp, the probability of missing school days because of illness by 11 pp, and the probability of having flu-like symptoms in the last 7 days by 7 pp, *ceteris paribus*. At the same time, we do not observe similar health effects during school breaks and holidays. This implies that regular school closings for planned breaks and holidays do not alter the risk of illness, it is only the pandemic-related school closures that help to lower the illness hazard. Predictably, the probability of illness decreases with a child's age, and

it is highly dependent on parent's health conditions and child's acquiring serious illness before the pandemic. The effect of COVID-19 cases on child's illness is positive but not statistically significant. In support of one of theoretical assumptions ($b^C = \zeta \cdot s$), we find a much stronger negative impact of school closure on illness rate at higher rates of COVID-19 spread: no effect at zero coronavirus infections, -15 pp at 1 additional COVID-19 case per 100 people, and -28 pp for 2 COVID-19 cases per 100 people.

Table 5 reports the key parameter estimates of parent's health equation (7). Full results can be found in Appendix 2. We see that parents have a higher likelihood of being ill when their kids are sick or having flu-like symptoms. Since children are less likely to get sick when schools are closed during the pandemic, school closures may have an indirect child-to-parent effect on parents' health. Through this indirect channel, the COVID-related school closure is predicted to reduce the probability of parents having health problems in the last 30 days by 1.6 pp for mothers and 1 pp for fathers. Yet, the direct effect of school closure on parents' illness is actually reverse, it is positive and fairly large in magnitude, 10.3 pp for mothers and 5.6 pp for fathers, but not statistically significant at the 10 percent level. This result indicates that school closure may deteriorate parent's health conditional on holding children's health constant. It can plausibly occur via the mental health channel, as our theoretical framework suggests. 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 quite a strong 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. The negative effect of school closure on mental health is found for both mothers and fathers, although the size of the effect for mothers is nearly twice as big as for fathers. 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.

5 Labor Supply Effects of School Closure

Next, we examine potential costs of school closure in 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.¹⁴ Yet, in the 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 equation with health conditions included:

$$L_{it}^P = f^L(S_{it}, \tilde{H}_{it}^C, H_{it}^P, X_{it}, Z_{it}^L, \theta_t, \eta_r) + \mu_i^L + \epsilon_{it}^L. \quad (8)$$

A parent's labor supply, L_{it}^P , is assumed to depend upon school closure mandates, S_{it} , health of young children, $\tilde{H}_{it}^C$, health of parent, H_{it}^P , control variables, X_{it} , labor supply shifters, Z_{it}^L , year and region fixed effects, θ_t and η_r , and individual-specific random effect, μ_i^L . Most of the variables were described in the previous section. Here, we introduce two new vectors, L_{it}^P and Z_{it}^L .

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, and hours of work at main job. We also consider outcomes that characterize work from home in terms of the probability of such work and hours spent on working at home. We keep zero hours of work at home by using MaCurdy and Pencavel (1986) transformation, $\log(\text{hours}+1)$, for working parents. All labor supply outcomes refer to the last 30-day period prior to survey interview.

Whether and how much parents can work may depend upon the availability of other caregivers. In Russian culture, “babushkas” or grannies often plays an important role in providing childcare. In the Z_{it}^L vector, we create a dummy variable for an older household member other than parents, age 55-80, who is not disabled and not in bad health, assuming that this family member may offer an additional childcare when it is needed. In the equations for hours of work and work from home, we also include industry fixed effects to control for industry-specific job types influencing hours and the ability to work from home. Finally, the Z_{it}^L vector includes 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

¹⁴ For example, the two largest U.S. surveys used in official labor force statistics – the monthly Current Population 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 interview.

working indoors).¹⁵ 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, and it would be useful to control for them.

We report the key parameter estimates of Equation (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, although the size of the employment effect for mothers is fairly large, -6.5 pp decrease in response to school closure for 21 business days. 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.¹⁶ The lack of response in working hours to school closure does not contradict our theoretical predictions in Section 2, however, it 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 by arranging alternative childcare or by reallocating hours across space (e.g., switching to remote work) and/or across time (e.g., working more hours during days when schools were open). 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 8.9 pp in response to closing schools for 21 business days. Hours of work at home are also predicted to go up by 38.5 percent (0.326 log points) which is equivalent to about 22 hours at home per month conditional on working remotely. The effect on remote work is only found for mothers and not for fathers. 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

¹⁵ We do not include industry and occupational characteristics in the employment equation, as they are only available for the employed individuals.

¹⁶ 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; unemployment rate increased 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.

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 that could be brought in by outside caregivers 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.

Our estimates reveal a few other interesting relationships. Mothers' hours of remote work tend to be higher in occupations with more task freedom and higher propensity of working indoors. They increase with a higher spread of COVID-19. Single mothers tend to work more hours than non-single mothers. An older non-parental family member who is able to provide childcare allows mothers (but not fathers) to work more hours in total and at home. Table 6 also shows the estimated labor supply response to worsening health conditions. If parents experience health issues, they tend to work fewer hours and spend more time working at home. However, when a child is sick, the childcare burden lies on mothers. The labor supply of fathers does not seem to respond to a child's illness at all. Russian mothers, on the other hand, when their child is sick, are more likely to leave employment, cut working hours, and extend hours working at home. Mothers' labor supply appears to be quite sensitive to child's health needs. 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 family (Eriksen et al., 2021; Jeon and Pohl, 2017).

The labor supply estimates together with the estimates of health effects in the previous section, on one hand, predict an increase in mothers' hours of work during school closure because of a lowered risk of child's illness, but, on the other hand, they predict a decrease in hours because of an amplified risk of own illness. The total indirect effect of school closure on hours worked through the health channel is close to zero.¹⁷

¹⁷The total indirect effect is obtained using a non-linear combination of parameter estimates within the seemingly unrelated estimation framework. The standard errors are computed with the delta method. The total indirect effect through health channel is close to zero and statistically insignificant, with p -value = 0.4804 for mothers and 0.2066 for fathers.

6 Joint Family Estimation and Robustness

Before summarizing the results, we would like to address some of the concerns with identification issues and estimation methods. In policy evaluations, one of the biggest concerns is that the estimated policy effects capture other confounding events or trends. Although we control for school breaks, workplace closure, and the COVID-19 spread, it is still possible that the estimated effects of school closure maybe biased by other simultaneous policies and events. To examine whether our results are robust to confounding events, we perform a falsification test by replicating our estimation procedures for population groups that should not be affected by school closure. Specifically, we consider two placebo groups: (i) childless adults (“no kids”) and (ii) parents with younger kids under age 7 who do not go to school and who do not have siblings in school (“younger kids”). We assign counterfactual schooling policies to both placebo groups based on the region of residence, date of interview, and a fake grade level: 1, 3, 5, and 7. In other words, we assume that placebo groups have a school-age child of the respective grade level. We report the results of the falsification test for the effect of school closure on labor supply and adult’s health in Appendix 2. Out of 96 tested placebo interventions, we find statistically significant effects of school closure in 2 cases. In both cases, the sign was opposite from the actual treatment effect – fake school closure is found to decrease hours of working from home for males. The results of the falsification test reassure us that the effects we find are attributed to school closure and not to simultaneously occurring COVID-19 trends and other policies.

Our estimates include an individual-specific random component along with fixed effects for region and year. The RE estimation relies on both within-person (over time) and between-person variation. We do not perform the fixed effect (FE) estimation for several reasons. We only have three or less observations per person. The FE estimation elevates the noise-to-signal ratio, and it differences away important variation between individuals. For example, demeaning shuts off cross-sectional variation in schooling policies, which is between regions as well as between time intervals within the survey round. It also removes most of the variation in dependent variables. The share of within-variation in labor supply variables (employment, hours, and work from home) is between 19 and 23 percent of total variation. The RE approach in combination with a carefully chosen rich set of control variables is better suited for our data and for the purpose of this analysis.

One concern with our previous analysis might be that the model equations are estimated

separately for mothers, fathers, and children. We test how robust our previous results are if we introduce the correlation of errors across equations through a common time-varying family component. With respect to health measures, we estimate the following 3 equations jointly:

$$\begin{aligned}
H_{iut}^M &= f^M(S_{it}, \tilde{H}_{it}^C, X_{it}, Z_{i,pre}^M, \theta_t, \eta_r) + \rho^M \zeta_{ut} + \varepsilon_{iut}^M \\
H_{iut}^F &= f^F(S_{it}, \tilde{H}_{it}^C, X_{it}, Z_{i,pre}^F, \theta_t, \eta_r) + \rho^F \zeta_{ut} + \varepsilon_{iut}^F \\
H_{iut}^C &= f^C(S_{it}, \tilde{H}_{it}^P, X_{it}, Z_{i,pre}^C, \theta_t, \eta_r) + \rho^C \zeta_{ut} + \varepsilon_{iut}^C.
\end{aligned} \tag{9}$$

Here, we assume that each family unit, u , consists of mother (M), father (F), and school-age child (C). The set of covariates is the same as in Equations (6) and (7). The difference is in the structure of error terms. In each estimated equation, the error term is decomposed into time-varying family unobserved heterogeneity, ζ_{ut} , and an i.i.d. component ε_{iut}^j .¹⁸ The time-varying family component is a latent factor influencing health of all family members; it may capture family habits, eating traditions, shared interests in exercise, common health shocks. During the pandemic, families may have shared similar attitudes towards mask wearing, social distancing, sanitizing, etc. Compared to separately estimated health equations, the intra-family joint system of equations in (9) does not have an individual-specific random component due to convergence issues, but it does allow for cross-equation correlation and for the common family unobserved heterogeneity.

As we can see in Table 7, based on the intra-family model, the pandemic-related school closing for 21 business days is predicted to reduce the risk of illness among children by 23 pp (or 1 pp decline in one business day of schools being closed), which is almost double of the previous estimate. The joint estimation produces a much greater illness-reducing effect on children. The corresponding effect on parent's illness is very similar to what is reported in Section 4, 11 pp increase in the illness rate for mothers and 5.3 pp for fathers, but the parameter estimate for mothers becomes statistically significant at the 10 percent level. Similar to separate estimates, joint estimates do not show any statistically significant changes in health outcomes of all family members during school breaks. The biggest

¹⁸ The latent factor, ζ_{ut} , follows a standard normal distribution with mean zero and variance one. It is common across all three equations, with equation-specific loading factors, ρ^j for $j = C, F, M$. The i.i.d. errors, ε_{iut}^j , are distributed normally with mean zero and variance σ_ε^2 and assumed to be independent across equations, $cov(\varepsilon_{it}^j, \varepsilon_{it}^{m \neq j}) = 0$.

difference between the separate and joint sets of estimates is the size of the indirect contagion effect on parents. Because of the considerable estimated effect of school closure on child's illness and due to a stronger association between child's and parent's health in the intra-family model, the estimated indirect effect implies a reduction in the illness rate by 10.9 pp for mothers and 7.2 pp for fathers in response to school closure for 21 business days. As a result, the total effect of school closure on parent's health goes to zero. This result is certainly interesting, as it implies that the positive direct effect, which is likely linked to mental health issues, fully counterbalances the negative indirect effect coming from a lower likelihood of children being ill when schools are closed during the pandemic. Our estimates suggest that the indirect effect increases with more spread of COVID-19, thus, making school closings more beneficial for parent's health at higher rates of disease transmission. There also could be health benefits for elderly household members which we plan to investigate in a separate paper.

We perform similar analysis for labor supply outcomes by estimating the following equations for mothers and fathers jointly.

$$\begin{aligned}
 L_{iut}^F &= f^F(S_{it}, \tilde{H}_{it}^C, H_{it}^F, X_{it}, Z_{i,pre}^F, \theta_t, \eta_r) + \rho^F \zeta_{ut} + \varepsilon_{iut}^F \\
 L_{iut}^M &= f^M(S_{it}, \tilde{H}_{it}^C, H_{it}^M, X_{it}, Z_{it}^M, \theta_t, \eta_r) + \rho^M \zeta_{ut} + \varepsilon_{iut}^M.
 \end{aligned}
 \tag{10}$$

The results are reported in Table 7 and Appendix 2. We find the new estimates to be consistent with the previously reported estimates in Section 5, with only one exception. Joint estimation shows a statistically significant (at the 10 percent level) decrease in total hours of work in response to school closure for fathers. It is plausible that fathers have to adjust total hours if the type of jobs they have does not allow them to work remotely. While this result makes sense, we treat it cautiously, as this is the first and only time we see a labor supply response by fathers to children staying at home during the school day. For instance, no such effect is detected for hours worked at the primary job. Maternal hours of work remain unaffected by school closure. Mothers respond to school closures and school breaks by switching to remote work and working more hours from home, although their response to school breaks is less than that of school closure. Similar to separate estimates, joint estimates show that both parents cut their labor supply and switch to remote work when they get sick. But it is only mothers who decrease labor supply when their children become ill. As a result, the indirect effect of

school closure on labor supply via the child's health channel is found only among mothers. The magnitude of the indirect effect is not big enough to make any substantive changes to the overall labor supply.

7 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 Fall 2020, regional authorities accumulated first knowledge about benefits and costs of school closure from lockdown experience in Spring 2020. Yes, there were doubts and public debates, but 64 regions or 77 percent decided to shut down schools again in Fall 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 a record number of COVID-19 cases and deaths. Authorities of 6 regions that did not implement a school closure policy in Fall 2020 reversed their decision one year later. Interestingly, 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 virus, 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 overwhelming support for this policy. Yet, the policy was not fully dismissed, as decision makers recognize 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. Regular school breaks and holidays do not have such an effect on children illness. 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 is 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 Tsutsui, 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 mean rate of COVID-19 spread in 2021 (which was about 1 additional case per 100 people over the 30-day period), 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.¹⁹ 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 almost 9 percentage points and the duration of working from home by 22 hours per month in response to closing schools for 21 business days. The absence of 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 a 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). 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; Donnelly and Patrinos, 2021; Goldhaber et al., 2023). 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.

¹⁹ In the recent U.S. study, Goldin (2022) also show that women's labor force participation and hours of work did not change during the pandemic.

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, the 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.

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9 Tables and Figures

Table 1: Definition of Variables

Variable	Vector	Definition
<i>Individual characteristics</i>		
Employed	L_{it}^P	=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_{it}^P	Hours worked at primary and secondary jobs in the last 30 days; includes hours worked from home.
Hours at primary job	L_{it}^P	Hours worked at primary job in the last 30 days; includes hours worked from home.
Work from home	L_{it}^P	=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_{it}^P	Hours worked from home at primary job in the last 30d. Set to zero if worked at primary job but not from home. When used in logs, MaCurdy and Pencavel (1986) transformation is applied, $\log(\text{hours}+1)$.
Parent's health issues	H_{it}^P	=1 if parent had any health issues in the last 30 days (parent-level analysis)

Any parent's health issues	$\tilde{H}_{kt}^P$	=1 if any parent had health issues in the last 30 days (child-level analysis)
Child's health issues	H_{kt}^C	=1 if child had health issues in the last 30 days (child-level analysis)
Any child's health issues	$\tilde{H}_{it}^C$	=1 if any child under age 15 had health issues in the last 30 days (parent-level analysis)
Child's flu-like symptoms	H_{kt}^C	=1 if child had flu-like symptoms in the last 7 days. Symptoms include sore throat, cold and runny nose, cough, and earache. Parents of children under age 14 answered the survey questions on symptoms.
Child's absent for illness	H_{kt}^C	=1 if child missed school due to illness in the last 30 days. Parents of children under age 14 answered the corresponding survey question.
Parent's age	X_{it}	3 categories: 18-29, 30-44, 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).
Single	X_{it}	=1 if single parent
Place of residence	X_{it}	3 categories: regional capital, other urban settlement, and rural area
Child's age	X_{kt}, X_{it}	Age of child (child-level analysis); Age of youngest school-age child in grades 1-8 (parent-level analysis)
Child's grade level	...	Grade level the child currently attends. The variable is used for linking the RLMS-HSE with grade-level policies. It is taken from the direct survey question. The grade level highly correlates with child's age (corr=0.97).
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
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 serious illness	$Z_{k,pre}^C, Z_{i,pre}^P$	=1 if a child or parent acquired any serious illness by 2018. Serious illnesses include infarction, stroke, cancer, diabetes as well as chronic diseases of the heart, lung, kidney, stomach, spine, and urogenital system. Non-participants in the 2018 survey are flagged with a dummy variable.

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.
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		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 holiday lasted for more than one working day in the last 30 days. Varies by region and date of interview.
<i>Regional characteristics</i>		
Workplace closure	X_{it}	Number of non-working days due to COVID-related reasons as the share of business days in the last 30 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.
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

	Mothers			Fathers		
	2019	2020	2021	2019	2020	2021
Employed	0.730	0.705	0.712	0.866	0.855	0.858
Total hours of work	174.6 (45.5)	171.3 (47.8)	169.6 (47.5)	193.0 (50.3)	192.7 (51.1)	191.4 (50.7)
Work from home	0.117	0.136	0.130	0.057	0.074	0.062
Hours worked from home (If worked from home)	37.4 (52.0)	50.2 (61.3)	60.1 (73.7)	33.1 (52.1)	67.8 (70.5)	60.5 (76.1)
Parent's health issues	0.211	0.217	0.224	0.175	0.154	0.175
Any child's health issues	0.374	0.295	0.369	0.368	0.301	0.370
Unemployment rate, %	4.5 (1.7)	6.0 (2.1)	4.2 (1.5)	4.5 (1.7)	6.0 (2.1)	4.2 (1.4)
COVID-19 spread	0 (0)	0.403 (0.320)	0.920 (0.365)	0 (0)	0.400 (0.319)	0.919 (0.365)
N observations	1,504	1,483	1,500	1,187	1,181	1,205

Notes: Table reports mean and standard deviation (in parentheses) of parents' characteristics by year. Standard deviations for binary variables are not shown. The sample consists of parents of school-age children in grades 1 to 8. The description of variables can be found in Table 1. Summary statistics for other variables used in the analysis are provided in Appendix 2. The number of observations is shown for the employment and regional variables; it is smaller for work-related variables.

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

Variables	Health Issues	Flu-like Symptoms	Absent for Illness
School closure	-0.128*** (0.047)	-0.072** (0.036)	-0.110* (0.061)
<i>By COVID-19 level of exposure:</i>			
No COVID-19 cases	-0.028 (0.095)	0.039 (0.074)	-0.009 (0.079)
COVID-19 cases =1 per 100	-0.152*** (0.041)	-0.101** (0.041)	-0.136** (0.064)
COVID-19 cases =2 per 100	-0.275*** (0.101)	-0.241** (0.108)	-0.262** (0.121)
School break	-0.035 (0.041)	0.005 (0.046)	-0.060 (0.041)
Long holidays	-0.023 (0.022)	-0.012 (0.024)	0.018 (0.024)
Child age	-0.010*** (0.003)	-0.010*** (0.002)	-0.004 (0.003)
Any parent's health issues	0.183*** (0.020)	0.161*** (0.021)	0.161*** (0.018)
Pre-pandemic serious illness	0.122*** (0.032)	0.108*** (0.035)	0.084*** (0.022)
Observations	5,610	5,126	5,127

Notes: Table presents estimates of Equation (6) using a random effect estimator with a child-specific random component and fixed effects for year and region. 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. Table also reports the average marginal effect of school closure by COVID-19 level of exposure. The effect is calculated on the basis of Equation (6) with an added interaction term between school closure and COVID-19 spread.

Table 5: Effect of School Closure on Parent's Health

Variables	Mothers	Fathers
<i>Effects of School Closure</i>		
Indirect effect	-0.016*** (0.006)	-0.010*** (0.004)
Direct effect overall	0.103 (0.068)	0.056 (0.044)
<i>Effects of Child's Health</i>		
Any child's health issues	0.127*** (0.016)	0.080*** (0.016)
Any child had flu-like symptoms last 7d	0.133*** (0.019)	0.070*** (0.016)
Observations	4,473	3,563

Notes: The direct effects of school closure and child's health are estimated using Equation (7). 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 indirect effect is the estimated coefficient on school closure in the child's health equation (in Table 4) multiplied by the coefficient on child's health issues in parent's health equations. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. Standard errors for the indirect effect are computed using the Delta method.

Table 6: Effect of School Closure on Labor Supply

	Employment		Log total hours		Log prime job hours		Work from home		Hours working from home	
	Mother	Father	Mother	Father	Mother	Father	Mother	Father	Mother	Father
School closure	-0.065 (0.045)	0.017 (0.042)	0.030 (0.040)	-0.033 (0.045)	0.029 (0.048)	-0.016 (0.042)	0.089** (0.040)	0.004 (0.040)	0.326*** (0.126)	0.061 (0.096)
School break	-0.005 (0.041)	-0.045 (0.031)	-0.020 (0.043)	0.013 (0.037)	0.004 (0.041)	0.035 (0.038)	0.065** (0.028)	0.026 (0.028)	0.142 (0.098)	-0.021 (0.054)
Any child's health issues	-0.034*** (0.011)	-0.011 (0.009)	-0.033*** (0.012)	0.010 (0.010)	-0.038*** (0.013)	0.009 (0.010)	0.013 (0.012)	0.001 (0.007)	0.043* (0.026)	0.002 (0.016)
Parent's health issues	-0.003 (0.014)	-0.043*** (0.016)	-0.026* (0.014)	-0.029 (0.019)	-0.023* (0.012)	-0.034* (0.020)	0.028* (0.017)	0.025# (0.016)	0.054 (0.047)	0.070** (0.035)
Older caregiver	0.004 (0.019)	0.019 (0.018)	0.030** (0.014)	-0.022 (0.022)	0.028* (0.017)	-0.020 (0.020)	0.049** (0.020)	-0.003 (0.013)	0.161** (0.067)	0.003 (0.028)
Indoor occupation	...	...	-0.002 (0.014)	0.002 (0.007)	-0.003 (0.015)	-0.004 (0.009)	0.020* (0.011)	0.015*** (0.005)	0.065** (0.026)	0.020** (0.010)
Unstructured job	...	...	-0.000 (0.007)	0.004 (0.008)	-0.005 (0.007)	0.008 (0.007)	0.031*** (0.009)	0.005 (0.009)	0.065*** (0.023)	0.012 (0.019)
COVID-19 spread	0.026 (0.016)	-0.033 (0.021)	-0.012 (0.023)	-0.051 (0.033)	-0.007 (0.022)	-0.039 (0.031)	0.038* (0.022)	0.034 (0.023)	0.153** (0.072)	0.067 (0.045)
Region + Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,470	3,561	2,866	2,580	2,861	2,579	3,111	2,954	3,044	2,915
Unique parent IDs	1,961	1,565	1,435	1,260	1,433	1,260	1,522	1,385	1,503	1,375
R-squared overall	0.122	0.208	0.078	0.078	0.087	0.081	0.143	0.096	0.136	0.093

Notes: Table presents estimates of Equation (8) using a random effect estimator with a parent-specific random component and fixed effects for year and region. 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. # indicates statistically significant estimates at the 10 percent level when robust standard errors are used instead of cluster robust.

Table 7: Joint Intra-Family Estimation

Panel 7a: Health Response

	Health Issues		
	Mother	Father	Child
School closure	0.110* (0.063)	0.053 (0.044)	-0.229*** (0.055)
School break	0.015 (0.052)	0.072 (0.049)	-0.039 (0.056)
Any child's health issues	0.478*** (0.020)	0.315*** (0.016)	...
Any parent's health issues	...	...	0.870*** (0.017)
Indirect effect of school closure	-0.109*** (0.025)	-0.072*** (0.018)	...

<i>By COVID-19 level of exposure:</i>			
No COVID-19 cases	-0.063 (0.058)	-0.042 (0.039)	...
COVID-19 cases =1 per 100	-0.114*** (0.025)	-0.077*** (0.018)	...
COVID-19 cases =2 per 100	-0.166*** (0.061)	-0.112*** (0.043)	...
Total effect of school closure	0.000 (0.052)	-0.019 (0.039)	-0.229*** (0.055)
Region + Year FE	Yes	Yes	Yes

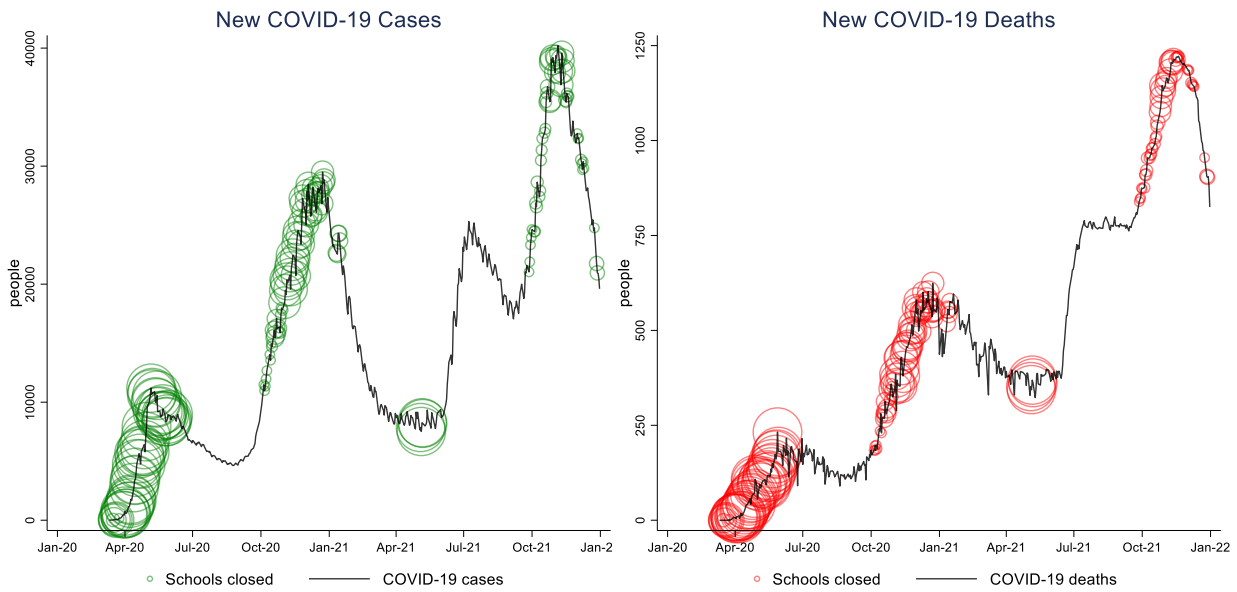
Panel 7b: Labor Supply Response

	Employment		Log total hours		Log prime job hours		Work from home		Hours working from home	
	Mother	Father	Mother	Father	Mother	Father	Mother	Father	Mother	Father
School closure	-0.062 (0.058)	0.011 (0.041)	0.031 (0.041)	-0.067* (0.039)	0.036 (0.049)	-0.055 (0.042)	0.119** (0.049)	0.019 (0.040)	0.368** (0.164)	0.070 (0.101)
School break	0.013 (0.053)	-0.034 (0.035)	-0.009 (0.046)	-0.003 (0.037)	0.012 (0.045)	0.008 (0.040)	0.071** (0.032)	0.011 (0.033)	0.206* (0.123)	-0.018 (0.065)
Any child's health issues	-0.051*** (0.015)	-0.003 (0.012)	-0.029** (0.013)	0.017# (0.011)	-0.032** (0.014)	0.015 (0.011)	0.024* (0.013)	-0.004 (0.007)	0.076** (0.037)	-0.011 (0.015)
Parent's health issues	-0.022 (0.017)	-0.069*** (0.020)	-0.027# (0.016)	-0.026# (0.016)	-0.028* (0.015)	-0.034** (0.016)	0.034* (0.018)	0.022# (0.015)	0.100** (0.048)	0.074** (0.034)
COVID-19 spread	0.018 (0.022)	-0.017 (0.021)	0.001 (0.026)	-0.040# (0.029)	0.006 (0.025)	-0.032 (0.028)	0.058** (0.023)	0.038* (0.022)	0.205*** (0.076)	0.076** (0.038)
Indirect effect of school closure	0.012*** (0.004)	0.001 (0.003)	0.007** (0.003)	-0.004 (0.003)	0.007** (0.004)	-0.003 (0.003)	-0.006 (0.004)	0.001 (0.002)	-0.017* (0.010)	0.002 (0.003)
Region + Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents estimates of Equations (9) and (10) allowing for the within-family correlation of error terms. We only show estimates that are cited in the text; full results can be found in Appendix 2, Table W6. The parent's sample includes parents of children in grades 1-8 under age 15. The children's sample includes the youngest school-age child. The indirect effect is the estimated coefficient on school closure in the child's health equation in Panel A multiplied by the coefficient on child's health issues in parent's health and labor supply equations. The indirect effect by the COVID-19 level of exposure is calculated on the basis of Equation (9) with an added interaction term between school closure and COVID-19 spread. Robust standard errors (in parentheses) are clustered at the regional level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors for the indirect effect are computed using the Delta method. # indicates statistically significant estimates at the 10 percent level when robust standard errors are used instead of cluster robust.

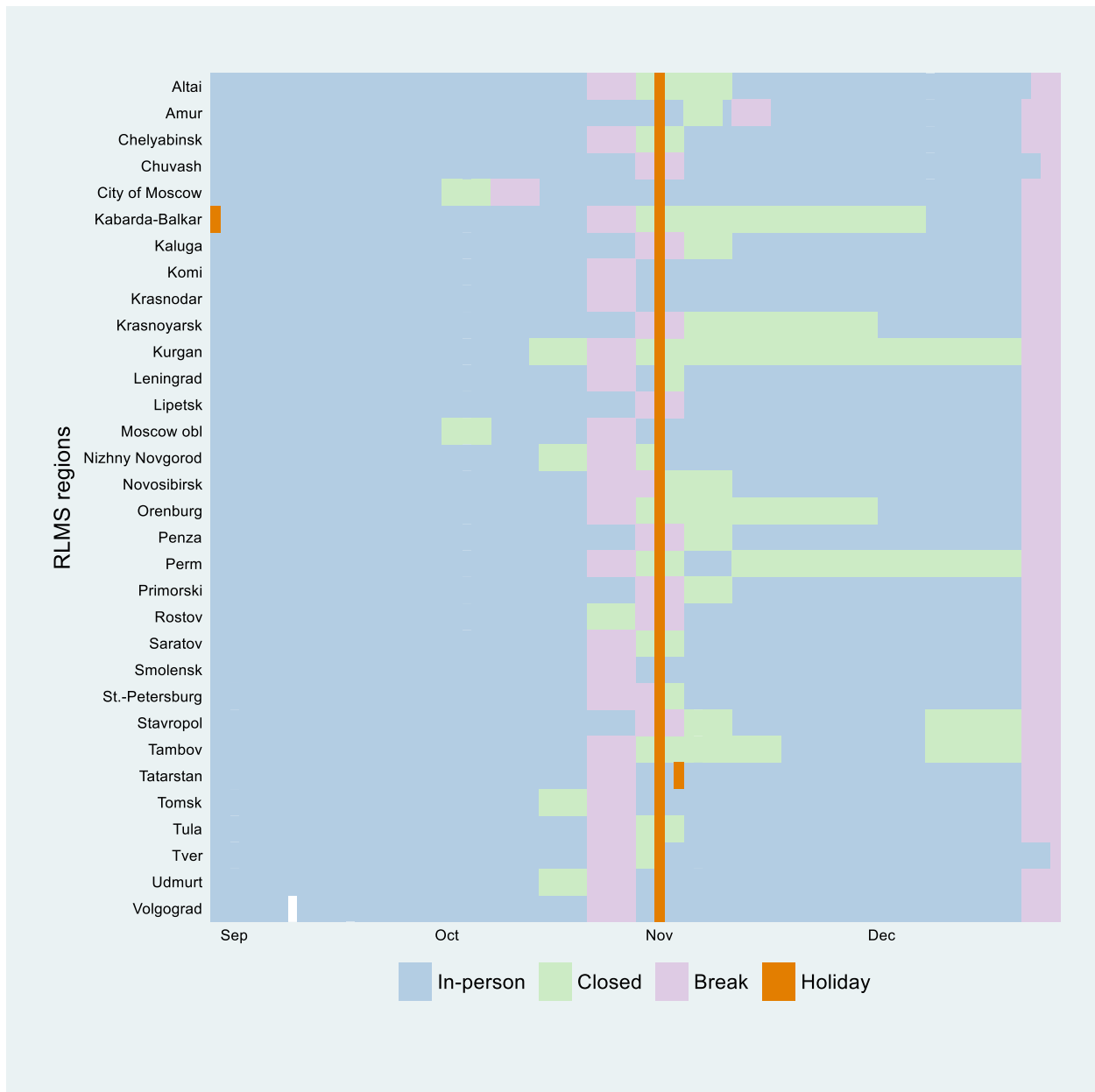
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Figure 2: School Closings and the Spread of COVID-19



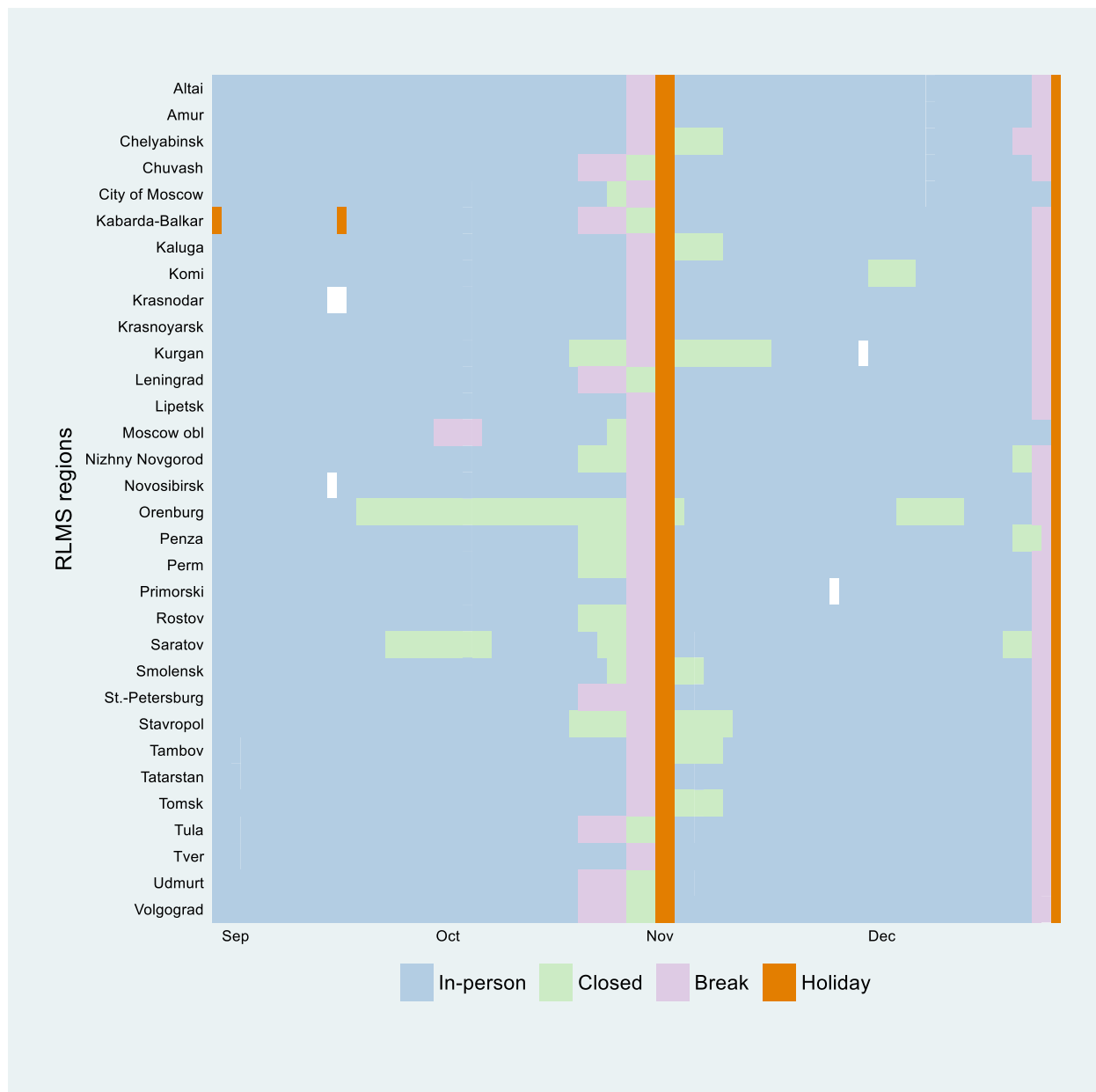
Notes: Figure plots the number of daily confirmed COVID-19 cases and deaths in Russia. The size of the hollow marker is proportional to the number of Russian regions (max 83) where schools have been closed due to COVID-related reasons. All regions had schools closed for in-person learning during non-working days from 03/30/2020 to 05/11/2020 and from 05/04/2021 to 05/07/2021.

Figure 3: Timeline of School Closings, Fall 2020



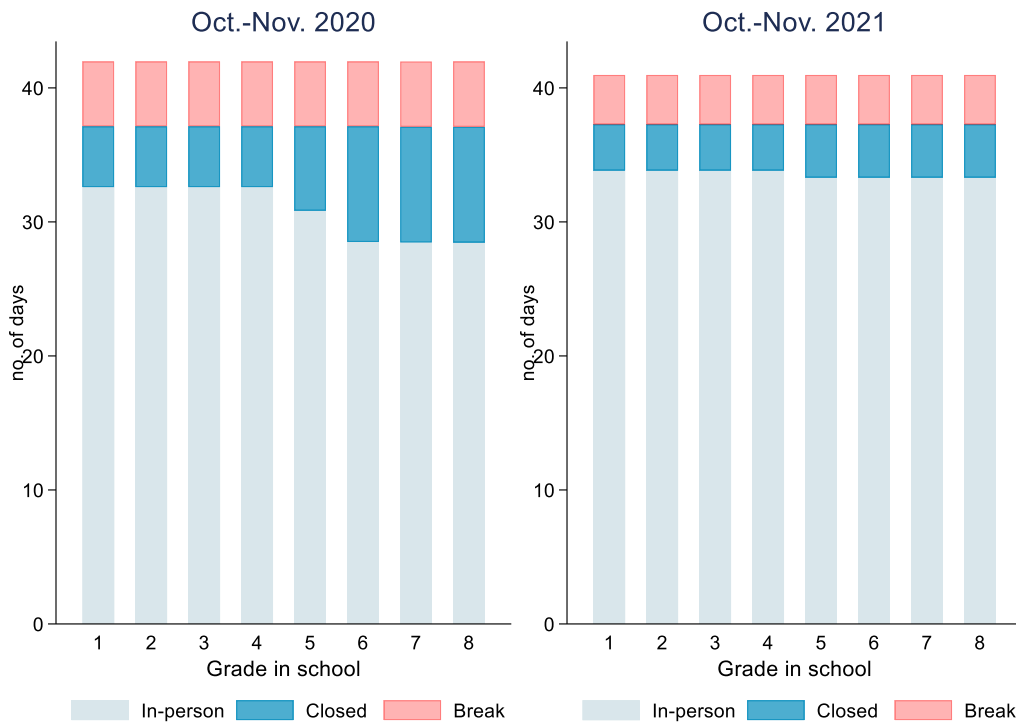
Notes: Figure presents the timeline of schooling modes for 5th graders in 32 RLMS regions beginning September 1, 2020, and ending December 31, 2020. Weekends are excluded from the timeline. White cells show days when schools are closed for reasons unrelated to COVID (voting, security, or inclement weather).

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.

10 Appendix 1: Theoretical Framework

See separate attachment

11 Appendix 2: Additional Tables and Figures

See separate attachment

12 Appendix 3: Effect of School Closure on Depression

See separate attachment

13 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

The utility maximization problem for parents is derived in the text as follows

$$\max_{t, \tau} \delta_1 \ln(\mathbf{t}) + \delta_2 \ln(\mathbf{l}^P) + \delta_3 \ln(\mathbf{I}) + \text{Const},$$

$$\text{where } \text{Const} = \delta_1 \ln(w) + \delta_3 \ln(A) - \delta_4 \ln(\lambda^{C \rightarrow P} \zeta s)$$

$$\mathbf{l}^P = 480 - t - \tau - \zeta s - \lambda^{C \rightarrow P} \zeta s$$

$$\mathbf{I} = s - \zeta s + \tau$$

$$\max_{t, \tau} \delta_1 \ln(\mathbf{t}) + \delta_2 \ln(480 - \mathbf{t} - \boldsymbol{\tau} - \zeta \mathbf{s} - \lambda^{C \rightarrow P} \zeta \mathbf{s}) + \delta_3 \ln(\mathbf{s} - \zeta \mathbf{s} + \boldsymbol{\tau}) + \text{Const},$$

We derive model solutions using first order conditions with respect to $\boldsymbol{\tau}$ (W1) and $\mathbf{t}$ (W2):

$$-\frac{\delta_2}{\mathbf{l}^P} + \frac{\delta_3}{\mathbf{I}} = 0 \quad (\text{W1})$$

$$-\frac{\delta_2}{\mathbf{l}^P} + \frac{\delta_1}{\mathbf{t}} = 0 \quad (\text{W2})$$

We first substitute the time constraints and child investment for $\mathbf{l}^P$ and $\mathbf{I}$ into Equation (W1) and derive the expression for $\boldsymbol{\tau}$:

$$\begin{aligned} \delta_2(\mathbf{s} - \zeta \mathbf{s} + \boldsymbol{\tau}) &= \delta_3(480 - \mathbf{t} - \boldsymbol{\tau} - \zeta \mathbf{s} - \lambda^{C \rightarrow P} \zeta \mathbf{s}) \\ \delta_2 \boldsymbol{\tau} + \delta_3 \boldsymbol{\tau} &= 480\delta_3 - \delta_2(1 - \zeta)\mathbf{s} - \delta_3\zeta(1 + \lambda^{C \rightarrow P})\mathbf{s} - \delta_3 \mathbf{t} \\ \boldsymbol{\tau} &= \frac{480\delta_3}{(\delta_2 + \delta_3)} - \frac{\delta_2(1 - \zeta) + \delta_3\zeta(1 + \lambda^{C \rightarrow P})}{(\delta_2 + \delta_3)}\mathbf{s} - \frac{\delta_3}{(\delta_2 + \delta_3)}\mathbf{t} \end{aligned} \quad (\text{W3})$$

Then, combining the two first order conditions (W1) and (W2) and the expression for $\boldsymbol{\tau}$ (W3), we derive an expression for $\mathbf{t}$:

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

$$\begin{aligned}
\mathbf{t} &= \frac{\delta_1}{\delta_3} (\mathbf{s} - \zeta \mathbf{s} + \mathbf{\tau}) = \frac{\delta_1(1 - \zeta)}{\delta_3} \mathbf{s} + \frac{\delta_1}{\delta_3} \mathbf{\tau} \\
\mathbf{t} &= \frac{\delta_1(1 - \zeta)}{\delta_3} \mathbf{s} + \frac{480\delta_1}{(\delta_2 + \delta_3)} - \frac{\delta_1\delta_2(1 - \zeta) + \delta_1\delta_3\zeta(1 + \lambda^{C \rightarrow P})}{(\delta_2 + \delta_3)\delta_3} \mathbf{s} - \frac{\delta_1}{(\delta_2 + \delta_3)} \mathbf{t} \\
\frac{\delta_1 + \delta_2 + \delta_3}{(\delta_2 + \delta_3)} \mathbf{t} &= \frac{480\delta_1}{(\delta_2 + \delta_3)} + \frac{\delta_1(1 - \zeta)}{\delta_3} \mathbf{s} - \frac{\delta_1\delta_2(1 - \zeta) + \delta_1\delta_3\zeta(1 + \lambda^{C \rightarrow P})}{(\delta_2 + \delta_3)\delta_3} \mathbf{s} \\
\frac{\delta_1 + \delta_2 + \delta_3}{(\delta_2 + \delta_3)} \mathbf{t} &= \frac{480\delta_1}{(\delta_2 + \delta_3)} - \frac{(\delta_2 + \delta_3)\delta_1(1 - \zeta) - \delta_1\delta_2(1 - \zeta) - \delta_1\delta_3\zeta(1 + \lambda^{C \rightarrow P})}{(\delta_2 + \delta_3)\delta_3} \mathbf{s} \\
\frac{\delta_1 + \delta_2 + \delta_3}{(\delta_2 + \delta_3)} \mathbf{t} &= \frac{480\delta_1}{(\delta_2 + \delta_3)} + \frac{\delta_1(1 - \zeta) - \delta_1\zeta(1 + \lambda^{C \rightarrow P})}{(\delta_2 + \delta_3)} \mathbf{s} \\
\mathbf{t} &= \frac{480\delta_1}{(\delta_1 + \delta_2 + \delta_3)} + \frac{\delta_1(1 - \zeta) - \delta_1\zeta(1 + \lambda^{C \rightarrow P})}{(\delta_1 + \delta_2 + \delta_3)} \mathbf{s} \\
\mathbf{t} &= \text{Const2} + \delta_1 \frac{(1 - \zeta) - \zeta(1 + \lambda^{C \rightarrow P})}{(\delta_1 + \delta_2 + \delta_3)} \mathbf{s} \tag{W4}
\end{aligned}$$

Alternative representation

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

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.

Several theoretical assumptions are empirically testable:

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 $b^P = \lambda^{C \rightarrow P} \cdot \zeta \cdot s$, $\lambda^{C \rightarrow P} \geq 0$
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, e.g., through the mental health channel.
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
<i>A. Variables used in health models</i>				
Any child's health issues	0.347	0.347	Child's health issues	0.251
Parent's health issues	0.217	0.168	Any parent's health issues	0.217
Parent's age			Parent's age	
18-29	0.060	0.034	18-29	0.054
30-44	0.817	0.747	30-44	0.831
45-60	0.123	0.219	45-60	0.115
Parent's education			Parent's education	
Basic general	0.090	0.127	Basic general	0.107
Secondary general	0.256	0.354	Secondary general	0.269
Secondary professional	0.215	0.212	Secondary professional	0.208
Tertiary	0.438	0.307	Tertiary	0.416
Single parent	0.183	0.018	Single parent	0.191
Place of residence			Place of residence	
Regional capital	0.398	0.393	Regional capital	0.383
Other urban settlement	0.345	0.346	Other urban settlement	0.340
Rural area	0.257	0.261	Rural area	0.278
Child's age (youngest)	9.9	9.8	Child's age	10.2
	(2.2)	(2.2)		(2.2)
Pre-pandemic serious illness	0.290	0.253	Pre-pandemic serious illness	0.077
Non-participant in 2018	0.115	0.130	Non-participant in 2018	0.120
N (parent's health model)	4,465	3,555	N (child's health model)	5,592

<i>B. Variables used in other models</i>				
Indoor occupation	0.216 (0.573)	-0.743 (1.007)	Child's flu-like symptoms	0.209
Unstructured job	0.101 (0.785)	-0.191 (0.838)	Child's absent for illness	0.190
Older caregiver	0.154	0.138	Non-HH member cared for child	0.198
Depression	0.078	0.043	A relative cared for child	0.141

Notes: This table reports summary statistics for variables not included in Table 2. Standard deviations are in parentheses, not shown for binary variables. The samples in Panel A are from the estimated health equations in Tables 4(W2) and 5(W3), cols 1. 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. Time period is 2019-2021. 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

	All children in grades 1-8			Youngest child in grades 1-8		
	Health Issues	Flu-like Symptoms	Absent for Illness	Health Issues	Flu-like Symptoms	Absent for Illness
School closure	-0.128*** (0.047)	-0.072** (0.036)	-0.110* (0.061)	-0.139** (0.057)	-0.076* (0.043)	-0.120 (0.076)
School break	-0.035 (0.041)	0.005 (0.046)	-0.060 (0.041)	-0.030 (0.048)	0.016 (0.049)	-0.053 (0.041)
Workplace closure	0.069 (0.101)	0.043 (0.142)	0.000 (0.109)	0.064 (0.103)	0.154 (0.149)	-0.017 (0.110)
Long holidays	-0.023 (0.022)	-0.012 (0.024)	0.018 (0.024)	0.005 (0.023)	-0.008 (0.025)	0.035* (0.021)
Child's age	-0.010*** (0.003)	-0.010*** (0.002)	-0.004 (0.003)	-0.011*** (0.003)	-0.010*** (0.002)	-0.005 (0.003)
Parent's age						
30-44	0.005 (0.029)	-0.031 (0.029)	-0.002 (0.021)	0.016 (0.032)	-0.026 (0.029)	0.007 (0.023)
45-60	-0.002 (0.038)	-0.015 (0.035)	-0.005 (0.025)	0.006 (0.041)	-0.010 (0.032)	0.012 (0.026)
Parent's education						
Secondary general	-0.006 (0.021)	-0.031 (0.019)	-0.026 (0.024)	-0.010 (0.028)	-0.029 (0.020)	-0.029 (0.025)
Secondary professional	-0.030 (0.021)	-0.048** (0.022)	-0.037 (0.025)	-0.042* (0.023)	-0.051** (0.021)	-0.045* (0.024)
Tertiary	-0.013 (0.020)	-0.024 (0.019)	-0.041* (0.024)	-0.016 (0.026)	-0.015 (0.016)	-0.040 (0.025)
Single parent	0.006 (0.014)	-0.014 (0.017)	-0.009 (0.015)	-0.005 (0.016)	-0.020 (0.016)	-0.010 (0.015)
Place of residence						
Other urban settlement	0.012 (0.027)	0.019 (0.039)	-0.029 (0.026)	0.013 (0.030)	0.022 (0.042)	-0.023 (0.024)
Rural	-0.028 (0.029)	-0.018 (0.043)	-0.042 (0.031)	-0.032 (0.029)	-0.004 (0.044)	-0.034 (0.030)
Unemployment rate	-0.002 (0.009)	-0.006 (0.009)	-0.004 (0.009)	-0.007 (0.010)	-0.008 (0.010)	-0.007 (0.009)
COVID-19 spread	0.002 (0.029)	0.013 (0.035)	0.010 (0.028)	0.008 (0.029)	0.011 (0.033)	0.019 (0.026)

Parents' health issues	0.183*** (0.020)	0.161*** (0.021)	0.161*** (0.018)	0.166*** (0.022)	0.156*** (0.022)	0.160*** (0.020)
Pre-pandemic serious illness	0.122*** (0.032)	0.108*** (0.035)	0.084*** (0.022)	0.130*** (0.033)	0.113*** (0.037)	0.083*** (0.024)
Non-participant in 2018	-0.015 (0.026)	0.043* (0.023)	-0.016 (0.024)	-0.017 (0.027)	0.036 (0.025)	-0.016 (0.023)
Observations	5,610	5,126	5,127	4,551	4,235	4,236
Unique children IDs	2,584	2,382	2,382	2,198	2,057	2,058
R squared overall	0.082	0.076	0.066	0.079	0.073	0.067

Notes: Table presents estimates of Equation (6) using a random effect estimator with a child-specific random component. All estimations include year and regional fixed effects. 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 18-29 for parent's age, basic general for parent's education, regional center for place of residence. Parent's age and education are for mothers. If the mother is absent, then father's characteristics are used.

Table W3: Parent's Health Equations

Variables	Mothers		Fathers	
	(1)	(2)	(3)	(4)
School closure	0.103 (0.068)	0.078 (0.076)	0.056 (0.044)	0.059 (0.050)
School break	-0.025 (0.046)	-0.072 (0.047)	0.048 (0.045)	0.035 (0.050)
Workplace closure	-0.205 (0.162)	-0.206 (0.159)	-0.252*** (0.083)	-0.267*** (0.076)
Long holidays	0.024 (0.021)	0.026 (0.022)	0.030 (0.021)	0.023 (0.019)
Child's age	0.003 (0.003)	0.004 (0.004)	0.003 (0.002)	0.005* (0.003)
Parent's age				
30-44	0.002 (0.023)	0.008 (0.022)	0.007 (0.031)	0.005 (0.030)
45-60	-0.005 (0.029)	-0.007 (0.029)	0.036 (0.033)	0.036 (0.034)
Parent's education				
Secondary general	0.008 (0.028)	0.003 (0.029)	0.024 (0.017)	0.021 (0.020)
Secondary professional	0.039 (0.035)	0.042 (0.036)	0.031 (0.020)	0.027 (0.023)
Tertiary	0.020 (0.027)	0.014 (0.026)	0.023 (0.026)	0.019 (0.027)
Single parent	0.007 (0.015)	0.004 (0.016)	-0.020 (0.053)	-0.026 (0.049)
Place of residence				
Other urban settlement	-0.063 (0.055)	-0.061 (0.047)	-0.041 (0.034)	-0.046 (0.034)
Rural	-0.095 (0.063)	-0.102* (0.052)	-0.049 (0.030)	-0.057* (0.032)
Unemployment rate	-0.018** (0.008)	-0.019** (0.009)	-0.003 (0.007)	-0.005 (0.008)
COVID-19 spread	-0.026 (0.031)	-0.028 (0.031)	-0.009 (0.022)	0.002 (0.021)

Any child had health issues	0.127*** (0.016)		0.080*** (0.016)	
Any child had flu-like symptoms		0.133*** (0.019)		0.070*** (0.016)
Pre-pandemic serious illness	0.136*** (0.018)	0.128*** (0.018)	0.126*** (0.029)	0.133*** (0.030)
Non-participant in 2018	0.059*** (0.019)	0.051*** (0.016)	0.020 (0.020)	0.019 (0.024)
Observations	4,473	4,242	3,563	3,402
Unique parent IDs	1,961	1,862	1,566	1,504
R squared overall	0.093	0.089	0.063	0.060

Notes: Table presents estimates of Equation (7) using a random effect estimator with a parent-specific random component. The dependent variable is whether parents had health issues in the last 30 days. All estimations include year and regional fixed effects. 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 18-29 for parent's age, basic general for parent's education, regional center for place of residence.

Table W4: Labor Supply Equations

Variables	Employed	Log total hours	Log prime job hours	Work from home	Hours working from home
<i>A. Mothers</i>					
School closure	-0.065 (0.045)	0.030 (0.040)	0.029 (0.048)	0.089** (0.040)	0.326*** (0.126)
School break	-0.005 (0.041)	-0.020 (0.043)	0.004 (0.041)	0.065** (0.028)	0.142 (0.098)
Workplace closure	0.158 (0.170)	0.077 (0.110)	0.088 (0.104)	-0.351** (0.161)	-1.008** (0.475)
Long holidays	-0.038 (0.025)	-0.035 (0.027)	-0.048* (0.024)	0.023 (0.020)	0.039 (0.059)
Any child's health issues	-0.034*** (0.011)	-0.033*** (0.012)	-0.038*** (0.013)	0.013 (0.012)	0.043* (0.026)
Parent's health issues	-0.003 (0.014)	-0.026* (0.014)	-0.023* (0.012)	0.028* (0.017)	0.054 (0.047)
Older caregiver	0.004 (0.019)	0.030** (0.014)	0.028* (0.017)	0.049** (0.020)	0.161** (0.067)
Indoor occupation	...	-0.002 (0.014)	-0.003 (0.015)	0.020* (0.011)	0.065** (0.026)
Unstructured job	...	-0.000 (0.007)	-0.005 (0.007)	0.031*** (0.009)	0.065*** (0.023)
COVID-19 spread	0.026 (0.016)	-0.012 (0.023)	-0.007 (0.022)	0.038* (0.022)	0.153** (0.072)
Child's age	0.010*** (0.004)	0.003 (0.002)	0.005** (0.002)	-0.002 (0.002)	-0.004 (0.005)
Parent's age					
30-44	0.019 (0.022)	0.015 (0.031)	0.013 (0.034)	-0.010 (0.019)	-0.021 (0.055)
45-60	0.013	0.017	0.017	0.003	-0.009

	(0.031)	(0.029)	(0.032)	(0.026)	(0.064)
Parent's education					
Secondary general	0.105***	0.048	0.048	0.001	-0.021
	(0.030)	(0.036)	(0.036)	(0.019)	(0.037)
Secondary professional	0.131***	0.015	0.020	-0.002	0.021
	(0.036)	(0.042)	(0.040)	(0.025)	(0.049)
Tertiary	0.231***	0.021	0.024	0.094***	0.260***
	(0.029)	(0.041)	(0.040)	(0.016)	(0.052)
Single parent	0.082***	0.045***	0.033***	-0.004	-0.008
	(0.020)	(0.011)	(0.011)	(0.012)	(0.037)
Place of residence					
Other urban settlement	0.010	-0.026	-0.016	-0.089***	-0.248***
	(0.023)	(0.027)	(0.024)	(0.023)	(0.051)
Rural	0.008	-0.056*	-0.046	-0.090***	-0.216***
	(0.018)	(0.032)	(0.029)	(0.026)	(0.046)
Unemployment rate	-0.006	-0.006	-0.008	-0.011	-0.005
	(0.007)	(0.010)	(0.009)	(0.008)	(0.020)
Industry					
Mining & manufacturing	...	-0.016	-0.014	-0.024	-0.039
		(0.052)	(0.052)	(0.027)	(0.052)
Housing & utilities	...	-0.117**	-0.109*	-0.100***	-0.250**
		(0.056)	(0.057)	(0.034)	(0.114)
Construction	...	-0.047	-0.048	-0.006	-0.068
		(0.062)	(0.063)	(0.056)	(0.114)
Transportation & communication	...	-0.087	-0.097*	-0.039	-0.035
		(0.059)	(0.056)	(0.028)	(0.068)
Trade & consumer services	...	-0.032	-0.036	0.007	0.037
		(0.049)	(0.050)	(0.025)	(0.040)
Health care & social assistance	...	-0.088*	-0.110**	-0.023	-0.064
		(0.053)	(0.052)	(0.024)	(0.081)
Education, science, culture	...	-0.118**	-0.135**	0.102***	0.259***
		(0.051)	(0.053)	(0.028)	(0.075)
Public administration	...	-0.048	-0.042	-0.046*	-0.123**
		(0.054)	(0.054)	(0.025)	(0.051)
Other/unknown	...	-0.107*	-0.119*	0.066*	0.178*
		(0.059)	(0.062)	(0.037)	(0.100)
Observations	4,470	2,866	2,861	3,111	3,044
Unique parent IDs	1,961	1,435	1,433	1,522	1,503
R squared overall	0.122	0.078	0.087	0.143	0.136

B. *Fathers*

School closure	0.017	-0.033	-0.016	0.004	0.061
	(0.042)	(0.045)	(0.042)	(0.040)	(0.096)
School break	-0.045	0.013	0.035	0.026	-0.021
	(0.031)	(0.037)	(0.038)	(0.028)	(0.054)
Workplace closure	0.042	-0.001	-0.042	0.031	0.054
	(0.104)	(0.097)	(0.084)	(0.094)	(0.218)
Long holidays	-0.004	-0.010	-0.003	-0.024*	-0.037
	(0.026)	(0.029)	(0.028)	(0.012)	(0.032)
Any child's health issues	-0.011	0.010	0.009	0.001	0.002
	(0.009)	(0.010)	(0.010)	(0.007)	(0.016)

Parent's health issues	-0.043*** (0.016)	-0.029 (0.019)	-0.034* (0.020)	0.025 (0.016)	0.070** (0.035)
Older caregiver	0.019 (0.018)	-0.022 (0.022)	-0.020 (0.020)	-0.003 (0.013)	0.003 (0.028)
Indoor occupation	...	0.002 (0.007)	-0.004 (0.009)	0.015*** (0.005)	0.020** (0.010)
Unstructured job	...	0.004 (0.008)	0.008 (0.007)	0.005 (0.009)	0.012 (0.019)
COVID-19 spread	-0.033 (0.021)	-0.051 (0.033)	-0.039 (0.031)	0.034 (0.023)	0.067 (0.045)
Child's age	-0.002 (0.002)	0.004 (0.002)	0.004* (0.002)	-0.001 (0.002)	-0.003 (0.003)
Parent's age					
30-44	0.042 (0.048)	-0.016 (0.032)	-0.013 (0.031)	0.008 (0.011)	0.020 (0.013)
45-60	-0.002 (0.045)	-0.029 (0.037)	-0.032 (0.038)	0.000 (0.011)	0.028 (0.018)
Parent's education					
Secondary general	0.060*** (0.023)	-0.004 (0.025)	-0.005 (0.025)	0.016 (0.010)	0.008 (0.011)
Secondary professional	0.089*** (0.029)	-0.015 (0.022)	-0.013 (0.024)	0.018 (0.011)	0.020 (0.021)
Tertiary	0.112*** (0.021)	-0.049* (0.029)	-0.045 (0.031)	0.073*** (0.019)	0.149*** (0.035)
Single parent	-0.208*** (0.054)	0.036 (0.067)	0.031 (0.062)	0.046 (0.042)	0.056 (0.074)
Place of residence					
Other urban settlement	0.041 (0.035)	-0.011 (0.026)	-0.014 (0.025)	-0.070*** (0.013)	-0.109** (0.046)
Rural	-0.061* (0.032)	-0.011 (0.023)	-0.008 (0.021)	-0.065*** (0.014)	-0.096** (0.042)
Unemployment rate	-0.007 (0.005)	-0.008 (0.008)	-0.013 (0.009)	0.001 (0.005)	0.010 (0.010)
Industry					
Mining & manufacturing	...	-0.068** (0.033)	-0.075** (0.034)	0.007 (0.012)	-0.007 (0.029)
Housing & utilities	...	-0.104*** (0.039)	-0.114*** (0.039)	0.016 (0.019)	-0.018 (0.032)
Construction	...	-0.013 (0.038)	-0.010 (0.039)	0.028* (0.015)	0.032 (0.032)
Transportation & communication	...	-0.027 (0.038)	-0.030 (0.038)	0.002 (0.014)	-0.008 (0.027)
Trade & consumer services	...	-0.047 (0.038)	-0.059 (0.040)	0.021 (0.016)	0.011 (0.030)
Health care & social assistance	...	-0.053 (0.049)	-0.057 (0.046)	0.018 (0.034)	-0.024 (0.067)
Education, science, culture	...	-0.104** (0.050)	-0.120** (0.053)	0.080* (0.047)	0.211* (0.125)
Public administration	...	-0.019 (0.047)	-0.023 (0.047)	-0.011 (0.013)	-0.034 (0.028)
Other/unknown	...	-0.099**	-0.099**	0.064**	0.034

		(0.039)	(0.040)	(0.030)	(0.049)
Observations	3,561	2,580	2,579	2,954	2,915
Unique parent IDs	1,565	1,260	1,260	1,385	1,375
R squared overall	0.208	0.0784	0.0808	0.0959	0.0926

Notes: Table presents estimates of Equation (8) using a random effect estimator with a parent-specific random component and fixed effects for year and region. 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 18-29 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. See notes to Table W6 for an explanation of this result.

Table W5: Falsification Test for the Effect of School Closure

Placebo groups/Outcomes	Grade 1	Grade 3	Grade 5	Grade 7	N
<i><u>Females Without Kids</u></i>					
Employed	0.026 (0.057)	0.026 (0.057)	0.049 (0.037)	0.002 (0.032)	3,615
Total hours of work, log	0.056 (0.044)	0.056 (0.044)	0.019 (0.038)	0.010 (0.035)	1,736
Hours at primary job, log	0.020 (0.059)	0.020 (0.059)	-0.021 (0.065)	-0.008 (0.044)	1,736
Work from home	0.077 (0.122)	0.077 (0.122)	0.049 (0.067)	0.006 (0.049)	1,911
Hours worked from home, log	0.293 (0.244)	0.293 (0.244)	0.132 (0.145)	0.088 (0.100)	1,859
Health issues	-0.048 (0.068)	-0.048 (0.068)	0.033 (0.028)	0.020 (0.019)	3,613
<i><u>Males Without Kids</u></i>					
Employed	0.046 (0.061)	0.046 (0.061)	-0.017 (0.035)	-0.043 (0.040)	4,367
Total hours of work, log	-0.076 (0.072)	-0.076 (0.072)	-0.000 (0.057)	-0.015 (0.043)	2,148
Hours at primary job, log	-0.086 (0.072)	-0.086 (0.072)	-0.001 (0.058)	-0.010 (0.043)	2,148
Work from home	-0.010 (0.035)	-0.010 (0.035)	-0.016 (0.024)	-0.040*** (0.013)	2,444
Hours worked from home, log	0.016 (0.043)	0.016 (0.043)	0.014 (0.028)	-0.023 (0.017)	2,411
Health issues	0.001 (0.065)	0.001 (0.065)	0.065 (0.051)	0.036 (0.045)	4,361
<i><u>Mothers with Young Kids</u></i>					
Employed	-0.116 (0.107)	-0.116 (0.107)	-0.081 (0.058)	-0.063 (0.047)	1,417
Total hours of work, log	-0.021 (0.155)	-0.021 (0.155)	-0.203 (0.199)	-0.211 (0.129)	566
Hours at primary job, log	-0.001 (0.124)	-0.001 (0.124)	-0.191 (0.196)	-0.183 (0.117)	564
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.

Table W6: Joint Estimation

	Health Issues			Employment		Log Total Hours		Log prime job hours		Work from home		Hours working from home	
	Mother	Father	Child	Mother	Father	Mother	Father	Mother	Father	Mother	Father	Mother	Father
School closure	0.110*	0.053	-0.229***	-0.062	0.011	0.031	-0.067*	0.036	-0.055	0.119**	0.019	0.368**	0.070
	(0.063)	(0.044)	(0.055)	(0.058)	(0.041)	(0.041)	(0.039)	(0.049)	(0.042)	(0.049)	(0.040)	(0.164)	(0.101)
School break	0.015	0.072	-0.039	0.013	-0.034	-0.009	-0.003	0.012	0.008	0.071**	0.011	0.206*	-0.018
	(0.052)	(0.049)	(0.056)	(0.053)	(0.035)	(0.046)	(0.037)	(0.045)	(0.040)	(0.032)	(0.033)	(0.123)	(0.065)
Workplace closure	-0.213	-0.224***	0.303**	0.196	0.108	0.120	-0.024	0.158	-0.051	-0.265	0.034	-0.918*	0.071
	(0.148)	(0.080)	(0.122)	(0.170)	(0.122)	(0.138)	(0.090)	(0.126)	(0.078)	(0.195)	(0.110)	(0.494)	(0.246)
Long holidays	0.035	0.047**	-0.026	-0.044*	-0.019	-0.055*	-0.002	-0.072**	0.005	0.014	-0.026*	0.026	-0.031
	(0.022)	(0.021)	(0.031)	(0.027)	(0.031)	(0.033)	(0.030)	(0.030)	(0.028)	(0.028)	(0.015)	(0.075)	(0.033)
Child's age	0.010***	0.008***	-0.013***	0.013***	0.001	0.004	0.002	0.006**	0.002	-0.003	-0.000	-0.010	-0.001
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.007)	(0.004)
Parent's age													
30-44	0.004	0.041	-0.010	0.078**	0.020	0.011	-0.027	0.002	-0.025	-0.000	0.006	0.014	0.019
	(0.024)	(0.037)	(0.036)	(0.033)	(0.051)	(0.027)	(0.032)	(0.030)	(0.032)	(0.020)	(0.014)	(0.063)	(0.017)
45-60	0.035	0.081**	-0.005	0.052	-0.054	0.030	-0.027	0.024	-0.028	0.026	-0.004	0.073	0.024
	(0.029)	(0.039)	(0.039)	(0.038)	(0.046)	(0.024)	(0.038)	(0.028)	(0.038)	(0.026)	(0.013)	(0.068)	(0.019)
Parent's education													
Secondary general	0.016	0.017	-0.010	0.129***	0.078***	0.035	-0.003	0.040	-0.002	0.005	0.017**	-0.001	0.011
	(0.031)	(0.017)	(0.028)	(0.038)	(0.029)	(0.033)	(0.023)	(0.033)	(0.025)	(0.018)	(0.008)	(0.036)	(0.010)
Secondary professional	0.057	0.027	-0.059*	0.158***	0.112***	-0.000	-0.025	0.004	-0.021	0.002	0.020**	0.023	0.021
	(0.038)	(0.019)	(0.030)	(0.047)	(0.033)	(0.040)	(0.020)	(0.037)	(0.023)	(0.026)	(0.009)	(0.050)	(0.015)
Tertiary	0.041	0.027	-0.023	0.254***	0.130***	0.015	-0.052**	0.018	-0.048*	0.100***	0.069***	0.263***	0.139***
	(0.031)	(0.020)	(0.026)	(0.037)	(0.025)	(0.039)	(0.026)	(0.037)	(0.028)	(0.016)	(0.017)	(0.049)	(0.035)
Single parent	0.024	0.006	0.072***	0.083***	-0.181***	0.042***	0.033	0.029**	0.023	0.001	0.046	-0.002	0.068
	(0.017)	(0.053)	(0.019)	(0.025)	(0.045)	(0.012)	(0.053)	(0.012)	(0.051)	(0.014)	(0.046)	(0.044)	(0.093)
Place of residence													
Other urban settlement	-0.056	-0.032	0.056	0.006	0.038	-0.025	-0.013	-0.016	-0.017	-0.077***	-0.063***	-0.195***	-0.090**
	(0.057)	(0.030)	(0.038)	(0.025)	(0.036)	(0.030)	(0.024)	(0.026)	(0.023)	(0.025)	(0.010)	(0.055)	(0.035)
Rural	-0.058	-0.022	0.055	0.018	-0.064*	-0.051	-0.013	-0.043	-0.010	-0.083***	-0.059***	-0.188***	-0.081**
	(0.069)	(0.031)	(0.048)	(0.019)	(0.034)	(0.036)	(0.023)	(0.032)	(0.022)	(0.024)	(0.011)	(0.040)	(0.036)
Unemployment rate	-0.015*	-0.001	0.003	-0.009	-0.013**	-0.007	-0.014	-0.010	-0.017*	-0.010	-0.003	-0.006	0.005
	(0.008)	(0.007)	(0.009)	(0.007)	(0.005)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.006)	(0.027)	(0.011)
COVID-19 spread	-0.012	-0.004	0.036	0.018	-0.017	0.001	-0.040#	0.006	-0.032	0.058**	0.038*	0.205***	0.076**
	(0.030)	(0.020)	(0.028)	(0.022)	(0.021)	(0.026)	(0.029)	(0.025)	(0.028)	(0.023)	(0.022)	(0.076)	(0.038)

Any child's health issues	0.478*** (0.020)	0.315*** (0.016)		-0.051*** (0.015)	-0.003 (0.012)	-0.029** (0.013)	0.017# (0.011)	-0.032** (0.014)	0.015 (0.011)	0.024* (0.013)	-0.004 (0.007)	0.076** (0.037)	-0.011 (0.015)
Parent's health issues	...	...	...	-0.022 (0.017)	-0.069*** (0.020)	-0.027# (0.016)	-0.026# (0.016)	-0.028* (0.015)	-0.034** (0.016)	0.034* (0.018)	0.022 (0.015)	0.100** (0.048)	0.074** (0.034)
Any parent's health issues	...	...	0.870*** (0.017)	...	...	...	...	...	...	...	...	...	...
Pre-pandemic serious illness	0.083*** (0.012)	0.088*** (0.018)	0.068*** (0.020)	...	...	...	...	...	...	...	...	...	...
Non-participant in 2018	0.034** (0.014)	0.012 (0.015)	-0.008 (0.027)	...	...	...	...	...	...	...	...	...	...
Older caregiver	...	...	...	0.006 (0.019)	0.031 (0.021)	0.026** (0.013)	-0.010 (0.018)	0.029* (0.016)	-0.011 (0.015)	0.034* (0.019)	-0.001 (0.011)	0.123** (0.057)	0.011 (0.023)
Indoor occupation	...	...	...	...	...	0.004 (0.013)	0.002 (0.006)	0.005 (0.015)	-0.002 (0.007)	0.022* (0.011)	0.015*** (0.006)	0.054** (0.026)	0.021* (0.011)
Unstructured job	...	...	...	...	...	0.000 (0.007)	0.004 (0.008)	-0.003 (0.007)	0.009 (0.007)	0.036*** (0.009)	0.010 (0.010)	0.084*** (0.027)	0.019 (0.019)
Cov (M, F)		0.043*** (0.004)			0.011** (0.005)		0.007*** (0.002)		0.006*** (0.002)		0.007** (0.003)		0.041* (0.025)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table presents estimates of Equations (9) and (10) allowing for the within-family correlation of error terms. The parent's sample includes parents of children in grades 1-8 under age 15. The children's sample includes the youngest school-age child. Robust standard errors (in parentheses) are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1. # indicates statistically significant estimates at the 10 percent level when robust standard errors are used instead of cluster robust. Omitted (base) categories are age 18-29 for parent's age, basic general for parent's education, regional center for place of residence.

Appendix 3: The Effect of School Closure on Depression

More and more 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 here. 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 create a 12-month cumulative measure of closed school days and school breaks in the last 12 months as the share of annual business days and estimate the following linearized model:

$$M_{it}^P = f^P(S_{it}, H_{it}^P, \tilde{H}_{it}^C, X_{it}, Z_{i,pre}^P, \theta_t, \eta_r) + \mu_i^M + \epsilon_{it}^M,$$

where M_{it}^P is a binary indicator for parents having psychological disorder or depression in the last 12 months, $\tilde{H}_{it}^C$ denotes cumulative measures of schooling disruptions over the 12-month period. Other variables are described in Section 4. 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 found for both mothers and fathers, although the size of the effect for mothers is nearly twice as big as for fathers.

Table W7: Equations for Parent’s Depression

	Mothers	Fathers
School closure 12m	0.385*** (0.146)	0.207** (0.104)
School break 12m	0.119 (0.389)	0.049 (0.401)
Workplace closure 12m	0.857 (0.881)	-0.518 (0.745)
Long holidays 12m	0.016 (0.016)	-0.002 (0.017)
Any child had health issues last 30d	0.019 (0.012)	0.006 (0.006)
Parent had health issues last 30d	0.047***	0.060***

	(0.011)	(0.011)
Child's age	0.001	-0.001
	(0.002)	(0.002)
Parent's age		
30-44	0.020	-0.025
	(0.019)	(0.020)
45-60	0.017	-0.012
	(0.023)	(0.014)
Parent's education		
Secondary general	0.018	-0.011
	(0.019)	(0.015)
Secondary professional	-0.021	-0.033**
	(0.014)	(0.017)
Tertiary	-0.048***	-0.036*
	(0.016)	(0.020)
Single parent	0.039**	0.111**
	(0.015)	(0.043)
Location type		
Other urban settlement	-0.012	-0.001
	(0.044)	(0.023)
Rural	-0.026	0.006
	(0.035)	(0.022)
Unemployment rate	0.010	-0.001
	(0.007)	(0.005)
COVID-19 spread 12m	-0.002	0.002
	(0.003)	(0.003)
Pre-pandemic serious illness	0.013	0.041***
	(0.010)	(0.009)
Non-participant in 2018	0.033*	0.016
	(0.020)	(0.015)
Pre-pandemic check-up	0.024	0.024
	(0.019)	(0.016)
Observations	4,445	3,536
Unique children IDs	1,957	1,560
R squared overall	0.0700	0.0733

Notes: Table presents estimates of equations for parent's depression using a random effect estimator with a parent-specific random component. The dependent variable is whether parents had a serious nervous disorder or depression in the last 12 months. All estimations include year and regional 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 18-29 for parent's age, basic secondary for parent's education, regional center for location type.

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 Equation (6) for child’s health except that child’s 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

	Outsiders	Relatives
School closure		
Average effect	-0.036 (0.034)	-0.031 (0.033)
Grade 1-4	-0.025 (0.063)	0.012 (0.058)
Grade 5-8	-0.038 (0.043)	-0.048 (0.039)
School break		
Average effect	0.057 (0.045)	0.041 (0.038)
Grade 1-4	0.115* (0.061)	0.122** (0.051)
Grade 5-8	-0.007 (0.049)	-0.051 (0.041)
N of observations	5,590	5,589

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 with a child-specific random component. The model includes a child’s health issues as a covariate. All other covariates are the same as in Equation (6) 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 RE method and the same set of covariates as it is specified in Equation (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; this relationship is stronger for parents of younger students in grades 1-4, although it is not statistically significant. At the same time, there is a negative effect of school breaks on excess hours among parents of older children. The results indicate that mothers have more flexibility in working hours than fathers do, and they can work extra hours on the days when they have the opportunity to go to work. This supports our hypothesis that mothers 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

	Mothers	Fathers
School closure		
Average effect	0.387** (0.172)	0.166 (0.151)
Grade 1-4	0.678 (0.452)	0.036 (0.139)
Grade 5-8	0.207** (0.096)	0.276 (0.203)
School break		
Average effect	-0.019 (0.101)	-0.126 (0.142)
Grade 1-4	0.167 (0.197)	0.090 (0.202)
Grade 5-8	-0.294** (0.146)	-0.436** (0.200)
N of observations	2,913	2,619

Notes: Table presents the average marginal effects (AMEs) of school closure and school breaks on parent’s excess hours per day. Estimation is done using the linear probability model with a parent-specific random component. All covariates are the same as in Equation (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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