School Closures in Russia: Unpacking Heterogeneous Labor Supply Effects*

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ABSTRACT: This study documents substantial heterogeneity in how Russian mothers and fathers responded to COVID-19 school closures. Using a correlated random coefficient model with individual fixed effects over a six-year panel, we find no statistically significant average effect on working hours for either parent, but significant declines in employment and increases in remote work, especially among mothers. Responses varied widely across parental and child characteristics: fathers' employment effects often mirrored mothers', particularly among older parents and those with preschool children. Interactions across multiple factors reveal a complex within-family production function determining parents' differential responses under diverse family circumstances.

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

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1 Introduction

The COVID-19 pandemic brought school closures to the forefront as a widely implemented policy to mitigate virus spread. With the possibility of future pandemics (e.g., Morens and Fauci, 2020), understanding the impact of such measures has become increasingly important. School closures significantly disrupted parental work arrangements, with parental labor supply responses varying across parental demographics, the child's age and health, reliance on outside family support, household composition, infection spread, and job market tightness. This paper examines the heterogeneity in parental labor supply responses to school closures along these dimensions in the context of Russia.

Prior research has predominantly focused on the U.S. and other Western economies, as evidenced in the comprehensive literature review by Lillard et al. (2026) on school disruptions and parental employment. This study broadens the geographic scope by focusing on Russia, where regional governments enacted school policies independently, resulting in substantial yet manageable regional variation in the timing and duration of closures.

Several features of Russia's COVID-19 policy make it particularly well suited for analyzing heterogeneous parental labor supply responses to COVID-19-related school closures. First, while school closures were determined at the regional level, workplace shutdowns were imposed almost exclusively at the federal level, facilitating a cleaner separation of school closure effects from other pandemic policies. Second, Russian school closures were grade-specific, enabling analysis of heterogeneity by children's grade. Finally, unlike the U.S., where homeschooling surged to 11.1% in fall 2020 and a hybrid mode was common according to the U.S. Census Bureau's Household Pulse Survey, homeschooling in Russia remained rare (<1%) (Petryaeva et al., 2024), and no region in our data implemented hybrid schooling during the period we study. Together, these features imply that regional school closures affected nearly all parents with children in the relevant age groups.

While Russia is not a high-income country, many characteristics of its labor market and population resemble those of developed economies, including near gender parity in labor force participation and relatively low prevalence of multigenerational households (around 15% of parents in our sample cohabitate with older generations, which is close to the share of multigenerational households in the U.S.[1]). However, the gender gap in unpaid domestic and care work is substantially larger than in Western economies, though smaller than in many Asian, African, and Latin American countries.[2] Pre-pandemic remote work was less common than in many Western economies, but more feasible than in lower-income settings (Dingel and Neiman, 2020). Thus, the Russian setting allows us to examine the effects of school closures on parental labor supply in an environment with high female labor force participation and limited extended family support, but low pre-pandemic adoption of remote work and pronounced gender asymmetries in unpaid domestic and care work.

We use COVID-19 school closures in Russia to examine how working hours are determined in the Russian labor market. The Russian labor market is known to adjust to negative shocks through reductions in working hours rather than layoffs (Gimpelson and Kapeliushnikov, 2013). It is less clear, however, whether these hour adjustments reflect workers' choices or employer-driven responses. School closures generate sharp and plausibly exogenous time constraints for parents while leaving labor demand largely unchanged. If workers have discretion over their hours, adjustments should occur along the intensive margin. If instead employers determine hours, adjustment may occur through employment changes or shifts to remote work rather than through reductions in hours worked.

To answer our research questions, we compile a novel dataset that records daily, grade-specific school closure policies, gathered directly for each regional decision-making body (governor or regional government) through the end of 2022. Unlike most existing studies that rely on aggregate or indirect

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1 See the Pew Research Center report.
2 See World Bank Group Gender Data Portal.

measures, often limited to the early stages of the pandemic,[3] our dataset enables precise identification of COVID-related school closures, distinguishing them from regular school breaks, extended holidays, weather-related closures, and business shutdowns.

Our analysis draws from the six years of the Russia Longitudinal Monitoring Survey-Higher School of Economics (RLMS-HSE), covering the period from 2017 to 2022. This panel survey collects data on parental labor supply, the health of both parents and children, and various characteristics for the same individuals and families for three years before the pandemic and three years after its onset. With known interview dates, we can precisely align the timing of school closures with the survey's reference periods.

We employ and compare results from several estimation methods. Our primary specification uses a correlated random coefficient (CRC) model with individual fixed effects (see Hsiao et al, 2019; Verdier, 2020). This method allows for the estimation of individual-specific responses to school closures while accounting for flexible selection patterns on unobservables. The CRC method relaxes restrictions on the relationships between school closure, on the one hand, and baseline pre-treatment heterogeneity, heterogeneous treatment effects, observables, and aggregate shocks, on the other hand. Our CRC estimates reveal that, on average, school closures in Russia had no discernible effect on working hours but led to reductions in employment and increases in remote work – effects that were especially pronounced among mothers. In contrast to school closures, which were largely unforeseen and required families to secure alternative childcare on short notice, regularly scheduled school breaks had no significant impact on employment or remote work. This finding highlights the importance of

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[3] Some examples of previously used school closure measures include Google searches (Kong and Prinz, 2020), 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., 2024), percent of the state's population exposed to school closure (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).

distinguishing between anticipated and unanticipated disruptions when assessing their effects on labor supply.[4]

Moreover, the absence of effects of COVID-19-related school closures on working hours contrasts with the well-documented pattern that the Russian labor market absorbs aggregate negative shocks primarily through reductions in hours and wages rather than layoffs (Gimpelson and Kapeliushnikov, 2013; Kapeliushnikov, 2023). Our findings suggest that this adjustment mechanism does not extend to labor supply shocks. When school closures impose binding time constraints on a subset of workers (parents of school-age children), hours worked do not decline, and adjustment instead occurs primarily along the extensive margin or through shifts to working from home. These results imply that the apparent flexibility of working hours in Russia largely reflects employer-driven adjustment mechanisms and does not provide effective insurance against negative labor supply shocks.

Furthermore, we contribute to the literature on the heterogeneous effects of school closures on parental labor supply (see Garcia and Cowan (2022), Goldin (2022), Hansen et al. (2024), and Kozhaya (2022)). Much of the existing work typically estimates heterogeneous treatment effects by examining a limited set of factors in isolation, such as marital status, child's age, or parental education. In this study, we instead explore variation in responses to school closures across a broader range of population groups, highlighting the complexity of within-family production functions and the division of responsibilities in Russian households. We find that employment participation declined more sharply in response to school closures among mothers with fewer resources and limited access to alternative childcare. Mothers facing greater caregiving demands or recent health challenges were also more likely to transition to remote work. Although fathers generally showed a weaker response to school closures in terms of remote work, their likelihood of working remotely also increased when confronted with caregiving responsibilities or health-related issues.

[4] See also Schroeter et al. (2025), who found similarly large effects of school closures compared to school breaks in Switzerland.

Growing literature shows that the COVID-19 pandemic challenged gender norms in domestic and care work (Sevilla and Smith, 2020; Del Boca et al., 2020). We contribute to this literature by documenting heterogeneity in parental labor supply responses to COVID-19 school closures in Russia, identifying scenarios in which fathers' responses mirrored those of mothers as well as cases in which only mothers adjusted their labor supply. In particular, employment responses of fathers with a college education and fathers aged 35 and older closely resemble those of similarly educated and older mothers. Parental labor supply responses are also similar when children are healthy but diverge sharply when children are ill. In these cases, mothers of elementary-school children were especially likely to exit employment, while fathers increased their working hours (not statistically significant, but large in magnitude), consistent with compensatory intra-household labor adjustments aimed at offsetting lost income.

Furthermore, the interaction between COVID-19 intensity and local labor market conditions adds another dimension of heterogeneity. In regions with high COVID-19 prevalence, both parents significantly reduced their labor supply, and those who remained employed were more likely to shift to remote work. However, in areas with weaker job markets, parents were less likely to leave their jobs or request remote work even amid widespread COVID-19, suggesting that limited employment opportunities constrained their ability to adjust work arrangements in response to health risks.

The remainder of the paper is organized as follows: Section 2 provides a framework for 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 average impact of school closures and school breaks on labor supply, Section 6 examines how these impacts vary across different parental and household characteristics, and Section 7 concludes with final remarks.

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. Lillard (2026) applies this framework to the context of school closures. We build on Lillard's model and adapt it to our research context by introducing an additional demand on parental time from household activities, including caregiving when a child is ill. Parents allocate time across market work, leisure, parental educational involvement, caregiving, and other household activities, while also facing a budget constraint that governs consumption and education-related expenditures. We present the formal model in Appendix. Guided by the model, we examine several sources of heterogeneity in the labor supply response to school closures:

- **Degree of substitutability between parent and teacher time ($\boldsymbol{\pi}$):** Higher among more educated parents and lower for older children. We use parent education, child's grade, and parent's birthplace (to capture potential challenges for immigrants) as proxies.
- **Productivity/wage shifters ($\boldsymbol{w}$):** Wage potential increases with education and age and decreases with poor parental health and adverse local labor market conditions (e.g., high unemployment, high poverty).
- **Budget constraint shifters ($\boldsymbol{y}$):** Spousal employment, unemployment benefits, child-related transfers, and other government assistance influence available resources.
- **Shifters of caregiving time for a sick child ($\boldsymbol{t^c}$):** Proxied by reported child health problems.
- **Other parental time supply shifters ($\boldsymbol{t^h}$):** 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 ($\boldsymbol{P_e, P_f}$):** Captured through fixed effects for time, region, and parent.
- **COVID-19 spread:** While not explicitly modeled above, the extent of COVID-19 spread could also influence how school closures impact labor supply.

Any single factor may alter labor supply responsiveness to school closures through various channels. Estimating how school closures affect labor supply across subgroups, defined by one or more of these dimensions, is an empirical question we address in the subsequent sections.

3 Data

3.1 Sample

This study uses data from the 2017-2022 rounds of the RLMS-HSE survey, which averages approximately 16,000 respondents per round[5] and draws from 38 randomly selected primary sample units from 32 out of 83 federal subjects of the Russian Federation.[6] The survey period covers two major COVID-19 waves in Fall 2020 and Fall 2021. Our estimation sample consists of parents aged 18 to 60 with school-age children (ages 6-14) in grades 1 to 8, restricting the sample to those with at least two survey rounds for fixed-effects estimation. Attrition does not pose a significant issue in this sample.[7] For parents with multiple school-age children, we link schooling policies to the youngest student, who typically requires more care.[8]

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" (hereafter, S.P. Tracker), a daily record of COVID-related regional restrictions by school grade level. The S.P. Tracker covers 83 regions and three academic years from September 1, 2019, to January 31, 2023. The dataset was compiled by the authors based

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

[6] 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.

[7] 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.

[8] We also considered an alternative approach that sums all days of school closure across all school-age children in the household. As shown in Online Appendix Figure A2, in 2020, the duration of school closures differed noticeably only between students in grades 1–4 and those in grades 5–8. Only 356 parents in our sample had children in both groups, and just 82 of them experienced school closures that occurred on different dates. Given this limited overlap, we focus on the youngest school-age child. This approach also simplifies the linking of children's characteristics to the parent.

on more than 1200 official documents and media reports on coronavirus-related educational restrictions. Data collection was conducted as part of the NIH-funded project (1R01AG071649-01).

Each non-weekend day in the S.P. Tracker is classified as one of five categories: (1) in-person schooling (schools fully open), (2) no in-person schooling due to COVID-19, (3) scheduled school break, (4) schooling disruptions for non-COVID reasons such as inclement weather, security threats, and elections, and (5) public holidays (federal or regional). For the purposes of this study, we define school closures as days classified as category (2). Even when instruction continues in alternative formats, such as online classes with teachers or studying at home with parents, we consider schools closed when in-person learning is suspended.

In Russia, school closure decisions were primarily made by regional authorities, resulting in substantial regional variation in schooling policies.[9] Figure 1 illustrates the relative number of regions mandating school closures at various stages of the COVID-19 pandemic. Most executive orders on school closure were issued during periods of rising daily COVID-19 cases and deaths. During the initial phase of the pandemic in Spring 2020, all regions closed schools for in-person learning. However, with each subsequent wave, fewer regions enacted such restrictive measures – even amid higher surges 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. During Fall 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 their differentiation by grade levels. As illustrated in Table 1 and Online Appendix A2, middle school students encountered more restrictions on in-person attendance than elementary school students, particularly during Fall 2020. By Fall 2021, this grade-level variation in closure days had become less pronounced.

[9] This variation is illustrated in the map provided in Online Appendix A1.

In addition to considerable regional variation in school closures and some grade-level differences, there was also significant variation in school closures over time within the same survey round. This is evident from the weekly timeline of school closures by region, reported in Online Appendix A3-A5. We take advantage of the published dates of survey interviews to exploit intertemporal within-round variation in schooling disruptions. 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. Specifically, we calculate the rolling sum of days in each of the five categories (including breaks and holidays) within a 30-day moving interval. These measures of schooling disruptions are then 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 in Russia 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 closures have attempted to account for and disentangle the impact of other concurrent COVID-19 restrictions (e.g., Amuedo-Dorantes et al., 2023; Garcia & Cowan, 2022).

By the time RLMS-HSE survey interviews began in September 2020, most mobility restrictions had been lifted. However, potential confounding effects from workplace closures remain a concern when assessing the relationship between school closures and labor supply. In response to a surge in coronavirus cases in the fall of 2021, Russia declared three business days in early November as 'non-working days.' Among the 32 RLMS regions, nine extended this federal measure by initiating the period of no work as early as October 25 and concluding it as late as November 15. To separate the effects of school closures from those of workplace shutdowns, we control for the 30-day rolling sum of non-working days by region and interview date.

At the regional level, we also control for monthly poverty and unemployment rates, as well as the COVID-19 spread. While the first two measures are standard, the third requires clarification. For each region and interview date, we calculate the number of new coronavirus cases per 100 people in the last 30-day period. The case counts are taken from the Yandex coronavirus database, compiled from daily government reports published on стопкоронавирус.рф. Although this data is widely used by respectable data aggregators such as the World Health Organization, the Coronavirus Resource Center at Johns Hopkins University, and Our World in Data, it is known to severely undercount case numbers and especially deaths. There is a vast discrepancy between the sum of daily cases and the end of the year statistics provided by the Russian Ministry of Health Care on COVID-19 morbidity and death certificates.[10] Our calculations suggest that daily reports account for only 62 percent of 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 data still effectively track the general trajectory of the pandemic, capturing its peaks and troughs. To address the undercounting issue, we adjust the number of reported coronavirus cases over the 30-day period using region-specific discrepancy factors. We acknowledge that our measure of COVID-19 spread might be noisy and should be interpreted with caution.

4 Estimation Methods

To analyze the effects of school closures on parental labor supply, we employ the fixed effects estimator with regional and individual heterogeneity, as well as a correlated random coefficient (CRC) estimator. In the baseline specification, a parent's labor supply, L_{it}^{P}, is assumed to be influenced by school closure mandates (S_{it}), a set of covariates (X_{it}), calendar year effects (θ_t), and individual fixed effects, α_i:

[10] 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 a 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.

$$L_{it}^{P} = \alpha_i + \gamma S_{it} + \beta X_{it} + \theta_t + \epsilon_{it}, \qquad \mathbb{E}(\epsilon_{it} | S_{it}, X_{it}, \theta_t, \alpha_i) = 0 \tag{4}$$

where S_{it} represents the number of days of COVID-related school closings in the last 30 days, varying by region, the child's grade level, and the date of the survey interview.

We examine the impact of school closures on various labor supply outcomes (L_{it}^{P}): employment status, total hours of work across primary and secondary jobs, and the probability of working from home. All labor supply outcomes refer to the last 30-day period preceding the survey interview. The covariate vector X_{it} includes indicators of other school disruptions (e.g., school breaks, non-COVID closures, extended holidays) and workplace shutdowns, all measured over the past 30 days. The selection of additional control variables is guided by the theoretical framework presented in Section 2.[11] These controls include:

- Parental characteristics: age, age squared, level of education, ethnicity, place of birth, and health problems.
- Child characteristics: grade level and health problems.
- Household characteristics: cohabiting with a spouse, spouse's employment status, presence of an older caregiver in the household, availability of outside family help, and receipt of child benefits, unemployment benefits, or other government assistance.
- Regional characteristics: poverty and unemployment rates, and the number of new COVID-19 cases.
- Occupational characteristics: the potential to work remotely, proxied by indicators for unstructured job (reflecting autonomy over tasks, priorities, and goals) and indoor occupations (indicating the extent of required indoor work). These variables are included only in the equations for hours of work and working from home, not in the employment equation.

[11] Variable details are provided in Online Appendix Table A6.

Using an individual fixed effects estimator is relatively uncommon in the school closure literature, as it requires longitudinal data with sufficient within-variation in school closure exposure. Several studies in this journal issue have successfully applied this method. However, this approach assumes no selection on gains – that is, selection into treatment is independent of γ – and typically estimates a constant effect across individuals and over time. However, policymakers deciding whether to close schools are likely to consider how sensitive labor supply is to such policy. This method also offers limited flexibility for estimating heterogeneous effects, usually relying on interactions between the school closure variable and individual covariates, examined one at a time.

Our preferred alternative is the correlated random coefficient (CRC) model, which allows for the estimation of individual-specific responses to school closures (γ_{it}) while simultaneously accounting for flexible patterns of selection on unobservables (see Hsiao et al., 2019; Verdier, 2020).

$$L_{it}^{P} = \alpha_i + \gamma_{it} S_{it} + \sum_{k=2017}^{2022} \beta_k I(t=k) X_{it} + \theta_t + \epsilon_{it}, \qquad \mathbb{E}(\epsilon_{it} | S_{it}, X_{it}, \theta_t, \alpha_i) = 0, \quad (5)$$

where covariates X_{it} are interacted with time fixed effects.

The estimation process involves the following steps. First, Equation (5) is estimated for untreated observations only ($S_{it} = 0$). 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., a parent's worsened health or the birth of an additional child during the COVID-19 pandemic) but also because of temporal shifts in the labor market structure. These shifts are captured through the interaction of each covariate with year fixed effects, as represented by β_k in Equation (5). This helps 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 difference between the actual and counterfactual outcomes, which varies across individuals and over time. These steps align with the approach of Borusyak, Jaravel, and Spiess (2024) for a binary treatment variable.

In the final step, we quantify the marginal effect of additional school closure days on labor market outcomes by regressing the estimated individual-specific treatment effects on the duration of school closures across all observations (i.e., the average treatment effect) or within specific groups of interest (e.g., by gender). Standard errors are estimated using bootstrap resampling and are clustered at the individual level.

The CRC framework is particularly well suited for our study because it accommodates selection on unobservables, does not assume a constant treatment effect, and permits treatment effects to interact flexibly with observed and unobserved characteristics. Regions and households that are less constrained in their labor supply are more likely to experience closures and less affected by them. Two-way fixed effects estimators average across these heterogeneous responses, attenuating estimated effects toward zero. By contrast, the CRC framework permits treatment effects to vary with both observed and unobserved characteristics, capturing larger labor-supply responses among constrained households and yielding larger estimated effects than TWFE. By leveraging CRC method, we are able to estimate effects for diverse subpopulations, including groups defined by multiple factors, such as young fathers without college degrees or mothers of elementary school children with health problems.

5 Average Treatment Effect of School Closures in Russia

This section presents estimates of the average treatment effect of school closures on employment, total hours of work, and the probability of remote work. Table 2 reports summary statistics for each parental labor supply variable, comparing two groups – ever-treated and never-treated – across two time periods: before the pandemic (2017-2019) and after its onset (2020-2022).[12] The ever-treated group consists of parents of children in grades 1-8 who experienced at least one day of COVID-19-related school closures during the 30 days prior to the interview, in at least one survey wave. The never-treated group includes other parents of children in grades 1-8, though some may have experienced school closures outside the 30-day reference window – for example, during the spring 2020 stay-at-home order, when no survey was conducted. Within the ever-treated group, we further distinguish between those recently treated (school closures in the past 30 days) and those not recently treated.

We use raw means to compute an unconditional DID effect by comparing changes in parental labor supply over time between recently treated and never-treated groups of parents. These unconditional estimates do not account for individual heterogeneity, labor supply determinants, or treatment intensity (any exposure, even for one day, is considered treatment). The comparisons suggest that school closures had little effect on employment or total working hours but were associated with a higher likelihood of remote work.

It is reassuring that the unconditional DID estimates are consistent with the results for total working hours obtained from the more advanced models presented in Table 3. This table reports the average treatment effect of an additional ten days of school closures using three alternative methods – including individual FEs and the CRC model – with one specification allowing for covariate-by-year interaction terms.[13] Results are shown separately for mothers and fathers. Mothers exhibited a significantly larger shift toward remote work in response to school closures, consistent with prior

[12] Summary statistics for all individual covariates by group and periods can be found in Online Appendix Table A7.

[13] Full estimates from the baseline specification with individual fixed effects, corresponding to Equation (4), are reported in Online Appendix Table A8. Table A9 presents robustness checks to alternative sets of covariates. Table A10 reports estimates from the baseline specification for the full sample of adults, assigning childless adults the average duration of school closures in their region and month of observation. The estimated effects for parents of primary and middle school children are consistent with the main results in Table 3.

research on women's greater caregiving responsibilities (Bertrand et al., 2015; Blau & Kahn, 2007) and their higher likelihood of holding jobs with flexible work arrangements (Goldin & Katz, 2011; Flabbi & Moro, 2012). While some studies find remote work increases for both parents (Garcia & Cowan, 2022), others report such effects primarily among mothers (Hansen et al., 2024; Yamamura & Tsutsui, 2021). Our findings indicate that school closures disproportionately affected how mothers adjusted their work arrangements.

Unlike the unconditional DID estimates, the individual fixed effects and CRC specifications reveal a negative effect of school closures on employment, particularly for mothers, with a 4.6-6.9 pp decline. All models unanimously show that mothers' working hours remained largely unchanged. Prior research on employment and hours responses is mixed.[14] Compared to studies in other countries, our findings indicate a sharper drop in employment and no adjustment in hours in Russia. While some of these cross-country differences may stem from variations in measurement or methodology, deeper structural factors may also be at play. The Russian labor market is characterized by high employment flexibility – low unemployment and high turnover. Each year, 11–14 percent of respondents report changing jobs or occupations. Methodologically, the discrepancy may also reflect the noisy nature of reported monthly hours and our definition of employment, which captures only those actively working in the past 30 days, excluding those on leave. The absence of changes in total hours suggests that mothers adjusted either by switching to remote work or by exiting the labor market, rather than by reducing their working hours, implying limited worker control over hours.

To assess the robustness of our results to potential confounding events, we conduct a falsification test by applying our estimation strategy to population groups unlikely to be affected by

[14] Some studies report no significant employment changes for fathers (Bak et al., 2025 for South Korea; Hansen et al., 2024 for the U.S.) or for either parent (Amuedo-Dorantes et al., 2023 for the U.S.; Eyal et al., 2025 for South Africa; Imre et al., 2024 for Germany; Raymo et al., 2025 for China). Others find employment declines for both parents, with stronger effects for mothers (Garcia & Cowan, 2022 for the US; Kozhaya, 2022 for Mexico; Salamancaa et al., 2025 for Australia). For hours of work, studies generally find a reduction either for both parents (Imre et al., 2025) or for mothers only (Bak et al., 2025; Eyal et al., 2025).

school closures. Specifically, we analyze four placebo groups: (i) married adults without children under 18, (ii) childless single adults, and (iii) parents of children under 6 years old (iv) parents of middle school children assigned primary school closure and vice versa with observations in which school closures affected both primary and middle school children being dropped. All groups are assigned the average number of school closure days (across all grades) based on their region of residence and interview date. While two of the coefficients reported in Table 4 are statistically significant and has the same sign as the actual treatment effect, it pertains only to fathers, rather than the primary affected group, mothers, and are small in magnitude or significant only at 10% level. These findings reinforce our confidence that the observed labor supply effects are driven by school closures rather than simultaneously occurring COVID-mitigation policies.

Finally, we compare labor supply responses to school closures with those to regular school breaks in Table 5. Unlike school closures, which were unanticipated, school breaks are scheduled in advance before the start of the academic year. We find no significant changes in employment or remote work during school breaks. This contrast suggests that unanticipated disruptions, such as school closures, have a greater impact on parents' behavior, likely due to the difficulty of arranging alternative care and support on short notice.

6 Heterogeneous Treatment Effects

While average effects are certainly useful – particularly for cross-country comparisons – they can mask substantial variation in labor supply responses across different segments of the population. As noted in the introduction, prior research typically explores heterogeneity along a limited set of isolated dimensions, such as marital status, child's age, or parental education. We build on this work by examining variation in labor supply responses across multiple population groups, capturing the complexity of within-family decision making and allocation of responsibilities in Russian households.

The selection of population groups is largely guided by the theoretical framework presented in Section 2. Figure 2 and Table A11 display the estimated effects of school closures on labor supply across these groups. Most parent groups experienced a statistically significant decline in employment rates, typically ranging from 4 to 8 percentage points. The largest declines were observed among mothers who are single (15.4 pp), young (10.4 pp), less educated (8 pp), have preschool-aged children (8.7 pp)[15], lack in-house or external caregiving support (7.1-7.3 pp), and live in low-unemployment areas (10.5 pp). In contrast, employment effects for fathers were generally smaller and sometimes statistically insignificant, particularly among those who were younger, had no children under age 7, had a child in elementary school, lacked outside childcare support, or lived in areas with lower COVID-19 prevalence. These findings indicate that school closures had a disproportionately large negative impact on maternal labor supply, especially among mothers with fewer resources or limited access to alternative childcare. These mothers are often less able to work remotely or afford private care, leading to larger disruptions in labor force participation.

The bottom panel in Figure 2 suggests that remote work served as an important adjustment mechanism for mothers during school closures, especially for those facing greater caregiving demands or health-related constraints. The probability of remote work increased notably when the child was ill (12.8 pp), when there was an additional younger child in the household (10.2 pp), and in the absence of in-house or external caregiving support (4.1 pp and 6.8 pp, respectively). Remote work uptake was also more common in regions with lower unemployment rates (5.7 pp) or higher COVID-19 incidence (6.4 pp). Fathers were generally less responsive to school closures in terms of remote work. However, their likelihood of working remotely increased under caregiving or health-related pressures. Specifically, fathers were more likely to transition to remote work when they had a sick child (7.9 pp), had an additional younger child in the household (8.9 pp), or lacked in-house (3.9 pp) or external (4.5

[15] In Table A12, we estimate the effects of school closures for subsamples of parents whose children are enrolled or expected to be enrolled in primary school in a given year between 2013 and 2022. Consistent with the results in Tables A11 and A13, parents of older children are more likely to switch to working from home, whereas parents of younger children are more likely to address school closures by leaving employment altogether.

pp) caregiving support. These results suggest that caregiving responsibilities can alter fathers' labor market behavior under certain conditions, provided that their job arrangements permit such flexibility.

The CRC model enables us to examine how labor market responses vary not only along single dimensions but also across combinations of variables. Figure 3 and Table A13 show the effects of school closures for subsamples defined by two-variable interactions. In several cases, we find that statistically insignificant effects of school closures at the group level are driven by specific subgroups within them. For example, the lack of a significant employment response among younger fathers is largely attributable to those without a college education, which is consistent with prior findings that less-educated parents spend less time with their children (Guryan et al., 2008). Among college-educated fathers under age 35, however, employment reduction was statistically significant (5.2 pp), aligning with evidence that higher education alters traditional gender roles (Du et al., 2020). Older, college-educated fathers also exhibited significant declines in employment in response to school closures (4.5 pp).

Figure 3 and Table A13 also suggest possible strategic intra-household labor reallocations in response to school closures. In line with existing literature (Eriksen et al., 2021; Jeon and Pohl, 2017), mothers' labor supply is more sensitive to health shocks within the family. When a child was ill, mothers of elementary schoolers were especially likely to leave employment (16.6 pp). However, fathers increased their working hours (not statistically significant but large in magnitude), presumably to offset the lost family income. Fathers also tended to work more hours during school closures when their spouse was not employed, which also points to compensatory labor responses (not statistically significant but sizeable in magnitude).

Finally, the interaction between COVID-19 intensity and local labor market conditions adds another layer of heterogeneity. In regions with high COVID-19 prevalence, both mothers and fathers significantly reduced their labor supply, while those who remained employed shifted to remote work. However, in regions with high unemployment rates, parents did not exit employment—even amid widespread COVID-19—suggesting that limited employment opportunities constrained their ability to adjust work arrangements in response to infection risks and children's learning losses.

7 Discussion and Conclusion

In this study, using six years of panel data from Russia and a novel dataset of daily, grade-specific school closure policies, we uncover the heterogeneous effects of school closures on labor supply that may have been overlooked in prior research. Our key contribution lies in deploying a correlated random coefficient model with individual fixed effects, which allows us to examine how labor market responses varied not only by single factors but also by combinations of multiple characteristics. We find that, on average, school closures decreased employment and increased remote work, with larger effects among mothers. However, these averages conceal substantial heterogeneity: employment declines were particularly steep for mothers of ill primary school children and for those living in regions with low unemployment rates and high COVID-19 incidence. The commonly reported finding that fathers' employment was unaffected by school closures is driven by labor supply responses of younger fathers without college education. We find that employment rates decreased for older and college-educated fathers.

These findings emphasize the need for flexible and targeted family leave and childcare policies during public health crises. One-size-fits-all interventions are unlikely to match the diverse needs of households. Future research should explore the long-term consequences of these labor market and educational disruptions on earnings, career trajectories, and child outcomes, and examine how more nuanced school closure policies – such as staggered school schedules or hybrid learning – can mitigate adverse effects in future crises.

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9 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: Unconditional DID Effect

	2017-2019			2020-2022				DID	
					Ever treated				
	Never treated	Ever treated	*p*-value	Never treated	Not treated	Treated	*p*-value (6) vs (4)	Absolute value	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employed	0.773	0.791	0.091	0.767	0.825	0.804	0.004	0.019	0.255
Total hours of work	184.858	185.524	0.651	181.842	182.714	182.729	0.618	0.221	0.924
	(51.304)	(47.495)		(48.095)	(47.075)	(51.399)			
Work from home	0.076	0.095	0.018	0.082	0.121	0.131	0.000	0.030	0.018
N observations	5,626	2,074		4,854	1,570	1,305			

Notes: The table reports means and standard deviations (in parentheses) of labor supply outcomes by treatment status, before and after the pandemic. Standard deviations for binary variables are omitted. The treated group includes parents who were exposed to school closures during the last 30 days preceding the survey interview. Unconditional DID estimates compare average changes over time between never treated and treated groups (ever treated before 2020). *P*-values are based on *t*-tests of mean differences. The sample includes adults aged 18–60 who were surveyed at least twice.

Table 3: The Average Treatment Effect of School Closures on Labor Supply

Estimation methods	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
Regional FEs	-0.018	-0.010	1.415	-0.853	0.045**	0.020
	(0.026)	(0.018)	(3.685)	(3.907)	(0.019)	(0.018)
Individual FEs	-0.048**	-0.007	-2.165	-0.575	0.022	0.008
	(0.021)	(0.020)	(3.417)	(4.288)	(0.020)	(0.015)
CRC with FEs	-0.046**	-0.034*	-0.867	0.199	0.043**	0.020
	(0.020)	(0.019)	(3.384)	(3.498)	(0.021)	(0.019)
CRC with FEs + covariate-by-year interactions	-0.069***	-0.049***	0.040	0.629	0.042**	0.036*
	(0.022)	(0.018)	(3.406)	(3.452)	(0.021)	(0.020)
Number of observations	8,299	6,536	5,530	5,089	5,758	5,531

Notes: The table reports average treatment effects of an additional ten days of school closures on parental labor supply. Column 1 lists four alternative estimation methods, the latter three including individual and year fixed effects. CRC denotes the Correlated Random Coefficient method. Full results for the individual fixed effects model are presented in Online Appendix Table A6. Standard errors are clustered at the individual level in the model with individual FEs, and on the regional level in the model with regional FEs. Weight decompositions following de Chaisemartin and D'Haultfœuille (2020) show that negatively weighted individual–year effects account for less than 2% of the total identifying weight across all specifications for individual FEs model. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Falsification Test

Estimation methods	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
Panel A. Married adults without children	Panel A. Married adults without children					
Individual FEs	0.002	0.007**	-0.736	0.763	0.001	-0.001
	(0.003)	(0.003)	(0.694)	(0.776)	(0.004)	(0.002)
CRC with FEs + covariate-by-year interactions	0.001	0.007***	0.741	1.490***	0.001	-0.001
	(0.003)	(0.002)	(0.529)	(0.537)	(0.003)	(0.002)
Number of observations	8,311	6,873	5,126	4,659	5,377	5,124
Panel B. Single adults without children	Panel B. Single adults without children					
Individual FEs	-0.000	-0.001	0.171	-1.238	0.003	0.004
	(0.004)	(0.005)	(0.702)	(1.328)	(0.004)	(0.004)
CRC with FEs + covariate-by-year interactions	-0.003	0.003	0.238	-0.948	0.000	-0.001
	(0.003)	(0.003)	(0.572)	(0.965)	(0.003)	(0.003)
Number of observations	8,049	6,408	4,217	2,843	4,381	3,057

Panel C. Parents of children under six years old	Panel C. Parents of children under six years old					
Individual FEs	-0.013	-0.006	-2.192	2.254	-0.001	0.009
	(0.009)	(0.008)	(1.534)	(1.393)	(0.009)	(0.008)
CRC with FEs + covariate-	-0.005	-0.017***	-1.258	-0.334	-0.009	0.003
by-year interactions	(0.007)	(0.006)	(1.384)	(0.956)	(0.007)	(0.005)
Number of observations	2,452	1,997	889	1,570	924	1,717
Panel D. Parents of primary school children are assigned middle school policies and vice versa	Panel D. Parents of primary school children are assigned middle school policies and vice versa					
Individual FEs	-0.052	0.013	-5.015	-6.966*	-0.040	-0.002
	(0.034)	(0.024)	(3.599)	(4.004)	(0.041)	(0.013)
CRC with FEs + covariate-	-0.044	0.004	-4.121	-3.772	-0.039	-0.004
by-year interactions	(0.034)	(0.024)	(3.513)	(4.129)	(0.044)	(0.016)
Number of observations	7,535	5,887	4,975	4,558	5,188	4,964

Notes: The table reports average treatment effects of an additional ten days of COVID-19-related school closures on adult labor supply for four placebo groups: (i) married adults without children under 18, (ii) childless single adults, and (iii) parents of children under six years old (iv) parents of primary school children are assigned middle school closures, and parents of middle school children are assigned middle school closures (specifically, closures are mapped across grades as follows: grade 1 - grade 5; grade 2 - grade 6, grade 3 - grade 7, grade 4 - grade 8, grade 5 - grade 1, grade 6 - grade 2, grade 7 - grade 3, and grade 8 - grade 4); observations in which school closures affect both primary and middle school children are dropped. All groups are assigned the regional average number of school closure days (across all grades) for the fall months of their interview. Results are reported for the individual FE model and for the CRC method, which includes individual FEs and covariate-by-year interactions. Standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

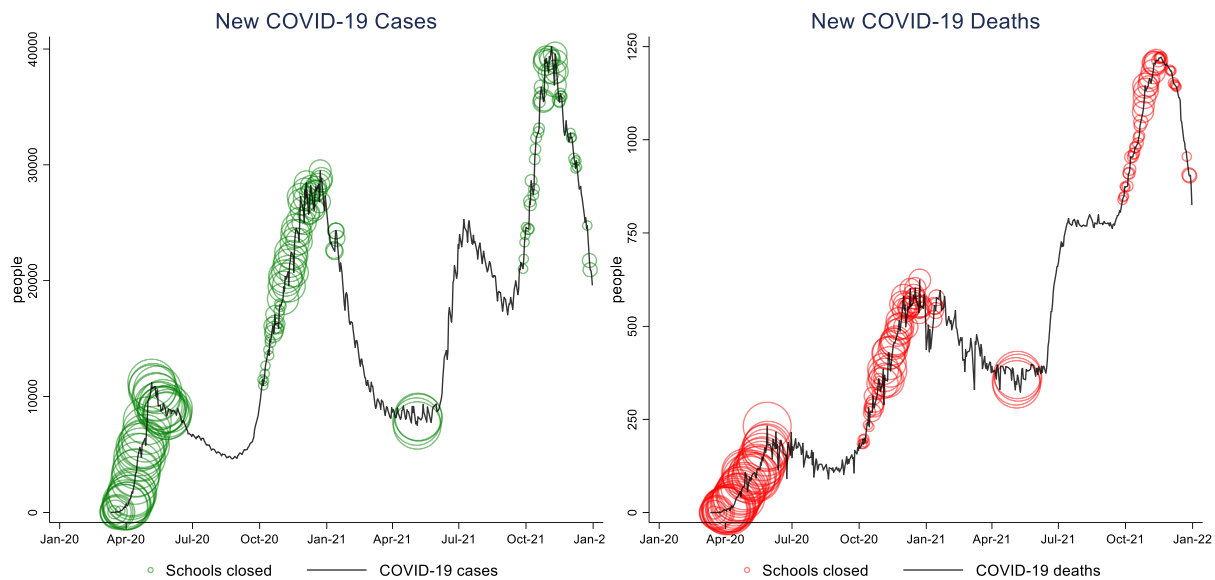
Table 5: The Average Treatment Effect of School Breaks on Labor Supply

Estimation methods	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
Regional FEs	0.010	-0.015	1.558	1.657	0.016	0.001
	(0.018)	(0.017)	(2.362)	(2.978)	(0.015)	(0.013)
Individual FEs	-0.005	-0.019	0.278	2.071	0.004	0.008
	(0.015)	(0.014)	(2.378)	(2.466)	(0.015)	(0.010)
CRC with FEs + covariate-by-year interactions	-0.005	-0.017	-5.010	1.646	0.008	-0.004
	(0.019)	(0.017)	(3.175)	(2.881)	(0.020)	(0.013)
Number of observations	8,299	6,536	5,530	5,089	5,758	5,531

Notes: The table reports average treatment effects of an additional ten days of school breaks on parental labor supply. Results are reported for the regional and individual FE models and for the CRC, which includes individual FEs and covariate-by-year interactions. Standard errors are clustered at the individual level in the model with individual FEs, and on the regional level in the model with regional FEs. Weight decompositions following de Chaisemartin and D'Haultfœuille (2020) show that negatively weighted individual–year effects account for less than 2% of the total identifying weight across all specifications for individual FEs model. *** p<0.01, ** p<0.05, * p<0.1.

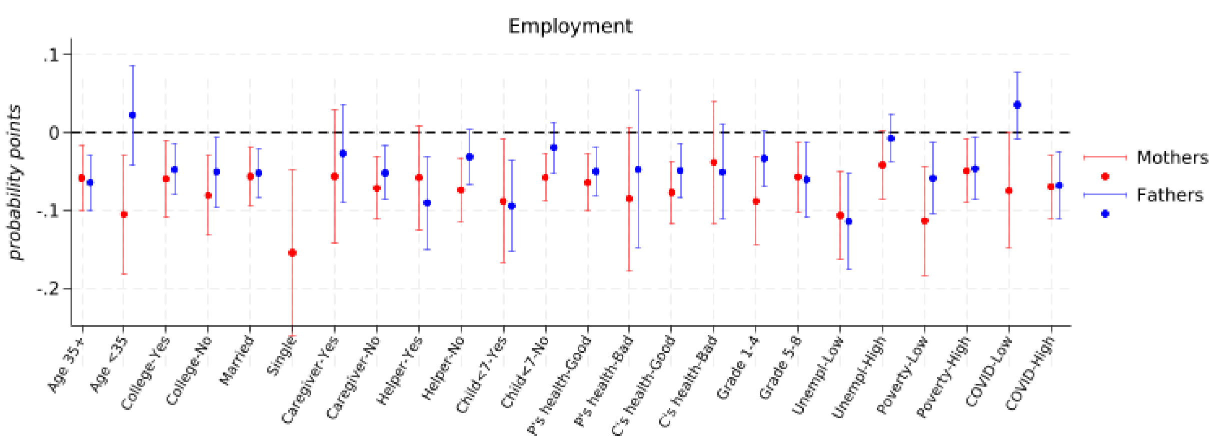
10 Figures

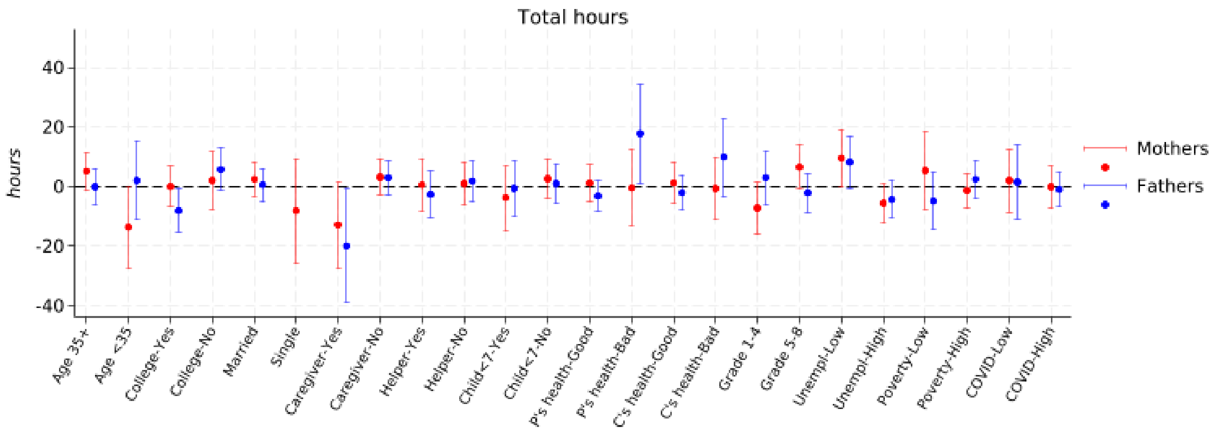
Figure 1: School Closings and the Spread of COVID-19

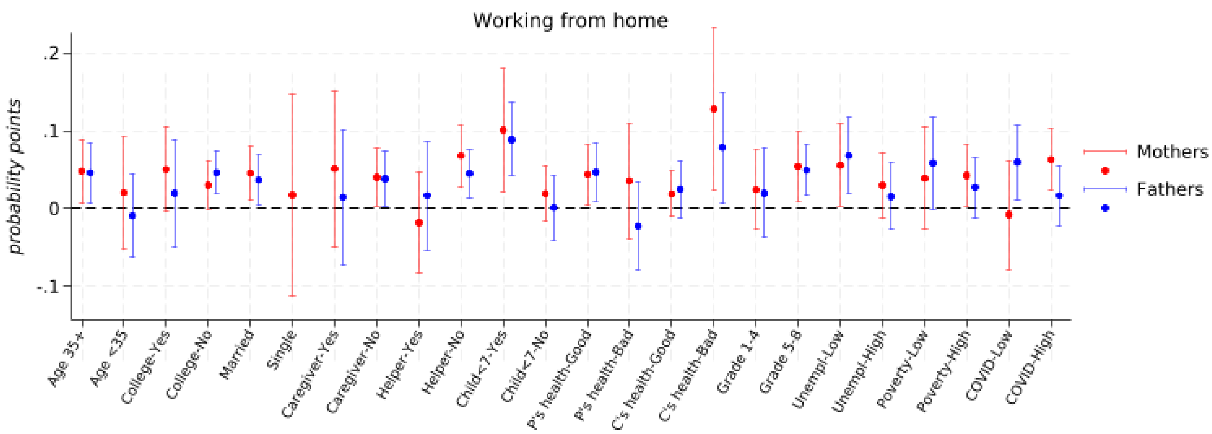


Notes: Figure plots daily confirmed COVID-19 cases and deaths in Russia. The size of the hollow marker is proportional to the number of Russian regions (max 83) where schools have been closed due to COVID.

Figure 2: Effects of School Closures by One-Factor Variables, CRC

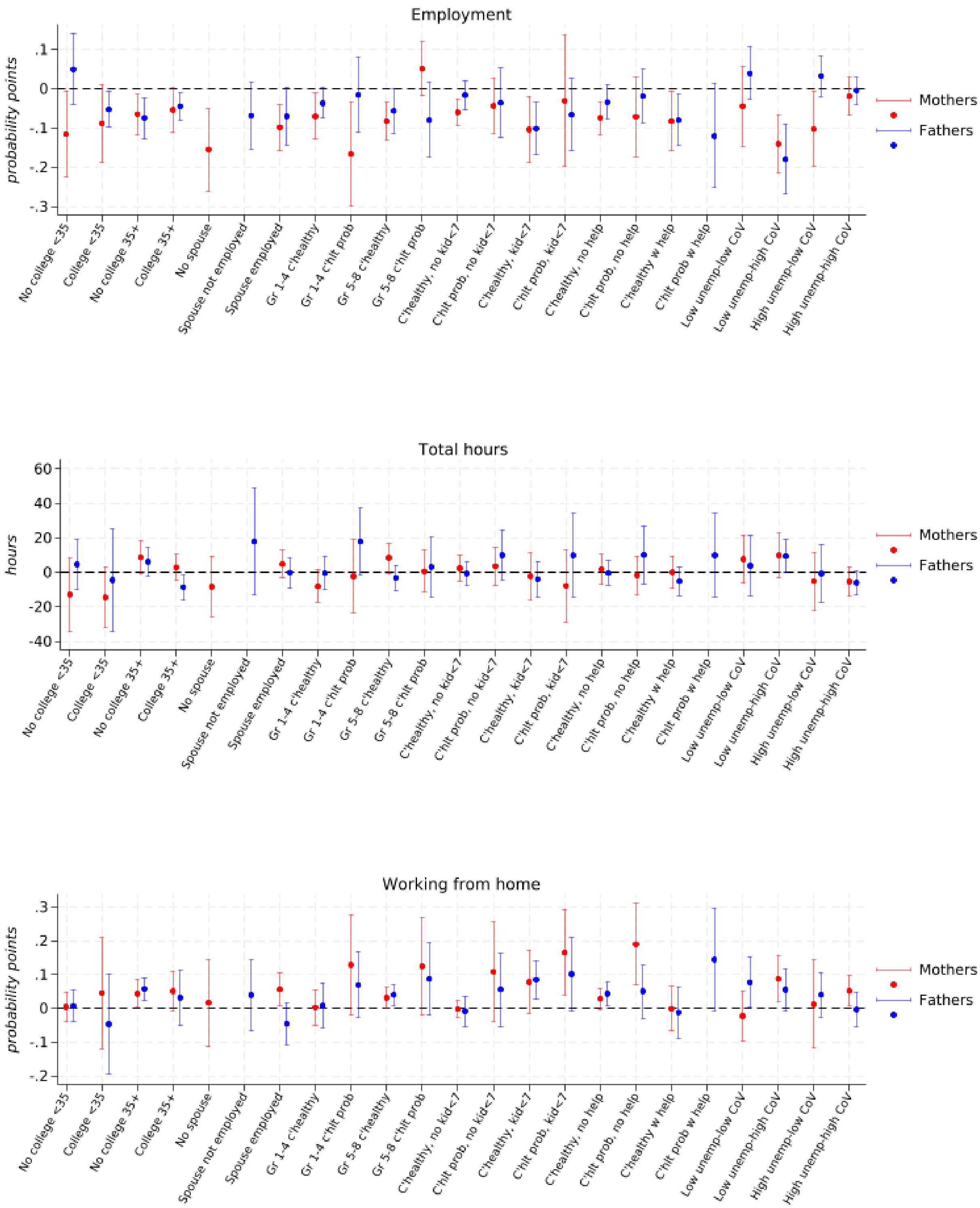






Notes: Figures include the heterogeneous effects of school closures on parental labor supply with respect to one-factor variables. The estimates are based on a correlated random coefficient model. Point estimates are also reported in Online Appendix Table A9.

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



Notes: Figures include the heterogeneous effects of school closures on parental labor supply with respect to two-factor variables. The estimates are based on a correlated random coefficient model. Point estimates are also reported in Online Appendix Table A13.

Online Appendix to

"Parental Labor Supply Responses to COVID-19 School Closures

in Russia: Unpacking Heterogeneous Effects"

Theoretical Framework

We assume that parents maximize utility derived from consumption (c), leisure (l), and their child's education (q), subject to time and budget constraints. The quality of the child's education is modeled as $q = A \cdot I = A(t^f + \pi t^e - t^c)$, where $A > 0$ is a productivity parameter, I is the net time investment in children, t^f is time spent in formal schooling, t^e is time lost due to child illness, $\pi > 0$ is a substitutability parameter reflecting the effectiveness of parental time relative to a teacher's time.

Normalizing total available time to 1, parents allocate their time across five activities: market work (t^w), leisure (t^l), education time with the child (t^e), caregiving for a sick child (t^c), and other household activities (t^h). For the purpose of our analysis, we treat t^c and t^h as exogenous and focus on the trade-offs among t^w, t^l, and t^e. The time constraint is:

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

The household budget constraint is:

$$w\, t^w + y = c + P_e t^e + P_f t^f \tag{2}$$

The total monetary resources on the left-hand side of Equation (2) consist of non-labor income (y) and earnings ($w\, t^w$) paid at a wage (w) per unit of time. Non-labor income may include government assistance. These total resources are allocated to consumption (c) and expenses associated with parental educational involvement ($P_e t^e$), such as books, educational materials, and extracurricular activities. Parents are also assumed to cover costs related to formal schooling ($P_f t^f$), including tuition (if applicable), transportation, and taxes that support public education.

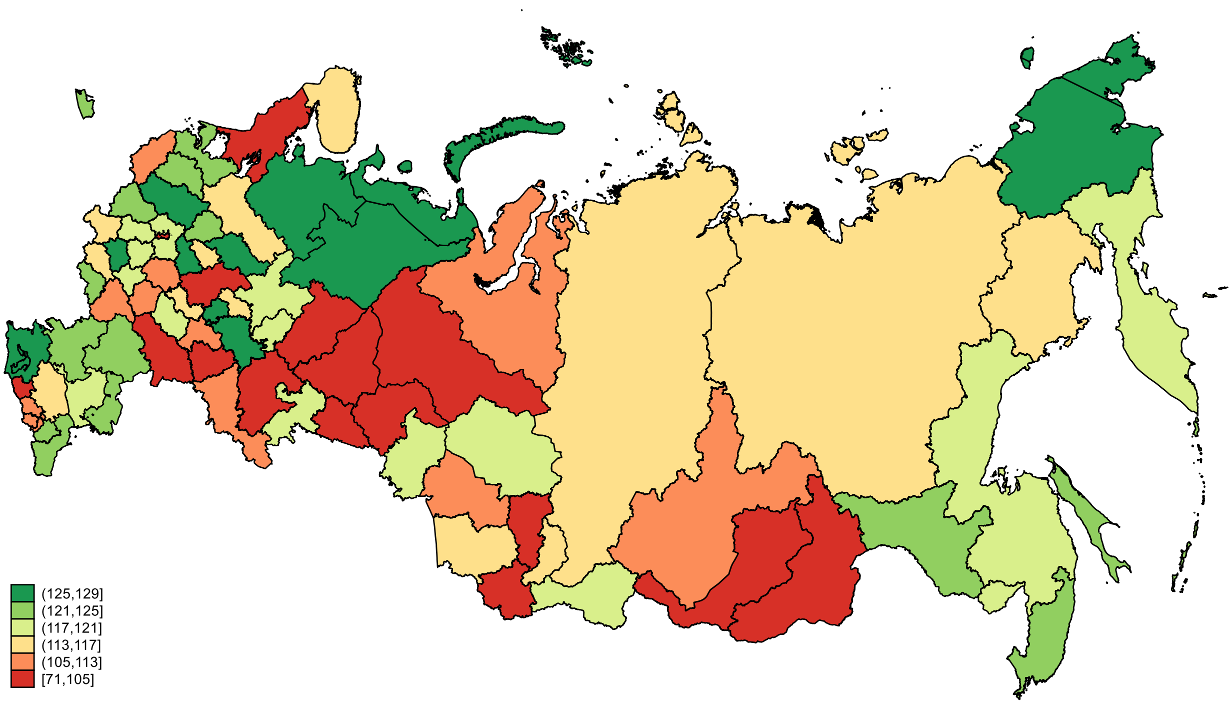
Maximizing utility subject to (1) and (2), we derive a labor supply function:

$$t^w = t^w(t^f, \pi, w, y, t^c, t^h, P_e, P_f) \quad (3)$$

This function not only identifies key determinants of labor supply but also sources of heterogeneity in the responsiveness of labor supply to school closures. The partial effect of school closures on labor supply, $\partial t^w/\partial s$, is a function of:

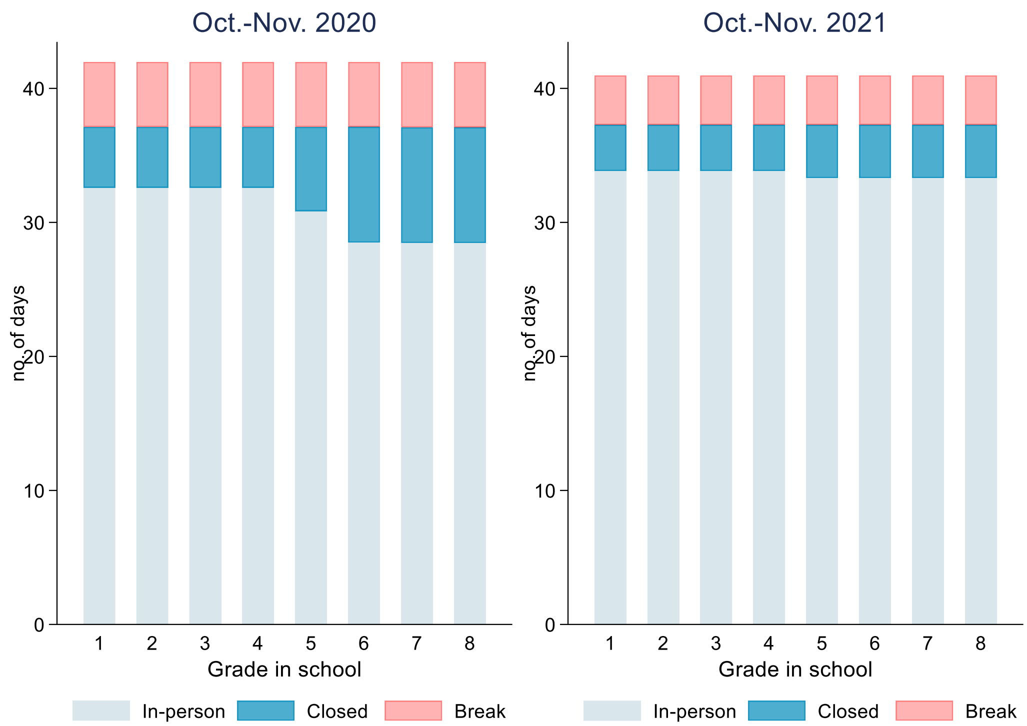
$$\partial t^w/\partial s = g(t^f, \pi, w, y, t^c, t^h, P_e, P_s).$$

A1: In-Person School Days, 2020



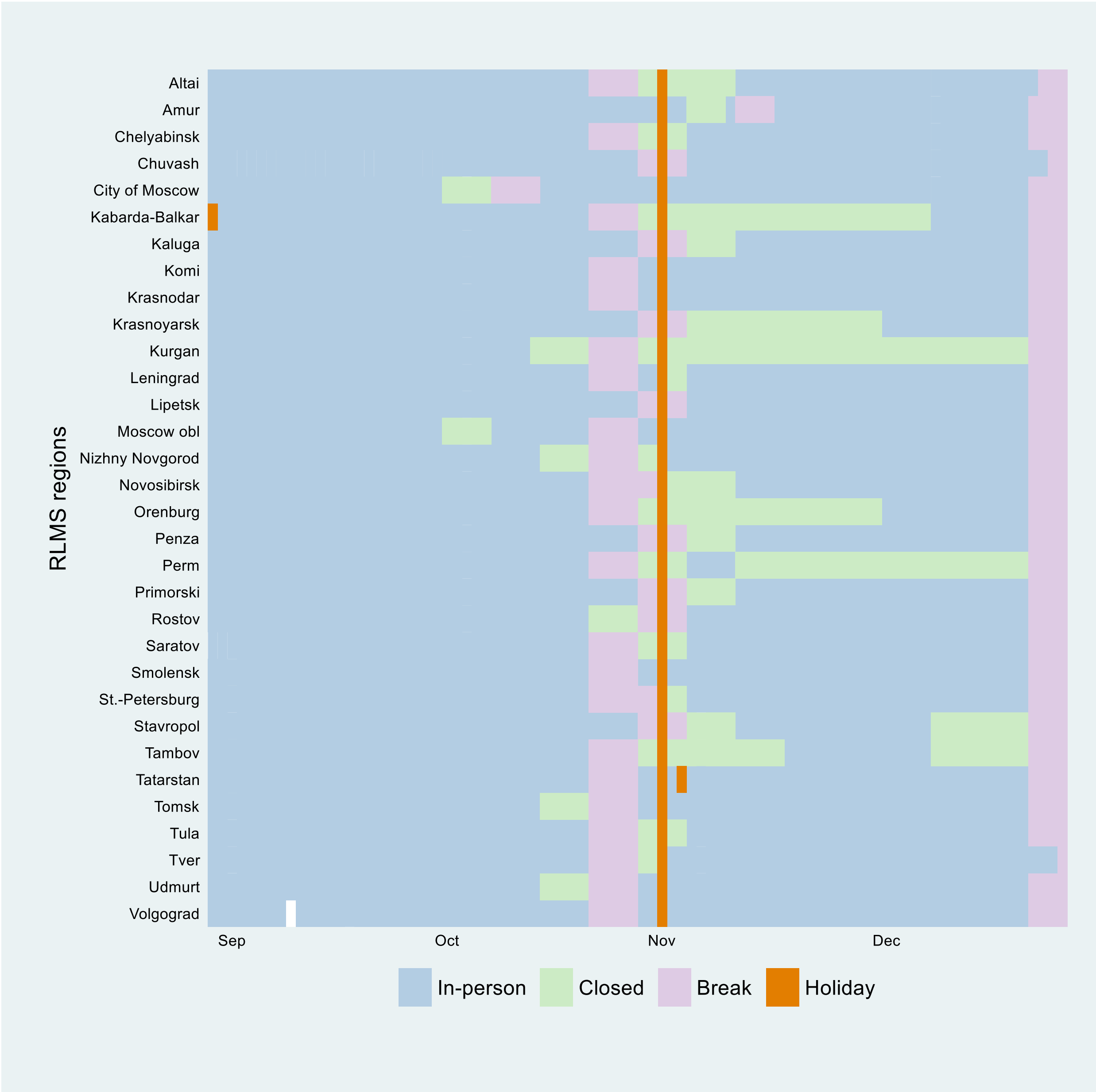
Notes: The map depicts the average number of in-person school days in 2020 for grades 1-8. The regional dispersion is extensive, with in-person days ranging from 71 days in Zabaikalsk Krai (Southeast Siberia) to 129 days in Chuvash Republic (in the Volga Upland). By comparison, a typical year includes about 170 in-person school days. The map reveals no visible clustering of in-person days within a broader geographic area. Both the map and our review of regional government policies suggest that regional authorities made their own schooling decisions in response to the spread of COVID-19, and there is no evident spatial spillover effect.

A2: Distribution of Business Days by Grade and Schooling Mode



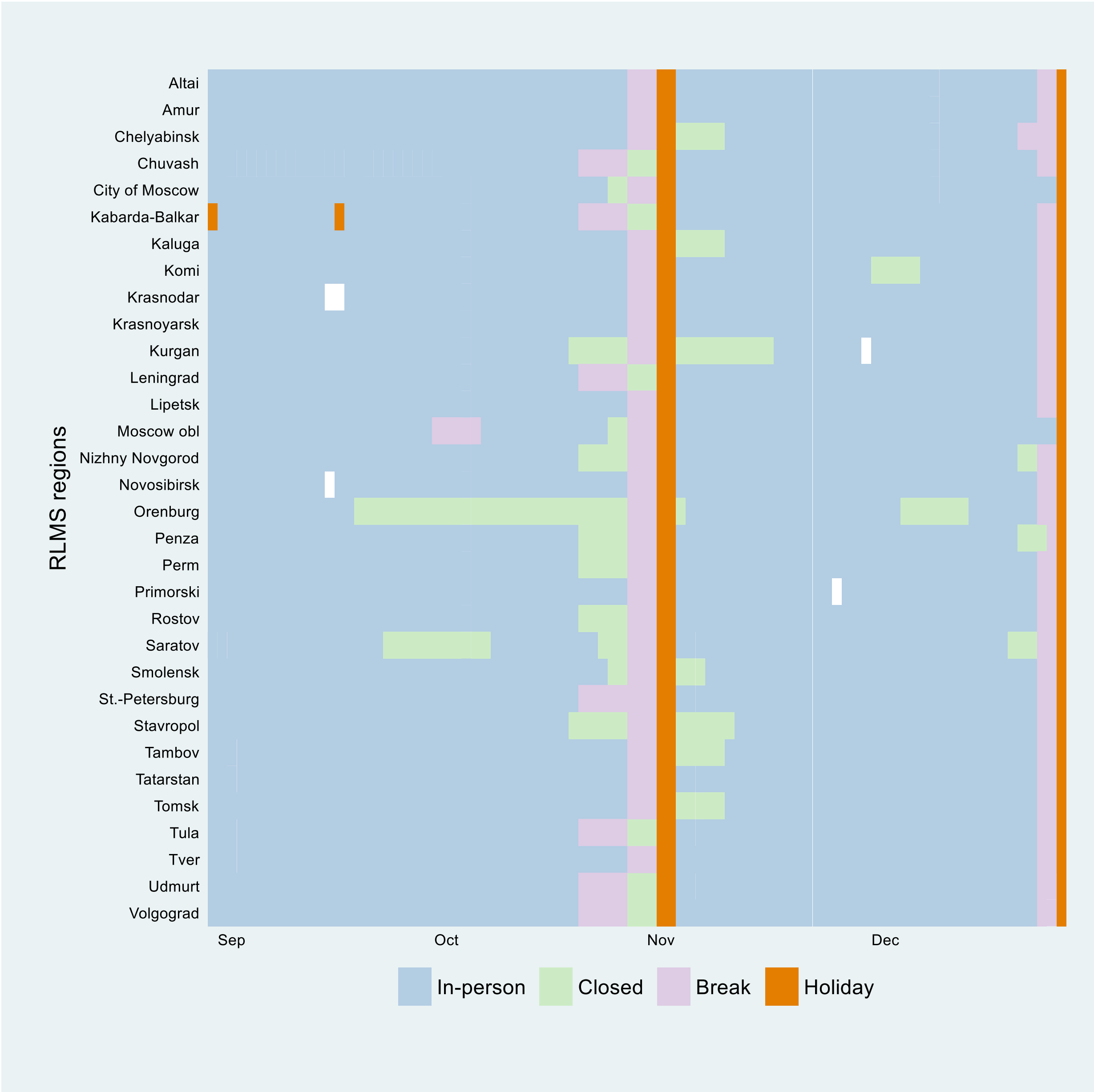
Notes: The figure plots the average number of business days during which schools were open for in-person learning, closed for COVID-19 reasons, or closed for a fall break. The average is calculated across 32 RLMS regions for the October-November time periods of each year.

A3: Timeline of School Closings, Fall 2020



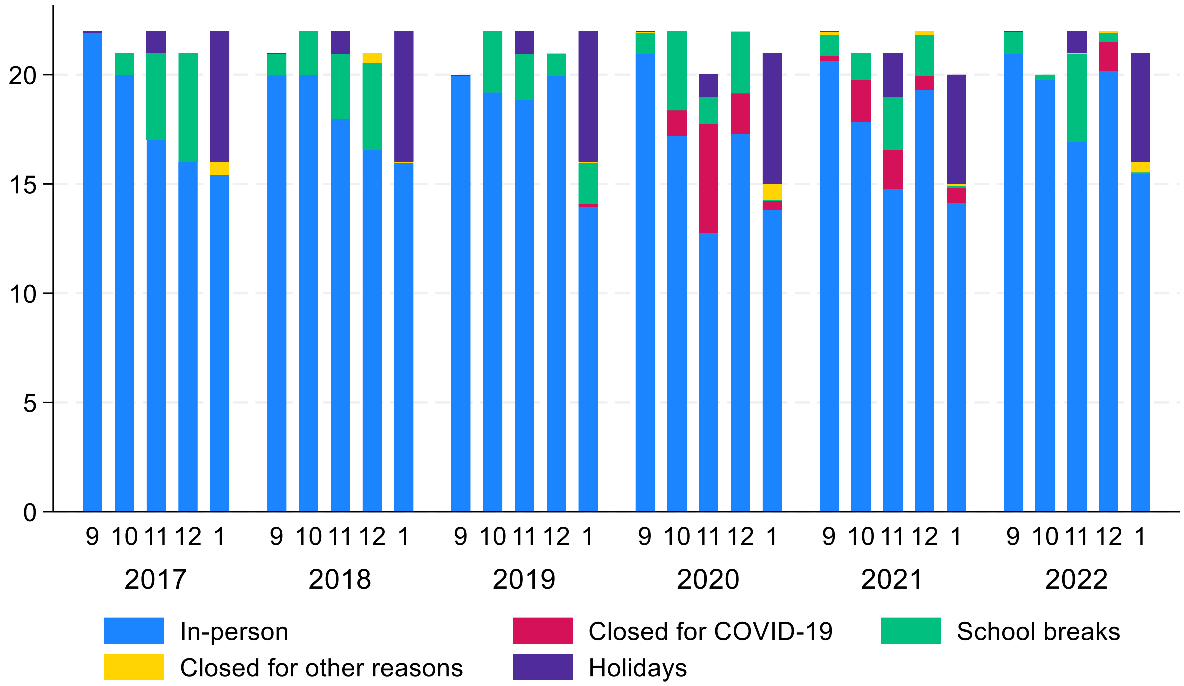
Notes: The figure presents the timeline of schooling modes for 5th graders in 32 RLMS regions from September 1, 2020, to December 31, 2020. The timeline indicates in-person days, no school days for COVID-related reasons, regular breaks, and holidays. Weekends are excluded from the timeline. White cells show days when schools were closed for reasons unrelated to COVID-19 (voting, security, or inclement weather).

A4: Timeline of School Closings, Fall 2021



Notes: The figure presents the timeline of schooling modes for 5th graders in 32 RLMS regions from September 1, 2021, to December 31, 2021. The timeline indicates in-person days, no school days for COVID-related reasons, regular breaks, and holidays. Weekends are excluded from the timeline. White cells show days when schools were closed for reasons unrelated to COVID-19 (voting, security, or inclement weather).

A5: 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 are averaged across 32 RLMS regions and school grades 1 through 8. Years indicate the survey rounds, spanning from September to January of the subsequent year.

Table A6: Definition of Variables

Variable	Definition
	Labor supply dependent variables
Employed	=1 if worked for pay or profit at a primary or secondary job in the last 30 days; =0 if did not work during that period, including those on long-term leave from a job.
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 available 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.
	Parents' characteristics
Age	Parental age
Age squared	Quadratic term for parental age

College	=1 if the parent has a college degree.
Russian ethnicity	=1 if the individual identifies ethnically Russian.
Birthplace	Categorized into four groups: born in the same place as current residence (omitted), born elsewhere in Russia, born abroad, or unknown place of birth.
Parent's health problems 30d	=1 if the parent had any health problems in the last 30 days.
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	Represents the grade level the child currently attends, obtained from a direct survey question. This variable is used to link the RLMS-HSE with grade-level policies. It is highly correlated with the child's age (corr=0.97).
Middle school	=1 if the youngest school-age child is in middle school.
Child's health problems 30d	=1 if the child had health problems in the last 30 days.
	Household Characteristics
Spousal employment status	Categorized into four groups: spouse is employed (omitted), spouse is not employed, no spouse, no data on spouse.
Older caregiver	=1 if there is an older household member, other than the parents, aged 55-80, who is not disabled and not in poor health.
Childcare by outside helper	=1 if any relative living outside the household helped the parents with childcare or housekeeping in the last 30 days.
Any child < age 7	=1 if there is another young child under age 7 in the household.
Government assistance 30d	=1 if the household received unemployment benefits or other government assistance in the last 30 days.
Children's benefits 30d	=1 if the household received children's benefits in the last 30 days.
	Schooling Policy Tracker
COVID-19 school closure 30d	The number of days when schools were closed for in-person learning due to COVID-related reasons in the last 30 days. Occasionally, closures may be due to other flu-like viruses.
School break 30d	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 longer than one working day in the

	last 30 days. This varies by region and date of interview.
	Regional characteristics
COVID-19-related workplace closure 30d	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 periods of high coronavirus spread. Except for essential businesses, all enterprises are closed during non-working days. This varies by region and date of interview.
COVID-19 spread 30d	The product of 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. This varies by region and date of interview.
Unemployment rate, %	The monthly unemployment rate, in percent. 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.
Poverty rate, %	The monthly poverty rate, in percent. This varies by region and year. Data source: Rosstat, https://rosstat.gov.ru/folder/13723.

Table A7: Summary Statistics

	2017-2019		2020-2022		
	Never treated	Ever treated	Never treated	Ever treated	
				Not treated	Treated
COVID-19 school closure 30d					
	0.000	0.000	0.000	0.000	0.521
	(0.000)	(0.000)	(0.000)	(0.000)	(0.386)
School break 30d	0.179	0.244	0.198	0.204	0.290
	(0.228)	(0.237)	(0.305)	(0.251)	(0.209)
Closure for other reasons 30d	0.001	0.002	0.004	0.003	0.002
	(0.018)	(0.023)	(0.027)	(0.025)	(0.013)
COVID-19-related workplace closure, last 30d	0.000	0.000	0.130	0.103	1.749
	(0.000)	(0.000)	(0.601)	(0.543)	(2.580)
Long holidays	0.034	0.027	0.067	0.066	0.296
Age	38.167	37.213	38.863	39.108	38.695
	(6.143)	(5.838)	(6.150)	(5.793)	(5.934)
College	0.358	0.381	0.383	0.402	0.402
Russian ethnicity	0.864	0.894	0.870	0.889	0.894
Birthplace					
Born elsewhere in Russia	0.339	0.321	0.324	0.339	0.344
Born abroad	0.080	0.076	0.070	0.073	0.076
Unknown place of birth	0.003	0.001	0.010	0.004	0.008
Parent’s health problems 30d	0.225	0.221	0.184	0.216	0.211
Middle school	0.446	0.242	0.402	0.415	0.400
Child’s health problems 30d	0.284	0.306	0.260	0.268	0.247
Spousal employment status					
Spouse not employed	0.089	0.075	0.093	0.066	0.064
No spouse	0.102	0.083	0.103	0.092	0.086
No data on spouse	0.459	0.466	0.454	0.467	0.475

Older caregiver	0.148	0.130	0.167	0.165	0.158
Childcare by outside helper	0.323	0.378	0.292	0.291	0.282
Any child < age 7	0.450	0.530	0.432	0.394	0.453
Government assistance 30d	0.040	0.049	0.102	0.059	0.051
Children's benefits 30d	0.328	0.376	0.360	0.339	0.314
COVID-19 spread 30d	0.000	0.000	0.680	0.629	0.839
	(0.000)	(0.000)	(0.568)	(0.555)	(0.433)
Unemployment rate, %	4.852	4.550	4.472	4.367	5.061
	(1.816)	(1.802)	(1.954)	(1.769)	(2.122)
Poverty rate, %	12.964	12.849	11.440	11.229	11.840
	(4.109)	(3.891)	(3.945)	(3.492)	(3.918)
Unstructured job	-0.018	-0.036	-0.017	-0.052	-0.040
	(0.810)	(0.847)	(0.803)	(0.836)	(0.836)
Indoor occupation	-0.257	-0.292	-0.258	-0.257	-0.261
	(0.946)	(0.956)	(0.947)	(0.962)	(0.953)
Observations	5,626	2,074	4,854	1,570	1,305

Notes: The table reports means and standard deviations (in parentheses) of covariates by treatment status, before the pandemic and after its onset. The *ever-treated* group includes parents of children in grades 1-8 who experienced at least one day of COVID-19-related school closures during the 30 days prior to the interview, in at least one survey wave. The *never-treated* group includes other parents of children in grades 1-8, although some may have experienced school closures outside the 30-day reference window – such as during the spring 2020 stay-at-home order, when no survey was conducted. Within the ever-treated group, we further distinguish between those recently treated (school closures in the past 30 days) and those not recently treated. Standard deviations for binary variables are omitted. The treated group includes parents who were exposed to school closures during the last 30 days preceding the survey interview. The sample includes adults aged 18–60 who were surveyed at least twice. Variable definitions are provided in Online Appendix Table A6.

Table A8: Complete Specification with Individual FEs

	Employment		Total hours		Total hours	
	Mother	Mother	Mother	Father	Mother	Father
COVID-19 school closure 30d	-0.048**	-2.165	-2.165	-0.005	0.022	0.008
	(0.021)	(3.417)	(3.417)	(0.023)	(0.020)	(0.015)
School break 30d	-0.005	0.278	0.278	0.016	0.004	0.008
	(0.015)	(2.378)	(2.378)	(0.013)	(0.015)	(0.010)
Closure for other reasons 30d	-0.085	-18.457	-18.457	-0.104	-0.037	-0.162
	(0.161)	(22.855)	(22.855)	(0.154)	(0.193)	(0.112)
COVID-19-related workplace closure, last 30d	0.007	-0.346	-0.346	0.002	-0.005	0.002
	(0.006)	(0.857)	(0.857)	(0.005)	(0.006)	(0.005)
Long holidays	-0.037*	-1.039	-1.039	-0.032*	0.000	-0.021
	(0.022)	(3.717)	(3.717)	(0.018)	(0.022)	(0.015)
Age	0.065***	4.902*	4.902*	0.014	0.054**	-0.024*
	(0.025)	(2.971)	(2.971)	(0.017)	(0.024)	(0.013)
Age squared	-0.001**	-0.060*	-0.060*	-0.000	-0.001**	0.000
	(0.000)	(0.036)	(0.036)	(0.000)	(0.000)	(0.000)
College	0.031	1.371	1.371	0.014	0.041	-0.011
	(0.035)	(5.079)	(5.079)	(0.037)	(0.034)	(0.025)
Russian ethnicity	0.073	0.471	0.471	0.018	0.059	0.019
	(0.166)	(13.790)	(13.790)	(0.118)	(0.081)	(0.153)

Birthplace		-7.234	-7.234			
Born elsewhere in Russia	0.061			0.005	0.162	0.018
	(0.065)	(8.854)	(8.854)	(0.041)	(0.103)	(0.016)
Born abroad	-0.021	-30.974***	-30.974***	0.029	-0.120	0.017
	(0.103)	(7.010)	(7.010)	(0.035)	(0.204)	(0.027)
Unknown place of birth	-0.410	-38.383***	-38.383***	0.120***	-0.346***	0.010
	(0.263)	(9.356)	(9.356)	(0.019)	(0.105)	(0.015)
Parent's health problems 30d	-0.000	-2.209	-2.209	-0.033***	0.005	0.009
	(0.011)	(1.461)	(1.461)	(0.012)	(0.010)	(0.009)
Primary school	-0.020*	0.016	-3.547**	0.353	0.002	0.005
	(0.012)	(0.010)	(1.626)	(2.013)	(0.010)	(0.007)
Child's health problems 30d	-0.021**	-3.514***	-3.514***	-0.006	0.010	0.006
	(0.010)	(1.308)	(1.308)	(0.009)	(0.009)	(0.007)
Spousal employment status						
Spouse not employed	0.018	-0.061	-0.061	-0.031	0.018	-0.006
	(0.029)	(3.351)	(3.351)	(0.021)	(0.022)	(0.011)
No spouse	0.063**	7.207	7.207	0.098	0.034	0.092
	(0.032)	(5.818)	(5.818)	(0.126)	(0.022)	(0.068)
No data on spouse	0.002	2.911	2.911	0.064	-0.015	0.118
	(0.036)	(5.134)	(5.134)	(0.129)	(0.026)	(0.089)
Older caregiver	-0.010	4.936	4.936	-0.030	0.063**	-0.002
	(0.026)	(3.924)	(3.924)	(0.028)	(0.027)	(0.021)
Childcare by outside helper	0.026**	2.097	2.097	0.005	0.002	-0.002
	(0.012)	(1.803)	(1.803)	(0.010)	(0.010)	(0.009)
Any child < age 7	-0.064***	-1.032	-1.032	-0.001	0.005	0.001
	(0.017)	(2.046)	(2.046)	(0.012)	(0.013)	(0.011)
Government assistance 30d	-0.071***	1.325	1.325	-0.015	0.005	-0.009
	(0.020)	(2.493)	(2.493)	(0.015)	(0.016)	(0.012)
Children's benefits 30d	-0.138***	-7.165***	-7.165***	0.035***	-0.007	-0.000
	(0.015)	(2.095)	(2.095)	(0.009)	(0.011)	(0.007)
COVID-19 spread 30d	-0.004	2.613	2.613	-0.008	-0.002	0.007
	(0.012)	(1.687)	(1.687)	(0.010)	(0.010)	(0.009)
Unemployment rate, %	-0.006	-1.246	-1.246	0.001	-0.006	0.001
	(0.007)	(1.033)	(1.033)	(0.007)	(0.007)	(0.005)
Poverty rate, %	0.010	-1.337	-1.337	-0.001	-0.006	0.001
	(0.009)	(1.676)	(1.676)	(0.010)	(0.011)	(0.009)
Unstructured job		1.455	1.455	0.003	0.018*	-0.001
		(1.736)	(1.736)	(0.008)	(0.010)	(0.006)
Indoor occupation		1.620	1.620	-0.019*	0.005	0.001
		(2.725)	(2.725)	(0.010)	(0.010)	(0.006)
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,299	5,530	5,530	5,089	5,758	5,531
R-squared	0.674	0.537	0.537	0.569	0.668	0.620

Notes: The table presents estimates of the baseline specification of Equation (4), including individual and year fixed effects. Robust standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. Omitted categories are *born in the same place* (birthplace) and *spouse is employed* (spousal employment status). Variable definitions are provided in Online Appendix Table A6. Variables typically assumed to be time-invariant, such as ethnicity and birthplace, are included due to minor changes in reporting or self-identification over time.

Table 9: The Average Treatment Effect of School Closures on Labor Supply with a Shorter List of Controls

Estimation methods	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
Regional FEs	-0.011	-0.003	1.577	-0.933	0.048**	0.020
	(0.024)	(0.017)	(3.590)	(3.838)	(0.019)	(0.018)
Individual FEs	-0.042**	-0.005	-2.080	-0.629	0.024	0.009
	(0.021)	(0.020)	(3.444)	(4.290)	(0.020)	(0.015)
CRC with FEs	-0.041**	-0.030*	-0.854	0.116	0.045**	0.020
	(0.020)	(0.018)	(3.462)	(3.466)	(0.021)	(0.019)
CRC with FEs + covariate-by-year interactions	-0.059***	-0.046**	0.457	0.261	0.046**	0.031
	(0.022)	(0.018)	(3.474)	(3.425)	(0.021)	(0.020)
Number of observations	8,316	6,549	5,536	5,096	5,765	5,541

Notes: The table reports average treatment effects of an additional ten days of school closures on parental labor supply using a reduced set of controls. In contrast to the main specifications, the control set excludes spouse's labor supply, receipt of welfare benefits, presence of older caregiver in the household, and the availability of outside family help. Relative to Table 3, only one coefficient changes in statistical significance: the coefficient on fathers switching to working from home becomes statistically insignificant. In the main specification, this coefficient was significant at the 10% level. Column 1 lists four alternative estimation methods, the latter three including individual and year fixed effects. CRC denotes the Correlated Random Coefficient method. Standard errors are clustered at the individual level in the model with individual FEs, and on the regional level in the model with regional FEs. Weight decompositions following de Chaisemartin and D'Haultfœuille (2020) show that negatively weighted individual–year effects account for less than 2% of the total identifying weight across all specifications for individual FEs model. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Complete Specification with Individual FEs for the Sample of All Adults

	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
COVID-19 school closure 30d	-0.000	0.004**	0.016	0.225	0.007***	0.001
	(0.002)	(0.002)	(0.413)	(0.472)	(0.002)	(0.002)
Have children in a primary or in a middle school	-0.061***	-0.016	-0.104	2.944	0.012	-0.005
	(0.014)	(0.013)	(2.055)	(2.316)	(0.013)	(0.010)
COVID-19 school closure 30d & have children in a primary or in a middle school	-0.047**	-0.026	-3.119	2.476	0.024	0.004
	(0.020)	(0.019)	(2.977)	(3.670)	(0.021)	(0.015)
School break 30d	0.002	-0.005*	0.197	0.390	-0.002	-0.001
	(0.003)	(0.003)	(0.430)	(0.445)	(0.002)	(0.002)
School break 30d & have children in a primary or in a middle school	-0.014	-0.018	1.009	1.550	0.011	0.003
	(0.015)	(0.014)	(2.268)	(2.417)	(0.014)	(0.010)
Closure for other reasons 30d	-0.005	-0.023	-7.188*	-0.637	0.020	-0.024
	(0.020)	(0.023)	(3.783)	(3.840)	(0.025)	(0.016)
Closure for other reasons 30d & have children in a primary or in a middle school	-0.230	-0.161	-10.226	4.127	0.036	-0.150
	(0.158)	(0.156)	(20.977)	(28.276)	(0.186)	(0.109)
COVID-19-related workplace closure, last 30d	0.002	0.002	-0.449	-0.618	0.001	0.001
	(0.003)	(0.003)	(0.448)	(0.545)	(0.003)	(0.002)

Long holidays	-0.012	-0.016	-1.597	-5.471***	-0.011	-0.008
	(0.010)	(0.011)	(1.940)	(1.971)	(0.011)	(0.008)
Age	0.110***	0.078***	2.864*	0.304	0.023*	0.012*
	(0.010)	(0.008)	(1.532)	(1.303)	(0.012)	(0.006)
Age squared	-0.001***	-0.001***	-0.041***	-0.012	-0.000**	-0.000
	(0.000)	(0.000)	(0.011)	(0.013)	(0.000)	(0.000)
College	0.166***	0.151***	1.386	1.024	0.011	0.018
	(0.023)	(0.024)	(3.140)	(4.216)	(0.024)	(0.019)
Russian ethnicity	0.034	0.010	-2.831	-10.505	-0.010	-0.007
	(0.070)	(0.072)	(7.608)	(14.404)	(0.045)	(0.027)
Birthplace	-0.051	0.019	-1.733	4.451	0.059	0.015
Born elsewhere in Russia						
	(0.038)	(0.034)	(4.579)	(6.305)	(0.039)	(0.018)
Born abroad	0.016	-0.036	-14.970**	11.795	-0.100	0.018
	(0.075)	(0.114)	(6.302)	(9.283)	(0.106)	(0.017)
Unknown place of birth	-0.092	-0.092	-2.696	1.414	-0.004	0.224
	(0.100)	(0.123)	(10.013)	(18.474)	(0.059)	(0.185)
Parent's health problems 30d	-0.011**	-0.031***	-2.917***	-4.359***	0.002	0.001
	(0.005)	(0.006)	(0.849)	(1.151)	(0.005)	(0.005)
No children	0.100***	0.016	0.195	3.615	-0.001	0.004
	(0.015)	(0.014)	(2.157)	(2.301)	(0.014)	(0.009)
Has children only under age 7	-0.131***	0.010	-6.326**	0.085	0.032*	0.012
	(0.020)	(0.014)	(2.805)	(2.508)	(0.018)	(0.010)
Primary school	-0.038***	0.005	-2.857**	-1.076	0.006	0.006
	(0.011)	(0.008)	(1.403)	(1.560)	(0.009)	(0.006)
Child's health problems 30d	-0.013	-0.003	-2.626**	-0.888	0.004	0.002
	(0.009)	(0.008)	(1.173)	(1.446)	(0.008)	(0.007)
Spousal employment status	-0.020	0.004	2.247	-0.763	0.010	-0.006
Spouse not employed						
	(0.014)	(0.014)	(2.192)	(2.459)	(0.012)	(0.008)
No spouse	0.060***	-0.083***	6.450**	0.885	-0.014	0.019
	(0.017)	(0.022)	(2.845)	(3.665)	(0.014)	(0.012)
No data on spouse	0.033*	-0.011	2.388	-1.066	-0.031*	0.022
	(0.019)	(0.027)	(3.193)	(4.617)	(0.017)	(0.018)
Older caregiver	0.002	-0.009	0.254	-0.224	0.003	0.003
	(0.010)	(0.010)	(1.698)	(1.917)	(0.010)	(0.007)
Childcare by outside helper	-0.003	-0.005	0.090	1.157	0.002	-0.001
	(0.008)	(0.006)	(1.246)	(1.328)	(0.007)	(0.005)
Any child < age 7	-0.058***	0.002	-1.991	-3.412**	0.003	0.005
	(0.011)	(0.009)	(1.568)	(1.593)	(0.009)	(0.007)
Government assistance 30d	-0.065***	-0.045***	-0.192	-0.780	-0.004	-0.002
	(0.010)	(0.010)	(1.581)	(1.702)	(0.009)	(0.007)
Children's benefits 30d	-0.133***	-0.001	-5.986***	0.933	0.007	0.001
	(0.009)	(0.007)	(1.419)	(1.177)	(0.008)	(0.005)
COVID-19 spread 30d	-0.006	-0.003	0.385	-0.591	0.004	0.005
	(0.006)	(0.005)	(0.881)	(1.000)	(0.006)	(0.004)
Unemployment rate, %	0.003	0.002	-0.910*	-0.300	0.006*	0.007**
	(0.003)	(0.003)	(0.546)	(0.646)	(0.003)	(0.003)
Poverty rate, %	-0.003	-0.017***	-0.238	0.760	-0.002	-0.002
	(0.004)	(0.004)	(0.734)	(0.996)	(0.004)	(0.004)
Unstructured job			1.053	1.158	0.006	0.006*

			(0.964)	(0.933)	(0.005)	(0.003)
Indoor occupation			0.674	-2.088**	0.001	0.012***
			(1.469)	(1.040)	(0.006)	(0.004)
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,245	25,795	18,693	17,112	19,468	18,621
R-squared	0.704	0.718	0.547	0.557	0.642	0.597

Notes: The table presents estimates of the baseline specification of Equation (4) for the sample of all adults regardless of the presence of children. Adults who do not have primary or middle school children are assigned the regional average number of school closure days (across all grades) for the fall months of their interview (as in falsification tests). The regressions include individual and year fixed effects. Robust standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. Omitted categories are *ambiguous presence (and age) of children (4,688 observations)*, *having middle school children indicator, born in the same place* (birthplace), *and the spouse is employed* (spousal employment status).

Table A11: The Effects of School Closures on Parental Labor Supply in Subsamples Defined by One-Factor Variables

	Employment		Total hours		Total hours	
	Mother	Mother	Mother	Father	Mother	Father
Age 18-35	-0.104**	-13.588	-13.588	0.032	0.023	-0.007
	(0.045)	(8.307)	(8.307)	(0.047)	(0.042)	(0.030)
Age 36-60	-0.058**	5.170	5.170	0.011	0.049**	0.047**
	(0.024)	(3.702)	(3.702)	(0.020)	(0.024)	(0.023)
No college degree	-0.080***	2.101	2.101	0.046*	0.031*	0.048***
	(0.030)	(5.893)	(5.893)	(0.025)	(0.018)	(0.016)
College degree	-0.059**	0.014	0.014	-0.035	0.052	0.021
	(0.030)	(4.178)	(4.178)	(0.025)	(0.033)	(0.042)
Parent's health problems 30d	-0.084	-0.409	-0.409	0.114**	0.035	-0.020
	(0.055)	(7.818)	(7.818)	(0.052)	(0.044)	(0.032)
No health problems 30d	-0.064***	1.271	1.271	-0.005	0.046**	0.048**
	(0.022)	(3.882)	(3.882)	(0.019)	(0.023)	(0.023)
Child in primary school	-0.087***	-7.249	-7.249	0.029	0.027	0.021
	(0.034)	(5.384)	(5.384)	(0.030)	(0.031)	(0.035)
Child in middle school	-0.056**	6.567	6.567	0.002	0.055**	0.050***
	(0.027)	(4.509)	(4.509)	(0.022)	(0.027)	(0.019)
Child's health problems 30d	-0.038	-0.692	-0.692	0.067	0.128**	0.079*
	(0.046)	(6.408)	(6.408)	(0.047)	(0.064)	(0.041)
No health problems 30d	-0.077***	1.289	1.289	0.003	0.019	0.025
	(0.024)	(4.024)	(4.024)	(0.020)	(0.017)	(0.022)
No child < age 7	-0.058***	2.630	2.630	0.026	0.021	0.003
	(0.018)	(3.981)	(3.981)	(0.023)	(0.021)	(0.026)
Any child < age 7	-0.087*	-3.677	-3.677	-0.002	0.102**	0.089***
	(0.047)	(6.654)	(6.654)	(0.031)	(0.047)	(0.027)
Single mother	-0.154**	-8.083	-8.083		0.017	
	(0.063)	(10.673)	(10.673)		(0.077)	
Married mother	-0.056**	2.502	2.502		0.047**	
	(0.022)	(3.549)	(3.549)		(0.021)	

No childcare by outside helper	-0.073***	1.031	1.031	0.021	0.068***	0.045**
	(0.024)	(4.426)	(4.426)	(0.024)	(0.025)	(0.019)
Childcare by outside helper	-0.058	0.609	0.609	0.005	-0.018	0.017
	(0.041)	(5.322)	(5.322)	(0.028)	(0.036)	(0.043)
No older caregiver	-0.071***	3.133	3.133	0.027	0.041*	0.039*
	(0.023)	(3.707)	(3.707)	(0.020)	(0.022)	(0.021)
Older caregiver	-0.057	-12.872	-12.872	-0.085	0.053	0.016
	(0.051)	(8.688)	(8.688)	(0.054)	(0.057)	(0.046)
Unemployment rate < median	-0.105***	9.544	9.544	0.053*	0.057*	0.069**
	(0.035)	(5.926)	(5.926)	(0.031)	(0.034)	(0.029)
Unemployment rate > median	-0.042*	-5.611	-5.611	-0.008	0.031	0.017
	(0.025)	(4.093)	(4.093)	(0.022)	(0.024)	(0.026)
COVID-19 spread < median	-0.075*	2.090	2.090	0.018	-0.007	0.062**
	(0.043)	(6.488)	(6.488)	(0.043)	(0.041)	(0.030)
COVID-19 spread > median	-0.069***	-0.012	-0.012	0.007	0.064***	0.017
	(0.025)	(4.260)	(4.260)	(0.020)	(0.024)	(0.024)
Poverty rate < median	-0.111**	5.345	5.345	-0.016	0.040	0.059*
	(0.043)	(7.960)	(7.960)	(0.036)	(0.041)	(0.036)
Poverty rate > median	-0.049**	-1.301	-1.301	0.028	0.044*	0.028
	(0.024)	(3.561)	(3.561)	(0.021)	(0.023)	(0.023)
Observations	8,132	5,374	5,374	4,948	5,596	5,387

Notes: Table presents the average marginal effects of an additional ten days of school closures on parental labor supply by population groups. The groups are defined using single-factor variables. The estimates are based on a correlated random coefficient model with individual FEs and with covariate-by-year interactions. Robust standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: The Effect of School Closures on Labor Supply in Subsamples Defined by Children's Age

Children are in a Primary School in a Year	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
2013	-0.123	-0.010	1.965	-2.609	0.113*	0.148***
	(0.078)	(0.038)	(6.223)	(8.614)	(0.063)	(0.045)
2014	-0.060	-0.026	-10.849*	-8.640	0.044	0.113***
	(0.046)	(0.035)	(6.298)	(5.822)	(0.034)	(0.042)
2015	-0.043	-0.023	1.337	-3.071	0.065**	0.088***
	(0.032)	(0.026)	(5.046)	(5.023)	(0.026)	(0.025)
2016	-0.074***	-0.073***	2.182	-0.715	0.049**	0.039*
	(0.027)	(0.026)	(4.217)	(4.481)	(0.023)	(0.021)
2017	-0.060**	-0.075***	-0.911	4.136	0.040*	0.043**
	(0.026)	(0.026)	(4.372)	(4.586)	(0.024)	(0.020)
2018	-0.052**	-0.060**	0.675	4.381	0.054**	0.042***
	(0.025)	(0.024)	(3.951)	(3.862)	(0.027)	(0.016)
2019	-0.073***	-0.040	-9.035**	-2.409	0.031	0.013
	(0.027)	(0.025)	(4.005)	(4.229)	(0.031)	(0.025)
2020	-0.068**	-0.018	-6.896	-1.641	0.039	0.025
	(0.031)	(0.024)	(4.451)	(4.582)	(0.033)	(0.029)

2021	-0.080**	-0.046*	-8.278*	-2.323	0.054	0.025
	(0.033)	(0.027)	(4.918)	(4.987)	(0.034)	(0.034)
2022	-0.096***	-0.060**	-6.179	2.578	0.055	0.018
	(0.034)	(0.029)	(5.294)	(5.719)	(0.039)	(0.033)

Notes: The table reports the average effects of an additional ten days of school closures on parental labor supply for subsamples of parents whose children are either enrolled in primary school or expected to enroll in primary school in a given year. For example, the subsample of parents whose children are enrolled in or expected to enroll in primary school in 2022 includes parents of children aged 1–5 observed in 2017. The coefficients are estimated using the Correlated Random Coefficient method with individual FEs and with covariate-by-year interactions. Standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

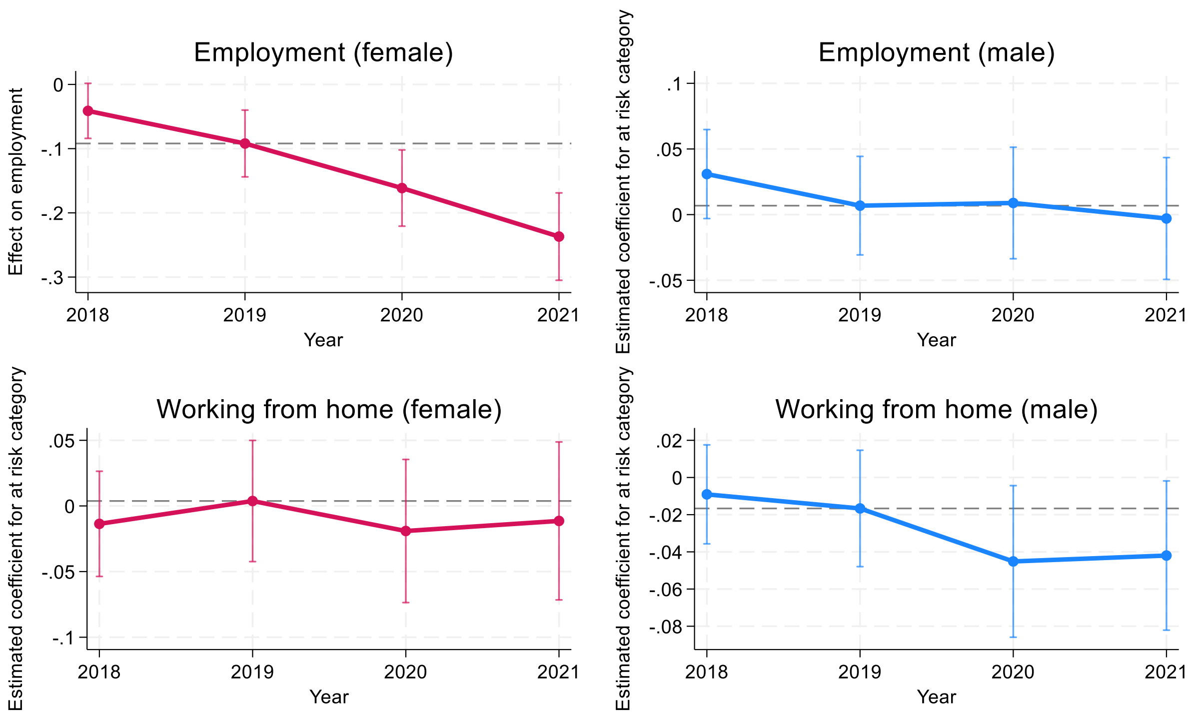
Table A13: The Effects of School Closures on Parental Labor Supply in Subsamples Defined by Two-Factor Variables

	Employment		Total hours		Work from home	
	Mother	Father	Mother	Father	Mother	Father
A. Parent's age and education						
Age 18-35 & No college degree	-0.115*	0.048	-12.856	4.623	0.007	0.008
	(0.066)	(0.051)	(13.124)	(9.043)	(0.023)	(0.026)
Age 18-35 & College degree	-0.088	-0.052**	-14.547	-4.411	0.046	-0.043
	(0.058)	(0.025)	(10.636)	(18.022)	(0.095)	(0.080)
Age 36-60 & No college degree	-0.064**	-0.075**	8.661	6.070	0.043*	0.058***
	(0.032)	(0.031)	(5.928)	(4.986)	(0.023)	(0.019)
Age 36-60& College degree	-0.054	-0.045**	2.898	-8.634*	0.052	0.032
	(0.035)	(0.021)	(4.704)	(4.449)	(0.035)	(0.048)
B. Child's age and health status						
Child in middle school & had no health problems	-0.082***	-0.056	8.324	-3.291	0.032*	0.040**
	(0.030)	(0.034)	(5.404)	(4.408)	(0.019)	(0.019)
Child in middle school & had health problems	0.051	-0.080	0.570	3.194	0.125	0.087
	(0.041)	(0.051)	(7.524)	(10.775)	(0.085)	(0.059)
Child in primary school & had no health problems	-0.070*	-0.037	-8.115	-0.495	0.002	0.008
	(0.037)	(0.022)	(5.919)	(5.874)	(0.032)	(0.040)
Child in primary school & had health problems	-0.166**	-0.015	-2.303	17.903	0.129	0.069
	(0.082)	(0.057)	(12.943)	(11.953)	(0.090)	(0.057)
C. Marital status and spousal employment						
Single	-0.155**	Small N	-8.304	Small N	0.017	Small N
	(0.063)		(10.652)		(0.076)	
Married with non-employed spouse	Small N	-0.069	Small N	17.899	Small N	0.039
		(0.048)		(18.880)		(0.052)
Married with employed spouse	-0.099***	-0.070*	4.774	-0.168	0.056*	-0.045
	(0.036)	(0.040)	(4.897)	(5.367)	(0.029)	(0.038)
D. Unemployment rate and COVID-19 spread						
Low unemployment rate & Low COVID-19 spread	-0.045	0.039	7.572	3.824	-0.021	0.078*
	(0.063)	(0.040)	(8.526)	(10.714)	(0.043)	(0.044)
Low unemployment rate & High COVID-19 spread	-0.139***	-0.178***	9.959	9.555	0.088**	0.055
	(0.044)	(0.053)	(7.798)	(6.037)	(0.044)	(0.037)
High unemployment rate &	-0.103*	0.031	-5.018	-0.819	0.013	0.042

Low COVID-19 spread	(0.055)	(0.030)	(10.199)	(10.203)	(0.075)	(0.039)
High unemployment rate &	-0.020	-0.005	-5.321	-6.003	0.053**	-0.003
High COVID-19 spread	(0.028)	(0.021)	(4.898)	(4.251)	(0.026)	(0.030)
Number of observations	8,132	6,387	5,374	4,948	5,596	5,387

Notes: Table presents the average marginal effects of an additional ten days of school closures on parental labor supply by population groups. The groups are defined using the combination of two factors. The estimates are based on a correlated random coefficient model with individual FEs and with covariate-by-year interactions. Robust standard errors (in parentheses) are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Comparing individuals "at risk" with individuals not at risk of treatment



Notes: This figure plots the coefficients on the interaction between the "at risk" indicator (i.e., having school-age children) and year dummies from regressions that include individual fixed effects and controls. The reference group consists of individuals not at risk of treatment (parents with younger children). Standard errors are clustered at the individual level and 95 percent confidence intervals are shown. This specification captures differential trends between the two groups but does not incorporate variation in treatment intensity, which is continuous and interview-date dependent in our setting, nor does it account for the timing of treatment within the 30-day recall window. The estimates show a decline in employment among females at risk, but no differential effect on working from home.