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Parental Labor Supply Responses to COVID-19 School Closures in Russia: Unpacking Heterogeneous Effects*

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ABSTRACT: This study reveals substantial heterogeneity in how mothers and fathers responded to COVID-19-related school closures in Russia. Employing the correlated random coefficient model with individual fixed effects across a 6-year panel, we find that, on average, school closures did not impact working hours but resulted in decreased employment and increased remote work, with the effect on mothers being notably more pronounced than on fathers. However, the variation in treatment effects is striking across parental characteristics, child's grade, child's health, reliance on outside family help, household composition, infection spread, and regional conditions. In several subsamples, the employment response of fathers closely mirrors that of mothers, especially among older parents, those with younger pre-school children, and in regions with high COVID-19 spread. When interacting two or more different factors, the study unveils a complex within-family production function determining the differential responses of parents under diverse regional, temporal and family circumstances.

KEYWORDS: school closure, labor supply, work from home, COVID-19, heterogenous treatment effects, correlated random coefficient model, Russia.

JEL CLASSIFICATION: J13, J22

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1 Introduction

The recent COVID-19 pandemic has brought school closures to the forefront as a widely implemented policy aimed at mitigating the spread of the virus. With the likelihood of future pandemics (e.g., Morens and Fauci, 2020), understanding the impact of past anti-pandemic measures becomes crucial. The COVID-19-related school closures have significantly disrupted parental work arrangements, and the consequences of children unexpectedly staying at home were far from uniform among parents. The responses of parents varied across parental characteristics, child's health, reliance on outside family help, household composition, infection spread, and regional conditions. This paper examines the heterogeneity of parental labor supply responses to school closures across all these factors in the context of Russia.

Prior research has predominantly focused on the U.S. and other developed economies, as evidenced by the comprehensive literature review on school disruptions and parental employment (Lillard et al., 2023). Our study broadens this focus, tapping into the unique experiences of countries with diverse socioeconomic conditions. The Russian case is particularly interesting due to regionally imposed school policies, resulting in considerable regional variation in the timing and duration of closures. Moreover, the data on school closures in Russia is daily and grade-specific, directly collected for each decision maker (governor or government of a region), extending until the end of 2022. This stands in contrast to most existing studies that rely on aggregate or indirect data on school closures, often sourced from the early pandemic period.[1] The unique dataset compiled by the authors offers the capability to distinguish COVID-related school closures from regular school breaks, extended holidays, closures due to inclement weather and other reasons, as well as business shutdowns.

Our analysis draws from the last six years of the Russia Longitudinal Monitoring Survey-Higher School of Economics (RLMS-HSE), covering the period from 2017 to 2022. This survey collects data on work duration, remote work, parents' and children's health, and various characteristics

[1] Some examples of previously used school closure measures include individual responses on the teaching modes aggregated at the state level (Lofton et al., 2021), changes in school visits based on mobile phone data (Garcia & 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 & West, 2022) and instructional modality (in-person or hybrid) by the school district and month available for Michigan and Washington states only (Goldhaber et al., 2022).

for the same individuals and families for three years before the pandemic and three years after its onset. This extensive dataset enables us to analyze how parents adjusted their labor supply during the pandemic years, conditional on previous labor supply decisions and family history. With known interview dates, we can precisely align the timing of school closures with the 30-day survey reference period.

We employ and compare results from several estimation methods, including the standard difference-in-difference (DID) approach with two-way fixed effects for region and time. We first estimate labor supply equations separately for mothers and fathers, then conduct a joint estimation with a correlated time-varying family component. We also leverage the panel feature of our dataset by incorporating individual fixed effects in the labor supply model – an approach that is relatively uncommon in the literature of school closures. These methods assume no selection on gains and often estimate a constant treatment effect that does not change across treated units and over time.

The conventional approach to capturing heterogeneous treatment effects involves either splitting the sample (e.g., mothers vs. fathers, younger vs older children) when the number of observations permits or interacting the treatment variable with one of the covariates. However, this approach imposes limitations on the number of ways the sample can be subdivided and the number of regressions with interactions that can be estimated within a single study. As demonstrated in the literature review in Section 2.1, previous studies on school closures typically estimate the treatment effects varying by a very limited number of factors taken separately from one another (e.g., marital status, child's age, or parent's education).

This study captures heterogeneity using the correlated random coefficient (CRC) model for panel data with individual fixed effects (see Hsiao et al, 2019; Verdier, 2020). This method estimates individual-specific treatment effects while simultaneously accounting for flexible patterns of selection on unobservables. The CRC model avoids imposing restrictions on the relationship between school closure, on one hand, and baseline pre-treatment heterogeneity, heterogeneous treatment effects, observables, and aggregate shocks, on the other hand. Individual-specific and time-varying treatment effects are further aggregated to obtain the average treatment effect for a given group of interest. This approach offers a flexible framework for estimating the treatment effects for groups that may have been overlooked in previous research, such as those related to parents' and children's health, parent's age, the presence of pre-school children, the availability of outside family helpers, job type, unemployment, COVID-19 spread, etc. Furthermore, it allows for obtaining treatment effects for subgroups created by two or more factors, such as college-educated older fathers or mothers of middle school children experiencing health problems.

The findings derived from the CRC model indicate that, on average, school closures in Russia had no discernible effect on working hours. However, they did result in a decline in employment and an increase in remote work, with a more noticeable impact on mothers compared to fathers. Yet, the variation in treatment effects is significant across various factors, especially by parent's age and education, the child's grade level, child's health, reliance on outside family help, within-family work arrangement, infection spread, regional unemployment, and others. In certain groups, the employment response of fathers closely mirrors that of mothers, particularly among older parents, those with younger pre-school children, and in regions with a high COVID-19 spread.

Our estimates reveal an even larger variation in treatment effects across subgroups defined by two or more different factors, emphasizing the complexity of within-family production functions and the distinct division of responsibilities within Russian households. For example, the labor supply responses to school closures range widely across gender-age-education groups. Young fathers without college education maintained their labor supply, whereas low-educated young mothers decreased their employment. In a less patriarchal response, both college-educated mothers and fathers reduced their employment rates. Older parents also adopted less patriarchal strategies, with both mothers and fathers decreasing employment rates, and older fathers notably transitioning to working from home.

Additionally, we observe significant variations in parental labor supply response based on the child's grade, child's health, and the presence of pre-school children. Mothers are more inclined to exit employment and reduce working hours when their child is in elementary school compared to middle school during school closures. The employment response of fathers is also negative, albeit smaller, and is more pronounced when the child is in grades 5 to 8. In instances of a child's illness, mothers of elementary school children exhibit a very high propensity of leaving employment, while fathers tend to increase working hours, possibly compensating for the loss of spousal employment income. Interestingly, fathers opt to leave employment in response to school closures when their middle school child experiences health issues. The probability of working from home significantly rises when children face health problems, particularly when mothers lack outside help. Similar substantial responses occur when a school-age child is sick, and there is another younger child requiring care. These results underscore the significance of considering a child's health during school closures, with potential implications tied to the spread of COVID-19.

We also find substantial heterogeneity in treatment effects based on the marital status of women and the employment status of spouses. Our primary focus in this part of research is on women due to the limited number of single fathers in our sample. Single mothers exhibit a more significant decline in employment when schools are closed compared to their married counterparts. Among married individuals, men increase their working hours when their spouse is not employed during school closures. At the same time, women tend to work more hours from home when their spouse is employed.

Finally, we show that parents respond differently to school closures depending on the unemployment rates and COVID-19 spread in their regions. Notably, both mothers and fathers significantly decrease their employment and increase remote work when COVID-19 is prevalent, but the unemployment rate is low. Conversely, parents are more reluctant to leave their workplaces and request remote work when job opportunities are scarce, even when COVID-19 is widespread.

The findings above represent only a small snippet obtained from the distribution of estimated individual-specific treatment effects, with more detailed results presented in Section 5. The remainder of the paper is organized as follows: Section 2 provides a literature review and a framework for understanding sources of heterogeneity, Section 3 describes the survey data and measures of schooling disruptions, Section 4 presents the estimation methodology, Section 5 reports findings on the impact of school closures on labor supply, and we conclude with final remarks in Section 6.

2 Background

2.1 Literature Review

A growing body of research examines the labor market consequences of school closures, predominantly at the micro level using household surveys. Numerous studies highlight the negative impact of pandemic-induced schooling disruptions, revealing a reduction in labor market participation and working hours among mothers of school-age children. This often necessitates mothers to transition to remote work (see Amuedo-Dorantes et al., 2023; Collins et al., 2021; Couch et al., 2022; Garcia & Cowan, 2022; Hansen et al., 2022; among others). In contrast, the corresponding effects on fathers' working hours are generally smaller, and in some cases, may even be negligible. The primary driver behind the labor supply response to canceling in-person classes is predominantly the increased demand for childcare due to children staying at home.

Several papers underscore the heterogeneity in the impact of school closures on parental labor supply across various dimensions, including parents' education, child's age, marital status, the presence of other adults, and regional characteristics. For instance, studies by Garcia and Cowan (2022), Goldin (2022), Hansen et al. (2022), and Kozhaya (2022) focus on parents' education. Their collective findings indicate that parents without college degrees were less likely to be employed, less prone to working from home, and experienced a greater reduction in working hours compared to their college-educated counterparts during the periods of school closures.

Some studies investigate how the labor supply effects of school closures vary based on children's age. Hansen et al. (2022) and Yamamura and Tsutsui (2021) find that mothers of primary school children were more inclined to work from home than mothers of middle and high school children during school closures. Yamamura and Tsutsui (2021) additionally demonstrate that fathers of primary school children were less likely to work from home than their peers with middle and high school children. Meanwhile, Hansen et al. (2022) conclude that mothers of older children were more likely to be employed and worked longer hours than those with younger children. These studies reveal a division of family responsibilities, with mothers more likely to work from home if they have elementary school children, while fathers tend to do so when facing school disruptions with older children.

Other important dimensions of heterogeneity include marital status and the presence of other adults. Evidence regarding the differential effects of school closures by marital status yields surprisingly mixed results. Garcia and Cowan (2022) find that single women were less likely to work and experienced a greater reduction in working hours in response to school closures than their married counterparts, while Kozhaya (2022) argues the opposite. In contrast, Hansen et al. (2022) assert that the labor supply of single mothers was affected by school closures in the same way as that of married women. According to Kozhaya (2022), the presence of a grandparent in the household does not seem to matter for labor supply responsiveness to school closures. However, Kalenovsky and Pabilonia (2020) find that school closures lead to a more substantial decrease in the labor supply of coupled mothers and single fathers when older adults reside in the household. The authors argue that the presence of an additional adult in the household raises the probability of at least one household member contracting an infection. This, in turn, increases the likelihood of all household members being infected and unable to contribute to the labor market.

Lastly, a number of papers have examined the regional differences in the employment effects of school closures. In the works of Koppa and West (2022) and Kozhaya (2022), the impact appears similar across areas characterized by high and low poverty rates. Additionally, Koppa and West (2022) find no heterogeneous treatment effects across regions with varying labor force participation rates and varying COVID-19 death rates. Kozhaya (2022) reveals that parents residing in larger settlements were more likely to reduce their labor force participation and working hours than their peers living in smaller settlements.

As evident, prior research on school closures has predominantly assessed the heterogeneity in treatment effects based on a limited set of individual factors often considered in isolation from one another. Through the comprehensive exploration of the entire distribution of individual-specific and time-varying treatment effects, we aim to present a more holistic understanding of the parental labor supply response across diverse regional, temporal, and family circumstances.

2.2 Sources of Heterogeneity

The main sources of heterogeneous effects can be identified through Gary Becker's 1965 framework, which outlines how individuals allocate their time (Becker 1965). Lillard (2023) applies this theory to the context of school closure. We introduce an additional demand on parental time from household activities, including care when a child is sick. Our assumption is that the parent seeks to maximize utility derived from consumption (c), leisure (l), and their child's education (q), subject to available time and total financial resources. The quality of a child's education can be expressed as $A \cdot I$, where A is the productivity parameter, and I is the net time investment in children:

$$q = A \cdot I = A(t^f + \pi t^e - t^c), \qquad A > 0, \qquad \pi > 0, \tag{1}$$

In this equation, the net time investment in children encompasses time spent at school (t^f), parental involvement in their child's education (t^e), adjusted by the substitutability parameter (π), and reduced by the time a child is ill (t^c). The substitutability parameter reflects the efficiency of parental time relative to that of a teacher.

If we normalize available time to one, parents are assumed to allocate time to five activities: work (t^w), leisure (t^l), educating their child (t^e), caring for a sick child (t^c), and other household activities (t^h). Here, we concentrate on the parental choice between t^w, t^l, and t^e, while considering caring time and time on other household activities as exogenous. Consequently, the parents' time constraint is expressed as:

$$1 = t^w + t^l + t^e + t^c + t^h \tag{2}$$

The total money resources in Equation (3) consist of non-labor income (y) and earnings ($w\, t^w$) paid at a wage (w) per unit of time. The non-labor income may include government assistance. These total resources can be allocated to consumption (c) and expenses associated with parental time with kids ($P_e t^e$), such as books, educational materials, and extracurricular activities. Additionally, parents are assumed to finance expenses associated with formal schooling ($P_f t^f$), such as tuition if applicable, transportation, and taxes for financing public schools.

$$w\, t^w + y = c + P_e t^e + P_f t^f \tag{3}$$

The maximization of the parent's utility, given time and budget constraints and under standard concavity assumptions, results in a labor supply function that is a function of wage rate, child's time at school, and all other exogenous shifters:

$$t^w = t^w(t^f, \pi, w, y, t^c, t^h, P_e, P_f) \tag{4}$$

This function identifies not only key labor supply shifters, but also potential sources of variance in the effect of school closures (s), representing a simple reduction in t^f, on labor supply, $\partial t^w / \partial s = g(t^f, \pi, w, y, t^c, t^h, P_e, P_s)$. Following this framework, we examine several sources of heterogeneity in the impact of school closures on labor supply:

- **Degree of substitutability between parents' and teachers' time (π):** According to Lillard (2023), substitutability rises with the higher education level of parents but diminishes with the higher student grade level. Even college-educated parents may encounter difficulties teaching advanced subjects. We use parents' education and child's grade as proxies for π, adding the place of birth to account for potential challenges that immigrants may face in teaching their children during school closures.

- **Productivity shifters influencing the wage rate (w):** Factors increasing w include parent's education and experience/age, while those decreasing w include parent's health problems and tight labor market conditions measured via regional unemployment and poverty rates.

- **Budget constrain shifters (y):** Spouse's employment, children's benefits, unemployment benefits, along with other government assistance, are assumed to alter available financial resources.

- **Shifters of time to care for a sick child (t^c):** Child's health problems are used as a proxy for t^c.

- **Other parental time supply shifters (t^h):** Factors like the availability of a caregiver or outside family help may increase parental time supply, while the presence of a younger child and parent's health problems may decrease available time for parental investment.

- **Price factors (P_e, P_f):** Captured through fixed effects for time, region, and parent.

- **COVID-19 Spread:** While not explicitly included in the above model, the extent of COVID-19 spread could also influence how school closures impact labor supply; see Peter and Suvorov (2023).

A single factor may alter the labor supply responsiveness to school closures through various channels. Evaluating and comparing the treatment effects of school closures across different population groups, defined by one or multiple factors, become an empirical question that we will explore in the subsequent analysis within the Russian context.

3 Data

3.1 Sample

This study uses data from the 2017-2022 survey rounds of the RLMS-HSE, with an average sample size of approximately 16,000 adult and child respondents per round.[2] The survey was carried out in 38 randomly selected primary sample units from 32 out of 83 subjects of the Russian Federation.[3] As demonstrated below, there exists considerable regional variation in schooling policies. The survey covers two giant COVID-19 waves in Fall 2020 and Fall 2021. Even though the data does not capture the initial large-scale implementation of restrictive measures in Spring 2020, it would not be possible to isolate the effects of school closure from the impacts of other restrictive measures during the complete lockdown period. However, from Fall 2020 onwards, it becomes feasible to

[2] The child questionnaire is filled out by a parent or another adult family member who looked after the child in the past seven days.

[3] The RLMS-HSE shares similarities with the U.S. Panel Study of Income Dynamics (PSID) in its sampling design. It is based on a stratified multistage random sample that represents the country's overall population, although it does not provide a representative sample for each region.

discern the net effects.

Our estimation sample includes parents aged 18 to 60 with school-age children (ages 6-14) in grades 1 to 8, and who have participated in the survey at least twice. Given that our estimation method includes individual fixed effects, all singleton observations are excluded. Attrition does not pose a significant issue in the sample of parents with school-age children.[4] In cases where a parent has more than one child in grades 1 through 8, we select the grade level of the youngest school-age child to link with the corresponding grade-specific schooling policy. This is done to avoid multiple observations per parent-year. Typically, the youngest child requires more attention in terms of childcare arrangements during school closures and demands more parental time when the child falls ill.

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" (S.P. Tracker after that), a daily dataset on COVID-related regional restrictive measures for each school grade level. The S.P. Tracker covers 83 regions and three academic years from September 1, 2019, to January 31, 2023. Authors assemble the dataset based on 1200+ official documents and news media reports on coronavirus-related restrictions on educational activities. The data collection effort is a 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).

Each non-weekend day in the S.P. Tracker is classified into five 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, (4) schooling disruptions for non-COVID reasons such as inclement weather, security threats, voting, etc., and (5) public holidays, whether federal or regional. For the purposes of this study, school closure means schools are closed for in-person learning due to coronavirus-related reasons, i.e., category 2. Even if learning continues in different formats, such as online classes with teachers or studying at home with parents, schools are considered closed when not conducting in-person learning.

[4] The percentage of singleton observations does not exceed 4 percent of the total 16,102 observations in the initial sample of parents with school-age children.

Main decisions regarding school closure in Russia were made by regional authorities, leading to substantial regional variation in schooling policies. Figure 1 illustrates the relative number of regions mandating school closures at various stages of the COVID-19 pandemic. Notably, most executive orders on school closure were issued during periods of increasing daily COVID-19 cases and deaths. In the initial phase of the pandemic in Spring 2020, all regions opted to close schools for in-person learning. However, with each subsequent wave of the pandemic, the number of regions implementing such restrictive measures decreased, even in the face of a heightened surge 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. In the fall of 2022, only two instances of regional-level school closures for flu-like viruses were recorded among RLMS regions, and these closures were also attributed to COVID-related reasons.

Another feature of Russian school closure policies is that they are tailored to specific grade levels. Through a single executive order, regional authorities have the flexibility to allow students at certain grade levels to attend school in person, while directing other students to take an extended break or engage in online learning. As illustrated in Table 1, middle school students encountered more restrictions on in-person attendance compared to elementary school students, particularly during the Fall of 2020. However, in the Fall of 2021, the variation in schooling closures days from one grade to another was not notably significant.

In addition to considerable regional variation in school closures and some variation by child's grade, there is also a significant variability in school closures over time within the same survey round. This is evident from Figure 2, which illustrates the overall distribution of non-weekend days by schooling mode for each survey month. The month-to-month shifts in the distribution are apparent, with the majority of schooling disruptions occurring in October-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 disruptions 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 interview day, we construct all measures of schooling disruptions for the same period. We calculate the rolling sum of days in each of the five categories (including breaks and holidays) within a 30-day moving interval. Subsequently, the rolling measures of schooling disruptions are merged with the RLMS-HSE using the interview date, region of residence, and the child's grade level.

3.3 Regional Factors

School closure policies were frequently enacted alongside other government responses to the COVID-19 pandemic, posing a challenge in isolating the effects of each policy. Only a handful of studies on school closure have made efforts to consider and disentangle the impact of other concurrent COVID-19 restrictive measures (e.g., Amuedo-Dorantes et al., 2023; Garcia & Cowan, 2022).

In Russia, by the time survey interviews commenced in September 2020, significant restrictions on people's movement had been lifted. However, there are concerns about the potential confounding effect of workplace closures on the association between school closures and labor supply. In response to a surge in coronavirus cases in Fall 2021, Russia declared three business days in early November as 'non-working days,' with employers covering the associated costs. Among the 32 RLMS regions, nine extended the federal non-working days by initiating the period of no work as early as October 25 and concluding it as late as November 15. To disentangle the impact of school closures from that of workplace closures, we introduce 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.

At the regional level, we also control the monthly poverty and unemployment rates, as well as the COVID-19 spread. If the first two measures are standard (see Table 2), the last one requires clarification. 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, compiled from daily reports by the Russian government published on стопкоронавирус.рф. Although this data source is widely used by respectable data aggregators such as the World Health Organization, the Coronavirus Resource Center at Johns Hopkins University, Our World in Data, etc., the daily numbers of COVID-19 cases and especially deaths are severely undercounted. There is a vast discrepancy between the sum of daily cases and the end-year statistics provided by the Russian Ministry of Health Care regarding COVID-19 morbidity levels and death certificates.[5] Our calculations suggest that, on average, daily reports account for 62 percent of

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

confirmed cases and 54 percent of COVID-19 deaths. However, there is a relatively high correlation (0.72) in annual coronavirus cases across regions between the two data sources. Despite the undercounting, daily reports are likely to reflect the general trend in COVID-19 cases, depicting the peaks and troughs of each pandemic cycle. To address the undercounting issue, we adjust the number of new coronavirus cases over the 30 days using a region-specific discrepancy factor. We acknowledge that our measure of COVID-19 spread might be noisy and should be interpreted with caution.

4 Estimation Methods

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

$$L_{it}^{P} = \gamma S_{it} + \beta X_{it} + \theta_t + \eta_r + \epsilon_{it}, \qquad E(\epsilon_{it} | S_{it}, X_{it}, \theta_t, \eta_r) = 0, \tag{5}$$

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

We examine the impact of school closures on various labor supply outcomes, L_{it}^{P}. These outcomes include employment and total hours of work in primary and secondary jobs, with the binary employment variable taking the value of one if the parent worked for pay or profit at primary or secondary jobs in the last 30 days. Additionally, we explore outcomes that characterize working from home, including the probability of engaging in such work and the number of hours spent working at home. To accommodate cases with zero hours of work at home for those who worked elsewhere at least one hour, we apply the MaCurdy and Pencavel (1986) transformation, log (hours+1). All labor supply outcomes pertain to the last 30-day period preceding the survey interview.

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

- Characteristics of parents: age, age squared, level of education, ethnicity, place of birth, and health problems.
- Characteristics of children: the child's grade and health problems.
- Household characteristics: living with a spouse, the spouse's employment status, the presence of an older caregiver in the household, having an outside family helper, receiving children's benefits, receiving unemployment benefits or other government assistance.
- Regional characteristics: the poverty and unemployment rates, and the number of new COVID-19 cases.
- Occupational characteristics capturing the potential of workers to work remotely from home: unstructured job (indicating the extent to which a job allows the worker to determine tasks, priorities, and goals) and indoor occupation (indicating the extent to which a job requires working indoors). These variables are only included in the equations for hours of work and work from home, not in the employment equation.

The selection of control variables is guided by the theoretical framework outlined in Section 2.2. Detailed description of all the variables employed in the estimation can be found in Table 2.

The second approach introduces the correlation of errors across equations through a shared time-varying family component, as shown in Equation (6):

$$\begin{aligned} L_{iut}^{F} &= \gamma^{F} S_{it} + \beta^{F} X_{it} + \eta_{r}^{F} + \rho^{F} \zeta_{ut} + \epsilon_{iut}^{F} \\ L_{iut}^{M} &= \gamma^{M} S_{it} + \beta^{M} X_{it} + \eta_{r}^{M} + \rho^{M} \zeta_{ut} + \epsilon_{iut}^{M}. \end{aligned} \tag{6}$$

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}.[6] The time-varying family component is a latent factor

[6] The latent factor, ζ_{ut}, follows a standard normal distribution with mean zero and variance one. It is common across equations, with equation-specific loading factors, ρ^{j} for $j = F\ (fathers), M(mothers)$. 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, $cov(\epsilon_{iut}^{M}, \epsilon_{iut}^{F})$=0.

influencing the labor supply of all family members.

The third approach entails estimating Equation (7) with individual FEs, thereby accounting for individual variations in consumption-leisure preferences, attitudes towards work, propensity for home-based work, and other time-constant elements of individual heterogeneity.

$$L_{it}^{P} = \gamma S_{it} + \beta X_{it} + \theta_t + \alpha_i + \epsilon_{it}, \qquad E(\epsilon_{it}|S_{it}, X_{it}, \theta_t, \alpha_i) = 0. \tag{7}$$

This approach is relatively uncommon in the literature of school closure, as it requires the longitudinal dataset with a sufficient level of within-variation in school closure variables. Several papers presented at this symposium have successfully implemented such an approach (*cite after the conference*). To test whether the treatment effects vary with observed characteristics, we interact the school closure variable with select covariates one at a time.

The model with individual FEs imposes several restrictions: (1) the treatment effect is constant over time, (2) the treatment effect does not change with the intensity of treatment (days of school closure), (3) no selection on gains, meaning the selection into treatment is independent on γ, and (4) the treatment status is independent on ϵ_{it}.

Our final and preferred approach relaxes the first three restrictions. As demonstrated in this study, the treatment effects of school closures exhibit significant heterogeneity across individuals and over time. We employ the correlated random coefficient (CRC) model to estimate heterogeneous treatment effects, γ_{it}, while simultaneously accounting for flexible patterns of selection on unobservables (see Hsiao et al, 2019; Verdier, 2020). The CRC model avoids imposing restrictions on the relationship between school closure (S_{it}), on one hand, and baseline heterogeneity (α_i), heterogeneous treatment effect (γ_{it}), observables (X_{it}), or aggregate shocks (θ_t), on the other hand. However, we continue to assume that school closing decisions are independent of ϵ_{it}: $E(\epsilon_{it}|S_{it}, X_{it}, \theta_t, \alpha_i) = 0$.

The estimation process involves the following steps. First, the individual FE model, as represented in Equation (8), is estimated for untreated observations only when $S_{it} = 0$.

$$L_{it}^{P} = \gamma_{it}S_{it} + \sum_{k=2017}^{2022} \beta_k I(t = k)X_{it} + \theta_t + \alpha_i + \epsilon_{it}, E(\epsilon_{it}|S_{it}, X_{it}, \theta_t, \alpha_i) = 0. \quad (8)$$

These untreated observations include all data points for 'stayers' who were never exposed to school closures during the sample period, as well as pre-treatment observations for 'movers' who experienced school closure at least once. In the second step, the linear prediction, $\hat{L}_{it}^{P}$, is obtained for both treated and untreated units, resulting in a predicted counterfactual outcome. It is important to note that the counterfactual individual outcomes vary over time not only due to changes in observed characteristics (e.g., worsened parent's health or birth of an additional child during the COVID-19 pandemic) but also because of temporal shifts in the labor market structure, captured through the interaction of each covariate with year fixed effects, as represented by β_k in Equation (8). This is done to isolate the net effect of school closure from the changing labor supply effects of other covariates, such as the varying impact of government assistance on employment or the time-varying contribution of household composition to labor supply during the pandemic.

In the third step, we compute the CRC treatment effect as the difference between the actual outcome and counterfactual outcome. This effect varies across individuals and over time. Subsequently, individual-specific treatments effects are averaged across all observations (i.e., the average treatment effect) or within a given group of interest. Standard errors are estimated through bootstrap resampling and clustered at the individual level. The CRC approach provides a straightforward method for estimating the treatment effects for diverse groups based on a multitude of observed characteristics, including parents' demographics, the child's health and grade level, the presence of young children, the availability of outside family helpers, job type, unemployment, COVID-19 spread, and many more. Additionally, it enables the estimation of treatment effects for subgroups defined by the combination of two or more factors, such as college-educated older fathers or mothers of elementary school kids experiencing health problems.

5 Results

5.1 Summary Statistics

We begin our empirical analysis by presenting summary statistics for two groups, 'stayers' and 'movers', and two time periods, before the pandemic (2017-2019) and after the onset of pandemic

(2020-2022). The group of 'movers' includes parents whose children in grades 1-8 have experienced COVID-19-related school closures during the 30-day period preceding their date of interview, while the group of 'stayers' includes parents who have never been treated. These summary statistics are for the Fall of each year, excluding the period of the stay-at-home order in Spring 2020.

Table 3 shows that the employment rate of individuals who have never been treated was not statistically significantly different from that of treated individuals before the pandemic. However, after the pandemic started, the difference in their employment rates became statistically significant. Contrary to our expectations, the employment rate of the treated group increased rather than decreased since the start of the pandemic, while the employment rate of those who have never been treated remained unchanged. No statistically significant differences were observed in the total hours of work for both never treated and treated parents, both before and after the pandemic. However, the average hours of work have not been constant over time, decreasing from around 185 hours before the pandemic to approximately 182 hours after its onset.

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

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

The average number of hours parents worked from home increased for both never treated and treated groups by approximately the same number of hours. Both groups of parents worked around 34-35 hours from home before the pandemic and 60-61 hours after its onset.

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

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

5.2 Average Treatment Effect

On average, school closures have been associated with a decrease in employment rates and a reduction in the hours parents worked from home, affecting both mothers and fathers. Table 4 illustrates that mothers experienced a greater decline in their employment rates and a higher shift towards working from home compared to fathers during school closures. The most consistent result across all four methods employed is the increase in the hours mothers work from home. Notably, including fixed effects reveals average decreases in the employment of mothers, and using the CRC model exposes average decreases in the employment of fathers. Additionally, only when we interact all control variables with time fixed effects can we identify average increases in the hours fathers worked from home. The closure of schools disrupted the working arrangements of both mothers and fathers, with mothers experiencing more interruption due to their predominant role in household responsibilities (Bertrand et al., 2015; Blau and Kahn, 2007).

Comparing our findings with existing literature on school closures, we observe variations. Some studies, unlike ours, did not find statistically significant changes in the employment of fathers (Garcia & Cowan, 2022), and others reported no changes in the employment of either fathers or mothers (Amuedo-Dorantes et al., 2023). A few papers demonstrated that the employment of both mothers and fathers decreased due to school closures (Hansen et al., 2022, and Kozhaya, 2022), with the employment of mothers decreasing more than that of fathers (Hansen et al., 2022, and Garcia & Cowan, 2022). Some studies even used fathers as a control group (e.g., Couch et al., 2022). Discrepancies extend to the effects on working hours, with some studies concluding that school closures decreased average working hours (Amuedo-Dorantes et al., 2023), while others reported decreases in both average employment rates and working hours (Couch et al., 2022, Hansen et al., 2022, and Kozhaya, 2022). The literature on the effects of school closures on the hours parents work from home presents mixed conclusions. Some researchers found that both fathers and mothers increased their hours working from home by similar amounts (Garcia & Cowan, 2022), while others reported that only mothers increased these hours, with fathers either maintaining or decreasing their hours working from home (Hansen et al., 2022, Yamamura and Tsutsui, 2021). These differences in average results may arise from variations in school closure measures alone. Our study is the first to consider the varying effects of school closures based on their duration, as revealed by employing the CRC model, showing average decreases in employment rates and shifts to working from home for both mothers and fathers.

Notably, both COVID-19-associated school closures and school breaks push mothers to switch to working from home, but the effects of school breaks on mothers' hours worked from home are smaller. Although the effects of school closures on the hours mothers work from home remain statistically significant, these effects on the hours fathers work from home are not. The impact of school closures unrelated to COVID-19 and the impact of long holidays on parental labor supply are substantial but statistically insignificant, while the effects of workplace closures, occurring rarely and for a short time in the Fall of 2021, are both small in scale and statistically insignificant. Mothers of middle school children work slightly more than mothers of primary school children, consistent with previous literature showing that mothers spend less time on childcare for older children. The effect of age on parental employment is initially positive but eventually switches to negative. The labor supply of college-educated parents differs noticeably from that of those without college degrees across all labor supply measures, with college-educated parents being more likely to be employed and work from home but working fewer hours. Interestingly, Russian mothers are more likely to work from home, and Russian fathers are more likely to be employed compared to their non-Russian peers, potentially linked to the higher likelihood of Russians living in urban areas and larger cities. Additionally, parents who have experience switching their place of residence are more likely to work from home. Health problems in parents and children reduce the likelihood of employment, lead to fewer working hours, and increase the likelihood of working from home. Single mothers are more likely to be employed and work more hours than their married counterparts. The presence of small children younger than 7 years old negatively affects mothers' employment but has no effect on fathers' employment. If these mothers continue to work, they are more likely to work from home. Government assistance and children's benefits drastically decrease mothers' employment; however, unlike the previous factor, this public financial support also decreases fathers' employment. In line with our expectations, those who had freedom in determining their tasks were more likely to work from home.

5.3 Heterogeneous Treatment Effects

The distribution of estimated treatment effects for various groups is presented in Figure 3. Notably, no single subgroup of parents exhibited a statistically significant increase in employment rates during school closures. Most parental subgroups, however, showed an increase in hours worked from home. Certain subgroups of fathers experienced a more pronounced decrease in employment rates compared to any other subgroup of mothers. Simultaneously, the majority of paternal subgroups did not see statistically significant decreases in their employment rates, whereas most maternal subgroups did. This suggests that while fathers reduced their employment rates under specific circumstances, when they did, the reduction was often more substantial than that of mothers. This phenomenon may be influenced by higher initial paternal employment rates.

Examining total working hours, only a few parental subgroups demonstrated significant changes in the overall time spent working. Our analysis of the heterogeneity of school closures' effects on parental labor supply considered both one-factor and two-factor variables (Table 5, Figure 4, Tables 6-9, Figure 5). Notably, the effects were more pronounced when considering two-factor variables, providing richer insights into the diverse impacts on different parental groups.

Figure 3 illustrates the effects of school closures on parental labor supply based on subgroups formed by both one-factor and two-factor variables. Notably, employment rates and hours worked from home exhibited more significant changes among subgroups formed by two-factor variables than among those formed by one-factor variables. Our examination of two-factor variables delved into parental, children's, household, and regional characteristics.

In Table 6, we explored the heterogeneity of labor supply responses concerning the demographic characteristics of parents. Combining age and education variables significantly enhanced our understanding of paternal labor supply responses. For instance, college-educated fathers under 36 exhibited a considerable decrease in employment rates in response to school closures, highlighting diverse strategies employed by young parents to adapt. This contrasts with less-educated fathers over 35, who decreased employment and switched to working from home, potentially due to differences in productivity.

Table 7 shows the heterogeneity of school closures' effects with respect to children's characteristics. The age and health status of the youngest school-age child played a crucial role in shaping parental responses. Notably, parents adjusted their labor supply differently based on whether their child was in primary or middle school, revealing insights into the substitutability of parents and teachers. The presence of health problems further influenced parental responses.

Our research extends to exploring how school closures affect mothers' labor supply based on marital status and external childcare support. Table 8 highlights that single mothers, without support from parents or grandparents, experienced more significant decreases in employment rates compared to their married counterparts. Additionally, the commonly observed increase in maternal hours worked from home was driven by married mothers without external childcare help.

Finally, Table 9 explores the relationship between school closures' effects on parental labor supply and regional statistics, including unemployment rates and COVID-19 trends. Parents in regions with low unemployment rates adjusted their labor supply more drastically in response to school closures and high COVID-19 rates compared to those in high unemployment regions. Furthermore, parents in regions with low unemployment and poverty rates experienced more substantial decreases in employment, exacerbating existing inequalities.

In conclusion, our analysis provides nuanced insights into the heterogeneous effects of school closures on parental labor supply, considering various demographic, familial, and regional factors.

[to be completed]

6 Discussion and Conclusion

In this study, we use micro-level data from Russia to uncover the heterogeneity effects of school closures on labor supply that may have been overlooked in existing literature. Our findings reveal substantial variations in labor supply responses among different age-education groups of both men and women. Additionally, we highlight the significance of parental and children's characteristics in shaping the reactions to school closures. Moreover, we demonstrate that mothers' responses to COVID-19-related school closures are intricately linked to household composition, marital status, and the presence of an older, non-working adult in the household. Finally, our estimates underscore how regional statistics play a pivotal role in determining individual labor supply responses.

It is important to acknowledge that our calculations reveal only a portion of the existing heterogeneity in the effects of school closures on parental labor supply. Further research, conducted on a much larger population sample than our study encompasses, would be necessary to provide a more detailed and comprehensive analysis of the intricate dynamics surrounding the labor supply implications of school closures.

[to be completed]

7 Bibliography

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, 138(1), 1–35.

Amuedo-Dorantes, C., Marcén, M., Morales, M., & Sevilla, A. (2023). Schooling and parental labor supply: Evidence from COVID-19 school closures in the United States. *ILR Review*, *76*(1), 56-85.

Baker, M., Gruber, J., & Milligan, K. (2008). Universal child care, maternal labor supply, and family well-being. *Journal of Political Economy, 116(4),* 709-745.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The economic journal*, *75*(299), 493-517.

Bertrand, M., Kamenica, E., & Pan, J. (2015). Gender identity and relative income within households. *The Quarterly Journal of Economics, 130(2),* 571-614.

Blau, F. D., & Kahn, L. M. (2007). Changes in the labor supply behavior of married women: 1980–2000. *Journal of Labor Economics, 25(3),* 393-438.

Collins, C., Landivar, L. C., Ruppanner, L., & Scarborough, W. J. (2021). COVID-19 and the gender gap in work hours. *Gender, Work & Organization*, *pp. 28*, 101–112.

Couch, K. A., Fairlie, R. W., & Xu, H. (2022). The evolving impacts of the COVID-19 pandemic on gender inequality in the U.S. labor market: The COVID motherhood penalty. *Economic Inquiry*, *60*(2), 485-507.

Garcia, K. S. D., & Cowan, B. W. (2022). *The impact of U.S. school closures on labor market outcomes during the COVID-19 pandemic* (No. w29641). National Bureau of Economic Research.

Goldhaber, D., Imberman, S. A., Strunk, K. O., Hopkins, B. G., Brown, N., Harbatkin, E., & Kilbride, T. (2022). To what extent does in-person schooling contribute to the spread of Covid-19? Evidence from Michigan and Washington. *Journal of Policy Analysis and Management*, *41*(1), 318–349.

Goldin, C. (2022). *Understanding the economic impact of COVID-19 on women* (No. w29974). National Bureau of Economic Research.

Hansen, B., Sabia, J. J., & Schaller, J. (2022). *Schools, Job Flexibility, and Married Women's Labor Supply* (No. w29660). National Bureau of Economic Research.

Heggeness, M.L. Estimating the immediate impact of the COVID-19 shock on parental attachment to the labor market and the double bind of mothers. *Rev Econ Household* **18**, 1053–1078 (2020).

Hsiao C, Li Q, Liang Z, Xie W. Panel Data Estimation for Correlated Random Coefficients Models. *Econometrics*. 2019; 7(1):7.

Koppa, V., & West, J. (2022). School reopenings, COVID-19, and employment. *Economics Letters*, *212*, 110310.

Kozhaya, M. (2022). The double burden: The impact of school closures on labor force participation of mothers. Ruhr Economic Papers 956, RWI - Leibniz-Institut für Wirtschaftsforschung, Ruhr-University Bochum, TU Dortmund University, University of Duisburg-Essen.

Lillard D. (2023). The COVID policy effects on employment and earnings: a household production approach. Draft.

Lofton, O., Petrosky-Nadeau, N., & Seitelman, L. (2021, February). Parents in a pandemic labor market. Federal Reserve Bank of San Francisco.

MaCurdy, T. E., & Pencavel, J. H. (1986). Testing between competing models of wage and employment determination in unionized markets. *Journal of Political Economy*, *94*(3, Part 2), S3-S39.

Morens, D. M., & Fauci, A. S. (2020). Emerging pandemic diseases: how we got to COVID-19. *Cell*, *182*(5), 1077-1092.

Rosstat (2020) *Итоги выборочного обследования рабочей силы* (Results of Labor Force Survey), 2nd Quarter. https://rosstat.gov.ru/compendium/document/13265.

Verdier, V. (2020). Average treatment effects for stayers with correlated random coefficient models of panel data. *Journal of Applied Econometrics*, *35*(7), 917-939.

Yamamura, E., & Tsustsui, Y. (2021). School closures and mental health during the COVID-19 pandemic in Japan. *Journal of Population Economics*, *34*(4), 1261-1298

8 Tables

Table 1: Average Number of School Closure Days by Grade and Month

	2020 m9	2020 m10	2020 m11	2020 m12	2021 m1	2021 m9	2021 m10	2021 m11	2021 m12	2022 M1
RLMS regions w school closures										
Grades 1-4	…	5.2	5.7	5.0	5.0	3.0	4.8	4.4	4.0	3.1
Grades 5-8	…	6.2	9.9	11.4	5.0	4.5	6.3	4.1	4.0	3.1
All RLMS regions										
Grades 1-4	0.0	1.0	3.6	0.2	0.3	0.1	1.7	1.8	0.6	0.7
Grades 5-8	0.0	1.4	6.4	3.6	0.5	0.3	2.2	1.8	0.6	0.7

Notes: The table shows the average number of workdays during which schools were closed for COVID-19 reasons. The data is averaged across 32 RLMS regions and school grades 1 to 4 and 5 to 8.

Table 2: Definition of Variables

Variable	Definition
	Labor supply dependent variables
Employed	=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	Hours worked at primary and secondary jobs in the last 30 days, including hours worked from home.
Work from home	=1 if worked from home at the primary job in the last 30 days; =0 if worked at the primary job but not from home in the last 30 days; no information is provided on working from home at a secondary job.
Hours worked from home	Hours worked from home at the primary job in the last 30 days. This variable is set to zero if the parent worked at the primary job but not from home. When used in logs, MaCurdy and Pencavel's (1986) transformation is applied, log (hours+1).
	Parents' characteristics
College graduate	=1 if the parent has a college degree.
Parent's age	Both linear and quadratic terms for parental age are included in the main regression. Heterogeneity is analyzed with respect to parents being above or below than 35 years old.
Parent's health issues	=1 if the parent had any health issues in the last 30 days.
Russian ethnicity	=1 if the individual identifies as Russian by ethnicity.
Birthplace	Categorized into four groups: born in the same place as current residence, born elsewhere in Russia, born abroad, birthplace is unknown
Unstructured job	A standardized score for a 4-digit occupation, indicating the extent to which a typical job in that occupation is unstructured for the worker. This measure reflects the degree to which the worker can determine tasks, priorities, and

	goals. Source: O*NET occupational database, using the crosswalk to the 4-digit ISCO-08 (International Standard Classification of Occupations) codes.
Indoor occupation	A standardized score for a 4-digit occupation, indicating the extent to which a typical job in that occupation requires working indoors in environmentally controlled conditions. Source: O*NET as above.
	Child's Characteristics
Child's grade level	Represent the grade level the child currently attends, obtained from a direct survey question. This variable is used for linking the RLMS-HSE with grade-level policies. It highly correlates with the child's age (corr=0.97). Heterogeneity is analyzed based on two categories for a child's grade level: elementary school (first four grades) and middle school (5-8 grades)
Child's health issues	=1 if the child had health issues in the last 30 days.
	Household Characteristics
Outside family help	=1 if any relative who lives outside of the household helped parents with childcare or housekeeping in the last 30 days.
Older caregiver	=1 if there is an older household member other than parents, age 55-80, who is not disabled and not in bad health.
Pre-school children	=1 if there is another young child under the age of 7 in the household.
Spousal employment status	Categorized into four groups: spouse is employed, spouse is not employed, no spouse, no data on spouse.
Government assistance	=1 if the household received unemployment benefits or other government assistance in the last 30 days.
Children's benefits	=1 if the household received children's benefits in the last 30 days.
	Schooling Policy Tracker
COVID-19 school closure	The number of days when schools were closed for in-person learning due to COVID-related reasons in the last 30 days. Occasionally, reasons may include other flu-like viruses.
School break	The number of days when schools are on break in the last 30 days.
Closure for other reasons	The number of days when schools were closed for inclement weather or other reasons unrelated to COVID-19 in the last 30 days.
Long holidays	=1 if a federal or regional holiday lasted more than one working day in the last 30 days. This varies by region and date of interview.
	Regional characteristics
COVID-19-related workplace closure	The number of non-working days due to COVID-related reasons 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. This varies by region and date of interview.
COVID-19 spread	The product of new confirmed COVID-19 cases per 100 people in the last 30 days and 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. This varies by region and interview date.

Poverty rate, %	The monthly poverty rate in percentage. This varies by region and year. Data source: Rosstat, https://rosstat.gov.ru/folder/13723.
Unemployment rate, %	The monthly unemployment rate in percentage. This varies by region and month of interview. Calculated using the International Labor Organization methodology. Data source: Rosstat, https://rosstat.gov.ru/folder/210/document/13211.

Table 3: Summary Statistics

	2017-2019			2020-2022				Unconditional DID Effect	
					Ever treated		*p*-value		
	Never treated	Ever treated	*p*-value	Never treated	Not treated	Treated	(for treated vs. never treated)	Absolute value	Percent change
Employed	.77	.79	.13	.77	.82	.8	<0.01***	0.01	1.27%
Total hours of work	184.93	185.53	.69	181.93	182.46	182.44	.77	-0.09	-0.05%
	(51.2)	(47.47)		(48.01)	(47.35)	(51.77)			
Work from home	.08	.1	.02**	.08	.12	.13	<0.01***	0.03	30%
Hours worked from home	33.71	34.87	.8	60.48	62.19	60.75	.97	-0.89	-2.55%
(If worked from home)	(48.74)	(39.7)		(70.7)	(78.06)	(60.85)			
Days of COVID-19-related	0	0		0	0	5.21			
school closures						(3.85)			
Days of school breaks	1.79	2.44	<0.01***	1.98	2.04	2.89			
	(2.28)	(2.37)		(3.05)	(2.51)	(2.09)			
Age	38.16	37.22	<0.01***	38.86	39.12	38.7			
	(6.14)	(5.84)		(6.15)	(5.79)	(5.93)			
College	.36	.38	.06*	.38	.4	.4			
Parent has a health problem	.23	.22	.78	.18	.22	.21			
Child has a health problem	.28	.31	.06*	.26	.27	.25			
Child under age 7 in household	.45	.53	<0.01***	.43	.39	.45			
Outside family help	.32	.38	<0.01***	.29	.29	.28			
Older caregiver in household	.15	.13	.06*	.17	.17	.16			
Government assistance	.04	.05	.09*	.1	.06	.05			
Children's benefits	.33	.38	<0.01***	.36	.34	.31			
Poverty rate, %	12.96	12.85	.29	11.44	11.23	11.84			
	(4.11)	(3.89)		(3.95)	(3.49)	(3.92)			
Unemployment rate, %	4.85	4.55	<0.01***	4.47	4.37	5.06			
	(1.82)	(1.8)		(1.95)	(1.77)	(2.12)			
COVID-19 spread	0	0		.68	.63	.84			
				(.57)	(.55)	(.43)			
N observations	5622	2081		4856	1575	1308			

Notes: The table reports the mean and standard deviation (in parentheses) of parents' characteristics by treatment status before and after the start of the pandemic. After the start of the pandemic, three groups of parents are considered, namely, never treated parents, those who have ever been treated but not treated in the last 30 days before the observation and those who are treated during the last 30 days before the observation. Standard deviations for binary variables are not shown. The sample consists of adults between 18 and 60 years old who participated at least twice. The description of variables can be found in Table 1. Total work hours are averaged over the sample of employed individuals and hours worked from home are averaged over the sample of individuals who worked at home at least one hour. Unconditional difference in differences effects of school closures is calculated as the difference in average change over time between never treated and treated groups (before 2020 we do not have a treated group, but only ever treated group). Percent change is calculated relative to average values for ever treated before 2020. P-values are calculated based on t-tests for mean differences between treated and never treated in 2017-2019 and for mean differences between recently treated and never treated in 2020-2022. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The Average Treatment Effect of School Closure on Labor Supply

Estimation methods	Employment		Log total hours		Work from home		Hours working from home	
	Mother	Father	Mother	Father	Mother	Father	Mother	Father
Region FEs	-0.018	-0.009	0.016	-0.011	0.044**	0.020	0.186***	0.102*
	(0.026)	(0.018)	(0.025)	(0.022)	(0.019)	(0.018)	(0.065)	(0.055)
Intra-family with region FEs	-0.036	-0.013	0.009	-0.009	0.030*	0.018	0.134**	0.097*
	(0.026)	(0.017)	(0.023)	(0.019)	(0.016)	(0.017)	(0.055)	(0.054)
Individual FEs	-0.048**	-0.007	-0.014	-0.005	0.022	0.008	0.121*	0.054
	(0.021)	(0.020)	(0.024)	(0.023)	(0.020)	(0.015)	(0.070)	(0.057)
CRC with individual FEs	-0.046**	-0.034*	-0.013	0.004	0.043**	0.020	0.206***	0.095
	(0.021)	(0.018)	(0.023)	(0.019)	(0.021)	(0.019)	(0.071)	(0.064)
CRC with individual FEs and covariates interacted with time fixed effects	-0.069***	-0.049***	0.000	0.015	0.043**	0.037*	0.192***	0.134**
	(0.021)	(0.019)	(0.024)	(0.019)	(0.021)	(0.020)	(0.071)	(0.065)

Notes: The table presents the average treatment effects of an additional ten days of school closures on parental labor supply. The first column indicates four alternative estimation approaches. The first three estimation approaches correspond to Equations (1) through (3), respectively. The last estimation approach is the correlated random coefficient model with individual fixed effects. Standard errors are clustered at the region level in models with region FEs and at the individual level in the model with individual FEs. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The Average Marginal Effects of School Closures on Parental Labor Supply in Subsamples Defined by One-Factor Variables, CRC

	Employment		Log total hours		Work from home		Hours working from home	
	Female	Male	Female	Male	Female	Male	Female	Male
Age 18-35	-0.104**	0.022	-0.110	0.032	0.023	-0.007	0.089	0.036
	(0.045)	(0.038)	(0.067)	(0.047)	(0.042)	(0.030)	(0.138)	(0.128)
Age 36-60	-0.058**	-0.064***	0.033	0.011	0.049**	0.047**	0.223***	0.156**
	(0.024)	(0.021)	(0.022)	(0.020)	(0.024)	(0.023)	(0.082)	(0.075)
No college degree	-0.080***	-0.050*	0.003	0.046*	0.031*	0.048***	0.080	0.148**
	(0.030)	(0.027)	(0.043)	(0.025)	(0.018)	(0.016)	(0.056)	(0.064)
College graduates	-0.059**	-0.047**	-0.002	-0.035	0.052	0.021	0.274**	0.111
	(0.030)	(0.018)	(0.025)	(0.025)	(0.033)	(0.042)	(0.115)	(0.132)
Parent has a health problem	-0.064***	-0.050***	-0.005	-0.005	0.046**	0.048**	0.224***	0.156**

	(0.022)	(0.019)	(0.027)	(0.019)	(0.023)	(0.023)	(0.082)	(0.076)
Parent does not have a health problem	-0.084	-0.047	0.019	0.114**	0.035	-0.020	0.084	0.017
	(0.055)	(0.062)	(0.046)	(0.052)	(0.044)	(0.032)	(0.141)	(0.090)
Child-s grade 1-4	-0.087***	-0.033	-0.060	0.029	0.027	0.021	0.136	0.139
	(0.034)	(0.021)	(0.043)	(0.030)	(0.031)	(0.035)	(0.114)	(0.116)
Child's grade 5-8	-0.056**	-0.060**	0.042*	0.002	0.055**	0.050***	0.229***	0.129*
	(0.027)	(0.029)	(0.025)	(0.022)	(0.027)	(0.019)	(0.088)	(0.068)
Healthy child	-0.077***	-0.048**	-0.004	0.003	0.019	0.025	0.108*	0.118
	(0.024)	(0.022)	(0.027)	(0.020)	(0.017)	(0.022)	(0.065)	(0.075)
Child has a health problem	-0.038	-0.051	0.017	0.067	0.128**	0.079*	0.486**	0.190
	(0.046)	(0.036)	(0.039)	(0.047)	(0.064)	(0.041)	(0.203)	(0.128)
No child under age 7 in household	-0.058***	-0.019	0.001	0.026	0.021	0.003	0.115	0.028
	(0.018)	(0.021)	(0.029)	(0.023)	(0.021)	(0.026)	(0.078)	(0.079)
Child under age 7 in household	-0.087*	-0.094***	-0.004	-0.002	0.102**	0.089***	0.391**	0.292***
	(0.047)	(0.034)	(0.039)	(0.031)	(0.047)	(0.027)	(0.153)	(0.101)
Single mother	-0.154**		-0.030		0.017		0.018	
	(0.063)		(0.057)		(0.077)		(0.290)	
Married mother	-0.056**		0.006		0.047**		0.219***	
	(0.022)		(0.026)		(0.021)		(0.068)	
No outside family help	-0.082***	-0.030	-0.001	0.024	0.066***	0.046**	0.271***	0.141*
	(0.025)	(0.022)	(0.030)	(0.024)	(0.025)	(0.019)	(0.086)	(0.073)
Outside family help	-0.034	-0.093***	0.003	-0.003	-0.012	0.017	0.005	0.118
	(0.036)	(0.035)	(0.034)	(0.028)	(0.036)	(0.044)	(0.121)	(0.122)
No older caregiver in household	-0.071***	-0.052**	0.011	0.027	0.041*	0.039*	0.210***	0.149**
	(0.023)	(0.021)	(0.026)	(0.020)	(0.022)	(0.021)	(0.072)	(0.070)
Older caregiver in household	-0.057	-0.028	-0.070*	-0.085	0.053	0.016	0.080	0.005
	(0.051)	(0.036)	(0.041)	(0.054)	(0.057)	(0.046)	(0.229)	(0.178)
Low unemployment rate (<median)	-0.105***	-0.112***	0.054	0.053*	0.057*	0.069**	0.280**	0.168*
	(0.035)	(0.037)	(0.033)	(0.031)	(0.034)	(0.029)	(0.113)	(0.099)
High unemployment rate (>median)	-0.042*	-0.008	-0.040	-0.008	0.031	0.017	0.116	0.113
	(0.025)	(0.018)	(0.032)	(0.022)	(0.024)	(0.026)	(0.086)	(0.086)
Low COVID-19 spread	-0.075*	0.035	-0.008	0.018	-0.007	0.062**	0.054	0.157
	(0.043)	(0.026)	(0.048)	(0.043)	(0.041)	(0.030)	(0.145)	(0.110)
High COVID-19 spread	-0.069***	-0.067***	0.002	0.007	0.064***	0.017	0.254***	0.095
	(0.025)	(0.025)	(0.028)	(0.020)	(0.024)	(0.024)	(0.081)	(0.079)
Low poverty rate (<median)	-0.111**	-0.057**	0.028	-0.016	0.040	0.059*	0.222	0.164
	(0.043)	(0.027)	(0.046)	(0.036)	(0.041)	(0.036)	(0.141)	(0.137)
High poverty rate (>median)	-0.049**	-0.047**	-0.014	0.028	0.044*	0.028	0.173**	0.123*

	(0.024)	(0.024)	(0.027)	(0.021)	(0.023)	(0.023)	(0.078)	(0.072)
Observations	8,132	6,387	5,374	4,948	5,596	5,387	5,536	5,338

Notes: Table presents marginal effects of additional ten days of school closures on the labor supply of parental subgroups described in the table. The estimates are based on a correlated random coefficient model (4). Standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The Average Marginal Effects of School Closures on Parental Labor Supply by Parents' Characteristics, CRC

	Employment		Log total hours		Work from home		Hours working from home	
	Female	Male	Female	Male	Female	Male	Female	Male
Parent is 18-35 & parent is not college-educated	-0.115* (0.066)	0.048 (0.051)	-0.120 (0.100)	0.063 (0.052)	0.007 (0.023)	0.008 (0.026)	-0.024 (0.074)	0.021 (0.121)
Parent is 18-35 & parent is college-educated	-0.088 (0.058)	-0.052** (0.025)	-0.094 (0.075)	-0.046 (0.108)	0.046 (0.095)	-0.043 (0.080)	0.251 (0.309)	0.071 (0.320)
Parent is 36-60 & parent is not college-educated	-0.064** (0.032)	-0.075** (0.031)	0.057 (0.037)	0.042 (0.028)	0.043* (0.023)	0.058*** (0.019)	0.129* (0.072)	0.183** (0.076)
Parent is 36-60 & parent is college-educated	-0.054 (0.035)	-0.045** (0.021)	0.017 (0.027)	-0.033 (0.024)	0.052 (0.035)	0.032 (0.048)	0.278** (0.123)	0.119 (0.144)
Observations	8,132	6,387	5,374	4,948	5,596	5,387	5,536	5,338

Notes: Table presents marginal effects of additional ten days of school closures on the labor supply of age-education groups of parents. The estimates are based on correlated random coefficient model (5). Standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: The Average Marginal Effects of School Closures on Parental Labor Supply by Children's Characteristics, CRC

	Employment		Log total hours		Work from home		Hours working from home	
	Female	Male	Female	Male	Female	Male	Female	Male
Youngest child is in middle school & no child in the household has a health problem	-0.082*** (0.030)	-0.056 (0.034)	0.051* (0.029)	0.000 (0.024)	0.032* (0.019)	0.040** (0.019)	0.123* (0.069)	0.119 (0.078)
Youngest child is in middle school & some child in the household has a health problem	0.051 (0.041)	-0.080 (0.051)	0.016 (0.045)	0.014 (0.058)	0.125 (0.085)	0.087 (0.059)	0.556** (0.251)	0.168 (0.129)
Youngest child is in primary school & no child in the household has a health problem	-0.070* (0.037)	-0.037 (0.022)	-0.077 (0.049)	0.006 (0.033)	0.002 (0.032)	0.008 (0.040)	0.087 (0.119)	0.117 (0.133)
Youngest child is in primary school & some child in the household has a health problem	-0.166** (0.082)	-0.015 (0.057)	0.020 (0.075)	0.131** (0.065)	0.129 (0.090)	0.069 (0.057)	0.343 (0.338)	0.214 (0.224)
Observations	8,132	6,387	5,374	4,948	5,596	5,387	5,536	5,338

Notes: Table presents marginal effects of additional ten days of school closures on the labor supply of parental subgroups described in the table. The estimates are based on a correlated random coefficient model (5). Standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: The Average Marginal Effects of School Closures on Parental Labor Supply by Household Characteristics, CRC

	Employment	Log total hours	Work from home	Hours working from home
	Female	Female	Female	Female
Single mother without childcare help from parents or grandparents who do not live in the household	-0.171**	-0.034	0.075	0.209
	(0.073)	(0.052)	(0.085)	(0.320)
Single mother who has childcare help from parents or grandparents who do not live in the household	-0.051	-0.004	-0.364**	-1.254**
	(0.097)	(0.277)	(0.155)	(0.528)
Married mother without childcare help from parents or grandparents who do not live in the household	-0.065**	0.004	0.065***	0.282***
	(0.027)	(0.034)	(0.025)	(0.080)
Married mother who has childcare help from parents or grandparents who do not live in the household	-0.032	0.010	0.010	0.087
	(0.038)	(0.032)	(0.037)	(0.124)
Observations	8,124	5,368	5,590	5,530

Notes: Table presents marginal effects of additional ten days of school closures on the labor supply of parental subgroups described in the table. The estimates are based on a correlated random coefficient model (5). Standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

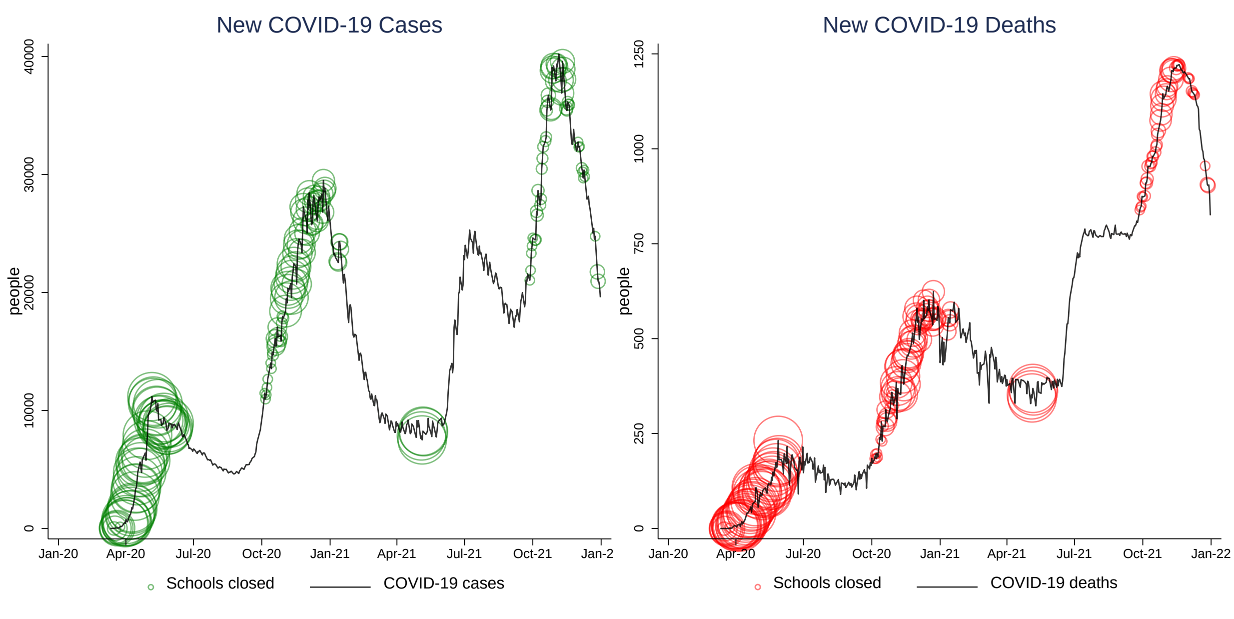
Table 9: The Average Marginal Effects of School Closures on Parental Labor Supply by Regional Characteristics, CRC

	Employment		Log total hours		Work from home		Hours working from home	
	Female	Male	Female	Male	Female	Male	Female	Male
Low unemployment and low COVID-19 spread	-0.045	0.039	0.039	0.012	-0.021	0.078*	0.063	0.145
	(0.063)	(0.040)	(0.054)	(0.065)	(0.043)	(0.044)	(0.157)	(0.146)
Low unemployment and high COVID-19 spread	-0.139***	-0.178***	0.058	0.070**	0.088**	0.055	0.369**	0.165
	(0.044)	(0.053)	(0.042)	(0.035)	(0.044)	(0.037)	(0.144)	(0.129)
High unemployment and low COVID-19 spread	-0.103*	0.031	-0.068	0.023	0.013	0.042	0.044	0.164
	(0.055)	(0.030)	(0.085)	(0.053)	(0.075)	(0.039)	(0.264)	(0.166)
High unemployment and high COVID-19 spread	-0.020	-0.005	-0.023	-0.022	0.053**	-0.003	0.193**	0.051
	(0.028)	(0.021)	(0.039)	(0.025)	(0.026)	(0.030)	(0.086)	(0.104)
Observations	8,132	6,387	5,374	4,948	5,596	5,387	5,536	5,338

Notes: Table presents marginal effects of additional ten days of school closures on the labor supply of parental subgroups described in the table. The estimates are based on a correlated random coefficient model (5). Standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

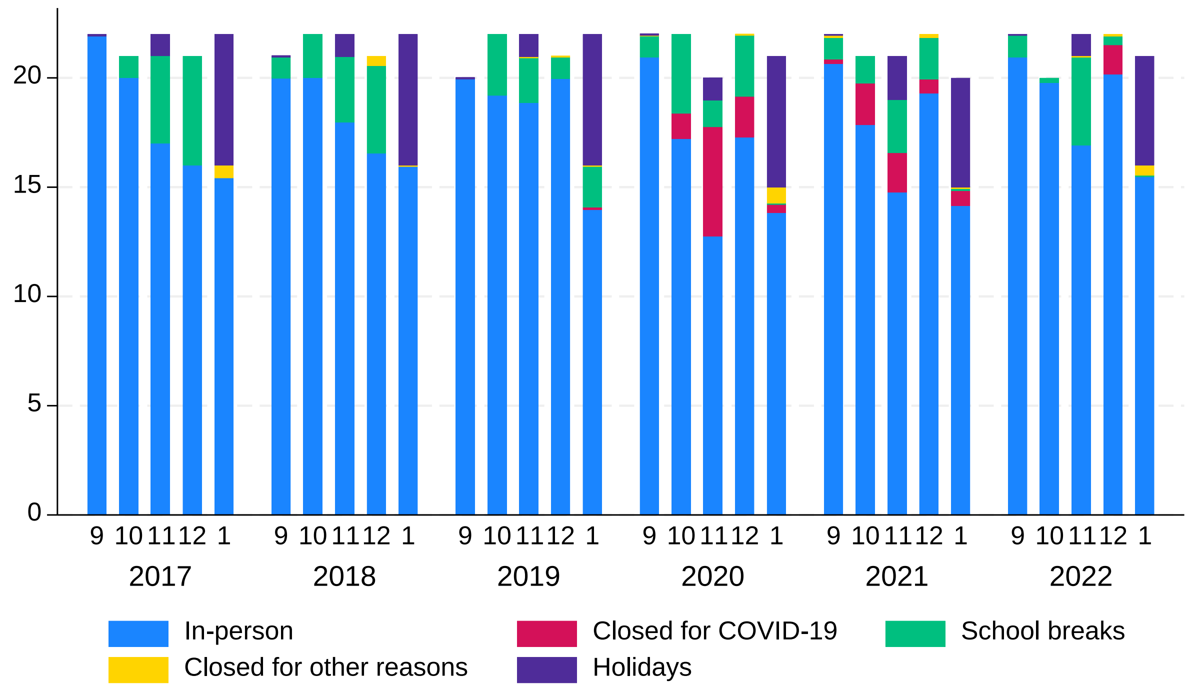
9 Figures

Figure 1: School Closings and the Spread of COVID-19



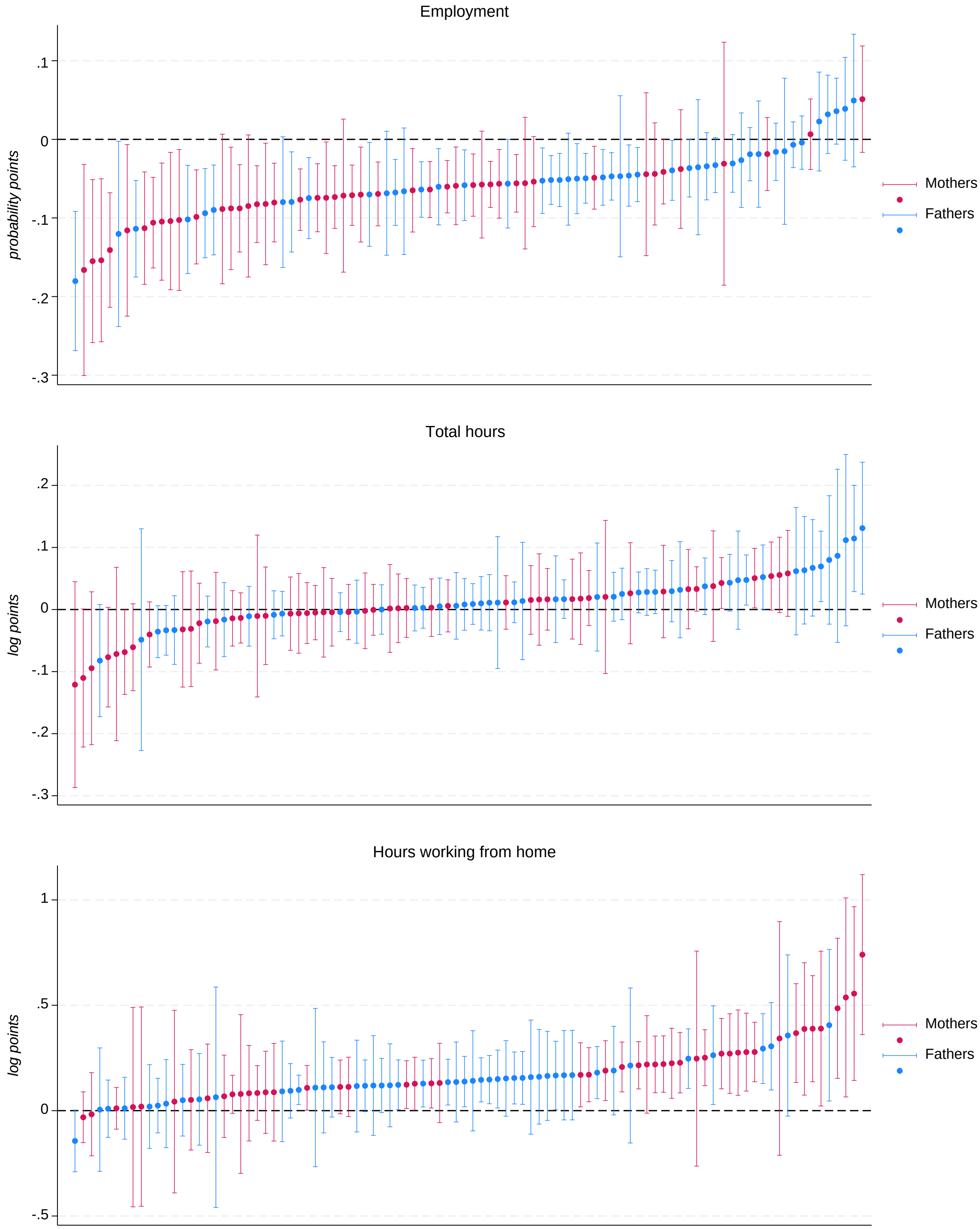
Notes: Figure plots the number of daily confirmed COVID-19 cases and deaths in Russia. The size of the hollow marker is proportional to the number of Russian regions (max 83) where schools have been closed due to COVID-related reasons. All regions had schools closed for in-person learning during non-working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

Figure 2: Distribution of Days by Schooling Mode and Survey Round



Notes: The figure shows the distribution of non-weekend days during which schools were open for in-person learning, closed for COVID-19 reasons, closed for fall break, closed for inclement weather and other reasons unrelated to COVID, and closed for federal or regional holidays. The data is averaged across 32 RLMS regions and school grades 1 to 8. Years indicate the survey rounds, spanning from September to January of the subsequent year.

Figure 3: Distribution of the Effects of School Closure on Parental Labor Supply, CRC



Notes: Figures include the heterogeneous effects of school closures on parental labor supply with respect to both one-factor and two-factor variables.

Figure 4: Effects of School Closures by One-Factor Variables, CRC

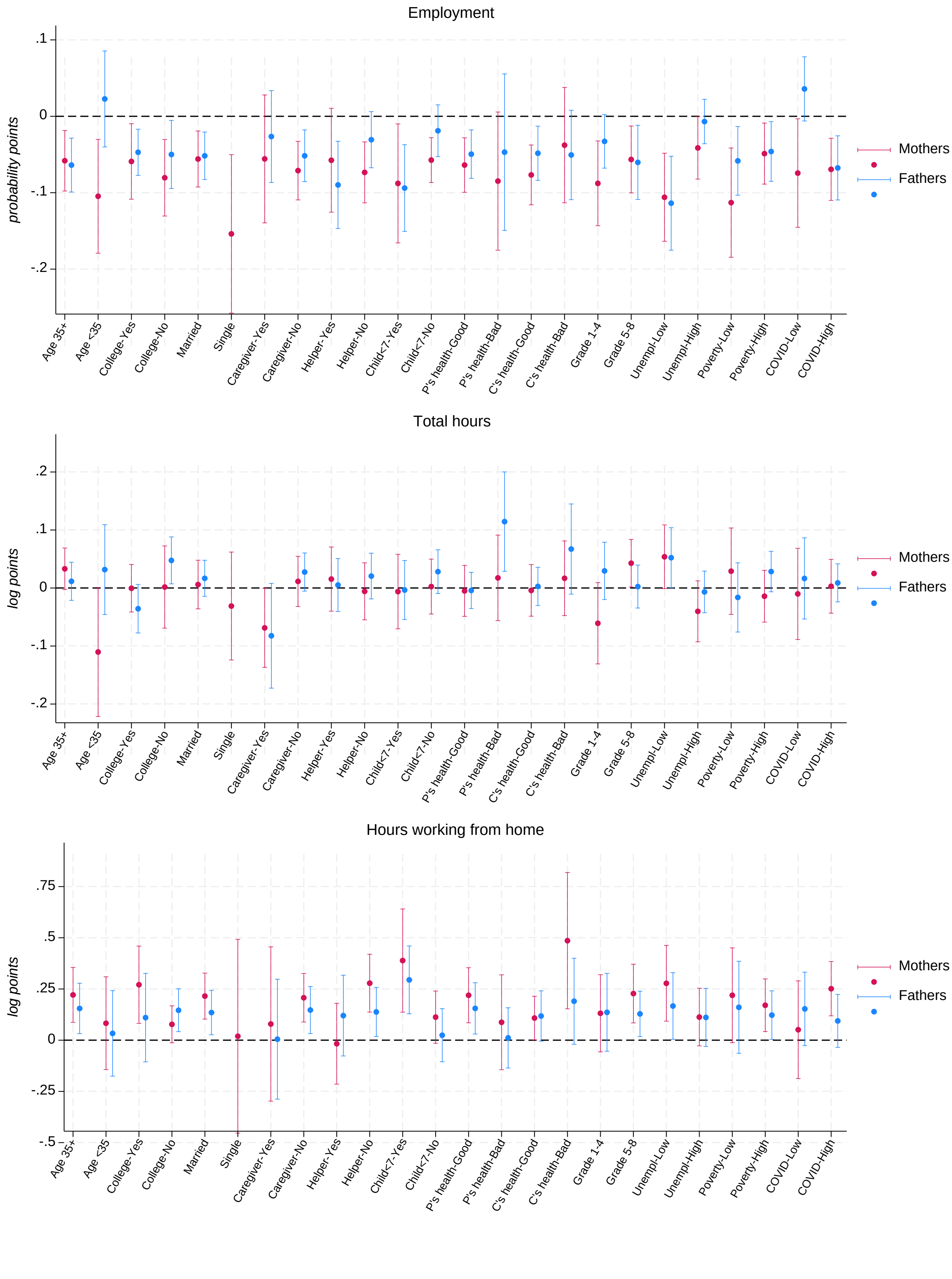


Figure 3: Effects of School Closures by Two-Factor Variables, CRC