

WORKING PAPER IDB-WP-01874

The Intergenerational Cost of Parental Illness: Children's School Engagement in Chile

Emilia Brito
Dante Contreras
Nicolás Libuy

Inter-American Development Bank
Gender and Diversity Division
Department of Research and Chief Economist

October 2026



The Intergenerational Cost of Parental Illness: Children's School Engagement in Chile

Emilia Brito*

Dante Contreras**

Nicolás Libuy***

* California Center for Population Research, University of California, Los Angeles

** Universidad de Chile

*** Universidad Adolfo Ibáñez

Inter-American Development Bank
Gender and Diversity Division
Department of Research and Chief Economist

October 2026



JEL Codes: I14, I21, J13, O15

Keywords: Parental health shocks, School engagement, School absenteeism, Human capital, Cancer, Chile

To explore more IDB publications, visit

<https://publications.iadb.org/en>

Copyright © **2026** Inter-American Development Bank (IDB). This work is subject to a Creative Commons Attribution 4.0 International Public License CC BY 4.0 (<https://creativecommons.org/licenses/by/4.0/legalcode>). The terms and conditions indicated in the URL link must be met and the respective recognition must be granted to the IDB.

Any and all disputes arising under this license that cannot be settled amicably shall be resolved in accordance with the following procedure. Pursuant to a notice of mediation communicated by reasonable means by either you or the licensor to the other, the dispute shall be submitted to non-binding mediation conducted in accordance with the World Intellectual Property Organization (WIPO) Mediation Rules. Any dispute that cannot be settled amicably shall be submitted to arbitration pursuant to the United Nations Commission on International Trade Law (UNCITRAL) rules. The use of the IDB name for any purpose other than the respective recognition and the use of the IDB logo are not authorized by this license and require an additional license agreement.

Note that the URL link includes terms and conditions that are an integral part of this license.

The opinions expressed in the work are those of its authors and do not necessarily reflect the views of the IDB, its Board of Executive Directors, or the countries they represent.



Abstract

Severe health events are among the most common shocks households face, and in low- and middle-income countries their consequences are absorbed largely within the family. We study how a parent's severe illness affects adolescents' education in Chile. Using linked administrative records for the universe of school-age children and quasi-random variation in the occurrence and timing of parents' first cancer hospitalizations, we compare exposed students with untreated classmates in a stacked difference-in-differences design. The shock reduces school enrollment and attendance and raises chronic absenteeism, with effects that persist for up to four years and roughly double for high-severity cancers. Disruptions are substantially larger for girls, consistent with caregiving and household responsibilities falling disproportionately on them. The educational response varies little with households' pre-shock labor market position, and children's hospitalizations do not rise. These findings point to an intergenerational cost of parental illness and a role for social protection in mitigating it.

Severe parental illness is one of the most common major shocks a family can face, and it disrupts the household on several fronts simultaneously: income falls, medical spending rises, and caregiving needs mount. In low- and middle-income countries, where social safety nets are thin, families themselves absorb most of this disruption, and children are directly exposed to its consequences. The scale is large and growing: each year, roughly 15 million adults die of chronic disease during their prime working and child-rearing years, 85% of them in low- and middle-income countries.¹

Most existing research on family health shocks, however, has focused on adult, working-age members, documenting substantial labor market consequences of severe illness for spouses (Fadlon and Nielsen, 2021) and for adult children (Brito and Contreras, 2025; Rellstab et al., 2020; Frimmel et al., 2025; Wen and Huang, 2024; Loken et al., 2017). Much less is known about how school-age children are affected. Children and adolescents may be particularly vulnerable because parental illness can disrupt investments in education during key formative years; in the United States, for example, parental cancer is associated with higher school absenteeism and worse mental health among children (Zheng et al., 2022). Moreover, these consequences are unlikely to be evenly distributed: responses to parental health shocks may differ by gender, as girls and boys can face different expectations around caregiving, and by family resources, which shape households’ ability to buffer disruptions and smooth investments in children’s education.

We study how severe parental health shocks affect school-aged children’s educational trajectories. We address this question empirically for Chile, a country where formal support beyond public coverage of direct health care costs is limited, a feature shared by many low- and middle-income countries. We assemble a unique, highly detailed individual- and family-level dataset from linked administrative records, providing longitudinal information on health, education, and household socioeconomic conditions for the full national population, a level of detail rarely available in low- and middle-income countries. Using these data, we provide causal estimates of the effect of a severe parental health shock on adolescents’ school enrollment and engagement, together with suggestive evidence on the channels behind it.

We exploit quasi-random variation in the occurrence and timing of severe parental health shocks, operationalized as the first cancer hospitalization of a parent, to estimate causal effects on students’ enrollment, attendance rates, and chronic absenteeism.² We focus on cancer for two reasons: it is severe and relatively common (nearly 20 million new diagnoses worldwide in 2022, a burden projected to grow by 77% by 2050 and fastest in developing

¹Deaths between ages 30 and 69, the World Health Organization’s definition of premature mortality from noncommunicable diseases (World Health Organization, 2025).

²Chronic absenteeism is an indicator for annual attendance below 85%, mirroring the threshold used in official Chilean education statistics.

countries; Bray et al., 2024), and hospital discharge records allow us to measure it consistently for every parent in the country. The outcomes we study are consequential margins: time in school raises achievement, and absences carry both short- and long-run costs (Carlsson et al., 2015; Liu et al., 2021), while leaving school early reduces lifetime earnings (Angrist and Krueger, 1991; Oreopoulos, 2006). We implement a stacked dynamic difference-in-differences design comparing treated students, those with a parent experiencing a health shock, to their untreated classmates, who serve as controls, holding constant local educational, institutional, and peer environments. We trace outcomes from five years before to four years after the shock.

We begin by documenting key features of the parental health shock that underpin our empirical strategy. The onset of illness is abrupt and medically salient: the first cancer hospitalization generates a sharp increase in hospital use and subsequent mortality, consistent with an acute and largely unanticipated health shock. Consistent with this characterization, we find that a parental cancer hospitalization leads to persistent declines in children’s educational engagement. Treated and control students follow similar trajectories in the years before the shock; at the first hospitalization, all three outcomes break sharply. In the year of hospitalization, enrollment falls by 0.6 percentage points, the attendance rate declines by 1.1 percentage points (roughly 1.9 fewer school days in a 170-day academic year), and chronic absenteeism rises by 2.2 percentage points, a 30% increase relative to the control mean of 7.1%. Enrollment and attendance remain depressed through four years after the shock, and chronic absenteeism remains elevated for three. These are meaningful disruptions: the enrollment decline, from a baseline above 99% among these students,³ is comparable in percentage points to the dropout effects of parental job loss documented in middle-income settings (Britto et al., 2022), and the shock arrives in grades 7–12, precisely when attendance and course completion shape secondary graduation and the transition to higher education. These averages also mask substantial heterogeneity.

The disruption follows a clear dose–response pattern. We classify shocks as high severity when the parent is hospitalized two or more times in the year of the shock, and as low severity otherwise. High-severity episodes generate attendance losses nearly twice as large as low-severity episodes and increases in chronic absenteeism almost three times as large; the gaps are concentrated in the first two years after the shock. Enrollment effects are present across all grades from 7th to 12th, while point estimates for attendance losses and

³Chile is a high-enrollment setting: net secondary school enrollment is roughly 89% nationally (World Bank, 2017). Baseline enrollment is higher still in our sample, 99.5% among control students at $t = -2$ (Table 3), because the design conditions on enrollment in the year of the shock: treated students and their classmates are, by construction, enrolled at $t = 0$, so their pre-period enrollment rates are mechanically close to universal.

chronic absenteeism are larger among students exposed in later grades, consistent with older adolescents being more able to take on responsibilities generated by the shock: caregiving, household tasks, or working to offset lost income. Differences by the gender of the affected parent are limited. Differences by the gender of the student, in contrast, are pronounced: while enrollment effects are similar for boys and girls, girls experience larger and more persistent attendance declines and substantially greater increases in chronic absenteeism. The response varies little, however, with the household’s labor market position: interacting the treatment effect with deciles of the parents’ pre-shock formal employment and formal labor income yields a flat profile across the distribution.

These patterns are informative about mechanisms. A parental health shock is a multidimensional disruption: it reduces household income and raises medical spending, generates new caregiving and household demands, and strains children’s emotional environment. We cannot observe each of these dimensions directly, but the incidence of the effects is suggestive: disruptions to school engagement are concentrated among girls, on whom household and care responsibilities disproportionately fall (Brito and Contreras, 2025; Aguilar-Gomez et al., 2026). We document that the shock persistently reduces the affected parent’s own formal employment while the other parent’s labor supply does not move, so the income loss is real and uninsured within the household; yet, the educational response is flat across the parents’ pre-shock position in the formal labor market. We also find no evidence for the psychological channel at its severe margin: children’s hospitalizations, all-cause or mental-health related, do not rise. The incidence of the response therefore points to the caregiving channel more than to the size of the income loss.

Our findings speak to two literatures. Evidence on parental illness and children’s schooling in low- and middle-income countries is largely correlational, relying on survey data and self-reported health (Sun and Yao, 2010; Alam, 2015; Bratti and Mendola, 2014; Mendolia et al., 2019; Luca and Bloom, 2018; Dinku et al., 2018), while register-based causal designs have so far been confined to high-income countries with strong social insurance (Joergensen et al., 2018; Kristiansen, 2021; Aaskoven et al., 2022; Glaser and Pruckner, 2023; García-Miralles and Gensowski, 2025). To our knowledge, we provide the first causal, population-scale estimates of how a severe parental health shock disrupts children’s educational trajectories in a low- or middle-income country, the setting where families, rather than the state, absorb such shocks. Because the linked registries also cover parents’ formal employment and earnings, and children’s hospital discharges, we can examine some of these channels directly rather than infer them from the educational estimates alone: we document a fall in the hospitalized parent’s formal employment with no response in the other parent’s labor supply, effects on children’s school engagement that are similar regardless of the parents’ pre-shock position in

the formal labor market, and no rise in children’s hospitalizations. These incidence patterns matter for policy: the disruption spans the income distribution and falls disproportionately on girls, pointing to support for affected families that goes beyond income targeting alone.

1 Analytical Framework and Main Mechanisms

Research on parental health shocks and children’s educational outcomes builds on human capital and parental investment frameworks in which skill formation depends on household resources and parental inputs that are vulnerable to health-related disruptions (Grossman, 1972; Becker and Tomes, 1979; Cunha and Heckman, 2007; Heckman, 2007; Cunha et al., 2010). Building on this framework, we outline the channels through which a severe parental illness can affect children’s education. Several of these channels plausibly operate at once, and our estimates are reduced-form effects that combine them; the framework serves to interpret the heterogeneity patterns we document, not to identify channels separately.

A severe parental illness can affect children’s education through at least four channels. First, a pecuniary channel: the sick parent’s earnings fall while medical spending rises, tightening the household budget; well-identified evidence shows that negative shocks to parental earnings alone harm children’s schooling (Oreopoulos et al., 2008; Rege et al., 2011; Hilger, 2016; Britto et al., 2022). Second, a time and caregiving channel: parents supply less of the time that fosters skill development (Fiorini and Keane, 2014), while children, most likely girls, given the gendered division of informal care work in low- and middle-income countries, may take on housework and informal care for the sick parent (Grabliak et al., 2007; Dinku et al., 2018; Brito and Contreras, 2025; Aguilar-Gomez et al., 2026). Third, a psychological and child-health channel: severe family illness is a major stressor with documented consequences for children’s mental health and non-cognitive skills (Persson and Rossin-Slater, 2018; Kristiansen, 2021; Glaser and Pruckner, 2023; García-Miralles and Gensowski, 2025), and it may also spill over onto children’s physical health as routines are disrupted and household attention shifts to the sick parent. Fourth, a family-stability channel: illness can trigger separations, residential moves, and household reorganization. At the extreme, parental death engages all of these channels together, with well-documented educational costs (Gertler et al., 2004; Gimenez et al., 2013). Survey-based studies from developing countries attribute observed schooling declines variously to medical expenditures or to income losses (Sun and Yao, 2010; Alam, 2015; Bratti and Mendola, 2014; Mendolia et al., 2019), but few designs, ours included, can separate channels sharply, and we treat such attributions as suggestive.

In Chile, as in much of Latin America, public insurance covers a substantial share

of the direct medical costs of cancer, but income insurance is thin outside stable formal employment, and care work is heavily familial and feminized (Section 2.1.3). In this context we expect the pecuniary and caregiving channels to be the most salient, and these are the two on which our data speak most directly: we observe parents’ formal employment around the shock, households’ pre-shock employment stability, and the gender incidence of the educational response. We also observe the children’s hospitalizations, which allow a direct test of the child-health margin of the psychological channel. Psychological responses below the hospitalization margin, and the family-stability channel, remain unobserved. Section 3.3 presents the corresponding evidence; throughout, we read heterogeneity as suggestive of mechanisms, not as identifying them.

2 Research Design

2.1 Institutional Background

2.1.1 Educational System

Chile’s educational system is organized into two main stages: primary education (grades 1 through 8) and secondary education (grades 9 through 12), covering children and adolescents roughly between the ages of 6 and 18. School attendance is compulsory through the end of secondary education, and public funding is predominantly channeled through a per-student subsidy mechanism tied to actual monthly attendance; attendance data are systematically collected and maintained by the Ministry of Education (MINEDUC) at the individual level. To the extent that the subsidy mechanism leads schools to over-report attendance, measured absences understate true absences, and our estimates of the attendance and absenteeism response would, if anything, be attenuated.

Student disengagement is a meaningful margin in Chile even in normal times, and it has become a first-order policy concern since the COVID-19 pandemic. During the period we study, average attendance was high (88.9% in 2018), but severe absenteeism, defined by the Ministry of Education as annual attendance below 85% (the threshold we use for chronic absenteeism), already affected roughly one in five students (19.3% in 2018) (Ministerio de Educación, Centro de Estudios, 2024). After the pandemic, average attendance fell to 84.8% in 2023, severe absenteeism reached about a third of students, and 50,814 students, 1.7% of enrollment, left the school system in 2023 alone (Ministerio de Educación, Centro de Estudios, 2025; Ministerio de Educación de Chile, 2023). Chronic absenteeism is strongly correlated with poorer academic outcomes, including grade repetition and dropout, and these outcomes are recorded at the student level in administrative data, allowing precise measurement of the

margins we study.

2.1.2 Health System and Cancer

Chile has a mixed public–private health insurance system: during our study period, 77–81% of the population was covered by the public insurer (Fonasa, *Fondo Nacional de Salud*), while private insurers (Isapres, *Instituciones de Salud Previsional*) covered a smaller, higher-income segment of 13–15% (Ministerio de Desarrollo Social, 2018). All healthcare establishments, public and private, are legally required to report every hospital discharge, which underlies the hospitalization records we use.

Cancer care is delivered within this system, complemented by the Explicit Health Guarantees (GES; *Garantías Explícitas de Salud*), which legally guarantee access to specified cancer services and a regulated level of financial protection. For cancers covered by GES, the bulk of direct treatment costs (hospitalizations, surgery, and treatment protocols) is covered. Fonasa sorts its beneficiaries into four income groups: in the public network, the two lowest-income groups paid no copayment for GES-covered cancer care during our study period, while the two higher-income groups paid regulated copayments of 10% and 20%.⁴ In the private system, coverage relies on GES and, in some plans, additional catastrophic-event coverage. Out-of-pocket spending nonetheless exists and can be meaningful, concentrated early in the care pathway and outside covered services: in a survey of patients in Santiago, nearly all respondents reported out-of-pocket spending between symptom onset and diagnostic confirmation (median USD 192), largely on private consultations, tests, and transport (Eguiguren et al., 2025).⁵ For insured families, then, the dominant financial exposure from a parent’s cancer is likely the accompanying loss of labor income rather than the direct cost of treatment.

2.1.3 Family-Based Care

Chile has essentially no public long-term care system (see Brito and Contreras, 2025, for a detailed account of adult caregiving in Chile). Public spending on long-term care amounts to roughly 0.02% of GDP (against an OECD average of 1.7%), and public and private facilities combined cover less than 5% of adults with some degree of dependency, with no subsidies for formal home care. When severe illness strikes, care is therefore organized within the

⁴Following the Copago Cero reform of September 2022, all Fonasa groups face zero copayments for care delivered in the public network, including GES cancer services; the reform falls at the very end of our observation window.

⁵Illustrative GES copayments for higher-income Fonasa and Isapre beneficiaries range from about USD 88 for pre-invasive cervical cancer treatment to roughly USD 1,197 for osteosarcoma surgery (Superintendencia de Salud, 2026).

family: over 95% of adult caregivers in Chile are unpaid, more than 80% live in the same household as the care recipient, and, as across Latin America, women account for more than three-quarters of caregivers (International Labour Organization, 2018). Social norms assign these responsibilities by gender: about two-thirds of Chileans consider it a child’s obligation to care for a parent who can no longer care for themselves, and daughters are perceived to bear the caregiving responsibility while sons bear the financial one. These arrangements make the caregiving channel, and its gendered incidence among children, directly relevant in our setting.

2.2 Empirical Strategy

Our empirical strategy exploits quasi-random variation in the occurrence and timing of parental cancer hospitalizations to estimate the causal effect of a parental health shock on children’s educational outcomes. We implement a *stacked* dynamic difference-in-differences model that combines multiple within school-grade sub-experiments (Deshpande and Li, 2019; Wing et al., 2024b; Cengiz et al., 2019; Wing et al., 2024a). In this framework, the event of interest is the first parental hospitalization due to cancer occurring between 2010 and 2018, when the child was enrolled in grades 7 through 12 and between approximately 12 and 18 years old; treated students are those whose mother or father experiences this event. The first hospitalization is defined over the full span of the hospital discharge records, which begin in 2007: parents with any cancer-related admission before 2010 are excluded from the treated group, so every shock, including those early in the 2010–2018 window, is preceded by at least three years with no observed parental cancer hospitalization.⁶ Control students are classmates of the treated students at the time of the first parental hospitalization, so treated and control students share the same school, grade, and cohort and are exposed to identical educational and contextual conditions.

We carefully restrict the comparison group to avoid the concerns associated with “forbidden” comparisons (Roth et al., 2023). In each sub-experiment, controls are classmates who never experience a parental cancer hospitalization, and already-treated students are never used as controls. Each treated-student sub-experiment in the final analysis sample contains a single treated student and a set of untreated classmates from the same school, grade, and cohort.⁷ The same school cohort can contribute multiple sub-experiments when different students experience the shock in different years; in every sub-experiment, the control group consists only of classmates who are never treated. This structure allows treatment to turn on cleanly

⁶Our sample was restricted to students for whom we could identify both parents in the vital statistics records, since the treatment is defined as a first cancer hospitalization of either the mother or the father.

⁷Appendix B describes the construction of the estimation sample in detail.

for one student within each sub-experiment and ensures that the comparison group remains untreated throughout the relevant event window.

We use a stacked design because it matches the structure of our variation: treatment occurs at the individual level within school-grade-cohort cells, and the natural comparison group (classmates facing the same curriculum, teachers, and peer environment, and drawn from households of broadly similar socioeconomic status given the high socioeconomic segregation of Chilean schools; Elacqua, 2012) is specific to each treated student. The stacked estimator shares the objective of recently proposed difference-in-differences estimators for staggered treatment settings (Callaway and Sant’Anna, 2021; Borusyak et al., 2024; de Chaisemartin and D’Haultfœuille, 2020): preventing comparisons that involve already-treated units. In our implementation, treatment within each sub-experiment switches on once, at a single date; controls remain untreated throughout the event window; and all sub-experiments share a common event-time window, so the estimator aggregates only clean comparisons (Cengiz et al., 2019; Deshpande and Li, 2019; Wing et al., 2024b). The choice of estimator is not consequential for our results. Appendix Figure A.8 re-estimates the dynamic effects with the interaction-weighted estimator of Sun and Abraham (2021) and the imputation estimator of Borusyak et al. (2024); the estimates are slightly attenuated but preserve the sign, timing, and persistence of the stacked results. Appendix Figure A.9 reports the sensitivity of the year-of-shock effects to violations of parallel trends (Rambachan and Roth, 2023): post-shock violations would need to reach 1.5 to 3 times the largest pre-shock violation before the effects become indistinguishable from zero, and larger still when $t = -1$ is considered as partially treated rather than as a pre-period.

To estimate dynamic effects, the stacked difference-in-differences model is formalized as follows:

$$Y_{ict} = \sum_{k=-5, k \neq -2}^4 \delta_k \cdot D_{ic}^k + \alpha_{ci} + \gamma_{ct} + \varepsilon_{ict} \quad (1)$$

where Y_{ict} denotes the educational outcome of student i in sub-experiment c and year t , and $D_{ic}^k = \mathbf{1}\{t - e_c = k\} \cdot \text{Treat}_{ic}$ is an indicator equal to one when student i is the treated student in sub-experiment c and year t falls k years from the shock year e_c of that sub-experiment (with $k = -2$ as the reference period). We take $t = -2$ rather than $t = -1$ as the reference period: the first cancer hospitalization marks the point at which the illness is severe enough to require inpatient care, and because the underlying diagnosis may precede it, outcomes at $t = -1$ can already reflect health deterioration between diagnosis and first admission. We therefore treat $t = -1$ as partially treated throughout the paper and do not count it as a pre-period when testing for differential pre-trends. The index c identifies the sub-experiments

defined at the school-grade-class level. The coefficients δ_k capture the dynamic effects at each relative period k compared to two years before the parental health shock; α_{ci} are sub-experiment-by-student fixed effects; γ_{ct} are sub-experiment-by-year fixed effects; and ε_{ict} is the error term, with standard errors clustered at the student level. The coefficients on the earlier leads (δ_{-5} , δ_{-4} , δ_{-3}) provide a test for differential pre-trends between treated students and their classmates; the coefficient at $t = -1$ instead captures responses in the window between diagnosis and first admission.

The event-study window is determined by the grade in which the parental health shock occurs. Each sub-experiment’s panel covers event years -5 through $+4$; observations from years before $t = -5$ are not part of the estimation sample. Since educational outcomes are observed only until students complete grade 12, or until age 18 if they do not complete secondary school, the length of the post-shock window declines mechanically for students exposed in later grades.⁸ The estimation sample is therefore unbalanced in event time: each sub-experiment is balanced within its own window, but the number of post-shock periods observed depends on the grade at exposure, so the coefficients at longer horizons are estimated from students exposed in earlier grades. Students exposed in later grades, for whom point estimates are, if anything, larger (Figure 3), mechanically exit the sample at longer horizons, so this compositional change works against finding persistent effects.

The core identifying assumption is that, conditional on time-invariant student characteristics and on shocks common to a sub-experiment in a given year, both absorbed by the fixed effects, the occurrence and timing of the parental health shock are as good as random with respect to children’s educational trajectories. Figure A.1 describes the identifying variation: treated-student sub-experiments are spread across shock years, grades at exposure, and school-grade-cohort cells, so no particular cohort or grade drives the estimates. Two pieces of evidence support the plausibility of the assumption. First, Figure 1 shows a sharp and discrete increase in parental hospitalizations, hospital days, and mortality at the time of the first cancer hospitalization, indicating that the event captures a medically salient shock rather than a smooth continuation of pre-existing health trends. Second, Figure A.2 plots raw trends in educational outcomes separately for treated students and untreated classmates; treated and control students follow broadly similar pre-shock trajectories. Table A.8 additionally shows that the composition of treated-student sub-experiments is broadly stable across shock cohorts in terms of student gender, grade at exposure, whether the mother or the father is the affected parent, shock severity (single versus multiple hospital admissions in the year of the

⁸Students exposed in grades 7–8 can be followed for up to four post-shock years, those exposed in grade 9 for up to three years, those exposed in grade 10 for up to two years, and those exposed in grade 11 for one post-shock year. Students exposed in grade 12 are observed only through the year of the shock.

shock, defined below), and school type, consistent with the absence of differential selection into treatment over time. Some outcomes display small deviations at $t = -1$, consistent with the post-diagnosis health deterioration discussed above. Taken together, the evidence indicates that the post-shock estimates capture a discrete educational response to parental illness rather than the continuation of large differential pre-existing trends.

To summarize the post-shock response in a single parameter, and to compare average effects across subgroups, where a single aggregated coefficient per group is more transparent than comparing full sets of dynamic coefficients, we also estimate a static version of Equation 1:

$$Y_{ict} = \beta (Post_{ct} \times Treat_{ic}) + \alpha_{ci} + \gamma_{ct} + \varepsilon_{ict}, \quad (2)$$

where $Treat_{ic}$ indicates the treated student in sub-experiment c and $Post_{ct}$ equals one from the shock year of sub-experiment c onward. With the same two sets of fixed effects, β measures the average post-shock difference in outcomes between treated students and their untreated classmates. Because this specification pools all pre-shock years, including $t = -1$, which may already reflect partial treatment, the static estimates are, if anything, slightly conservative relative to the event-study estimates, which take $t = -2$ as the reference period.

To study heterogeneity, we estimate fully interacted versions of Equations 1 and 2 by subgroup indicators measured before the parental health shock. Specifically, for each baseline characteristic G_i , we interact G_i with the relative-time treatment indicators in the event-study model and with $Post_{ct} \times Treat_{ic}$ in the static model. This allows us to recover subgroup-specific effects and to formally test whether the impact of parental illness differs by student, family, or illness characteristics. One dimension we examine throughout is the severity of the shock: following Brito and Contreras (2025), we classify shocks as low severity when the parent has a single hospital admission in the year of the shock, and high severity with two or more. Repeated admissions are an informative marker of the severity and progression of the underlying illness: within cancer diagnoses, mortality is difficult to predict, and hospital use rises sharply as the disease advances (Zeltzer et al., 2023); consistent with this, high-severity cases exhibit far larger increases in hospital days and subsequent mortality (Section 3.1).

2.3 Data

2.3.1 Data Sources

We combine rich administrative microdata from multiple government sources in Chile to construct a linked dataset covering health events, family structure, and educational and labor market outcomes for the universe of school-age children born between 1992 and 2006. Our

primary sources are (i) Hospital Discharge Records from the Ministry of Health; (ii) individual-level educational records from the Ministry of Education; (iii) the Social Household Registry (Registro Social de Hogares), which provides socioeconomic and demographic characteristics of families; (iv) vital statistics; and (v) unemployment insurance and pension contribution records.

(i) Hospital Discharge Records. Hospital discharge data contain detailed information on every hospitalization episode nationwide from 2007 to 2022, including patient identifiers, dates of admission and discharge, and main diagnoses (ICD-10).⁹ These records allow us to precisely identify the first instance in which a parent was hospitalized with a cancer diagnosis (ICD-10 codes C00–C97 and D00–D09). We identify these first cancer hospitalizations, the health shocks in our design, between 2010 and 2018; the records extend through 2022, so parental hospital use is observed through four years after the latest shocks.

(ii) Educational records. Educational records include monthly attendance data, grade progression, repetition, and dropout flags, as well as high school graduation status and timing. These data are reported by schools and compiled by the Ministry of Education at the student level, covering every school in the country.

(iii) Social Household Registry (Registro Social de Hogares; RSH). The Social Household Registry (RSH), administered by Chile’s Ministry of Social Development and Family, is the primary information system used to allocate social services, welfare benefits, and other public assistance programs. The registry integrates administrative records from multiple government sources with self-reported household information and provides detailed data on household composition, parental education, socioeconomic status, and geographic location. In 2023, the RSH covered approximately 5 million households and 13 million individuals, roughly 75% of the national population. Households not included in the registry belong primarily to the upper-income segment.

(iv) Vital statistics. Vital statistics records through 2023 provide information on date of birth as well as date and cause of death. These records also include parental identifiers, enabling us to link children to their biological parents.

(v) Unemployment insurance and pension records. We use administrative records from Chile’s unemployment insurance system and mandatory pension contributions to measure parents’ formal employment around the health shock. These records provide monthly formal employment status and earnings for formal-sector workers, which we use to characterize households’ pre-shock exposure to labor income risk and to estimate the effect of the shock

⁹Reporting is mandatory for all hospitals (public, private, military, and mutual organizations) under Ministry of Health technical guidelines (Decree No. 127, 2007); the standardized discharge form (*Informe Estadístico de Egreso Hospitalario*) records demographics, ICD-10 diagnoses, procedures, and length of stay.

on the parents' own labor supply.

2.3.2 Outcomes

Our three main outcomes are constructed from the education records. *Enrollment* equals one if the student is enrolled in any school in the national system in a given year, so a decline in enrollment reflects an exit from the school system rather than a transfer across schools. The *attendance rate* is the share of official school days attended during the academic year. *Chronic absenteeism* equals one if the student's annual attendance rate falls below 85%, mirroring the threshold used in official Chilean education statistics. All three outcomes are defined for every student in every year: a student not enrolled in a given year has an attendance rate of zero and is classified as chronically absent.

2.3.3 Analysis Sample

Our analysis sample focuses on children whose parent experienced a first hospitalization due to cancer between 2010 and 2018, and who were enrolled in any grade between 7th and 12th in the year of the health shock. Treated and control students are paired within sub-experiments, indexed by c in the stacked difference-in-differences model and defined at the school-grade-class level in the year the health shock was observed. We identify 32,098 treated students, mostly between ages 12 and 18 at the time of the health shock, and 505,768 control students. Table 1 provides summary statistics for the final sample. Treated and control students are balanced on family size and parental education. Parents of treated students are older, as expected given that cancer risk rises with age, and their children are accordingly less likely to be firstborn; gender composition differs only slightly. Standardized differences are at most 0.201 for all characteristics.

2.3.4 Descriptive Statistics

Figures A.3 and A.4 display the distribution of students' ages in the year of the health shock, overall and by treatment status and gender, and Tables A.6 and A.7 summarize the distribution of classes and average class sizes by grade and school type. Classes are distributed relatively evenly across grades, with each level representing roughly 15–18% of all classes in our sample. Most classes belong to subsidized schools, followed by municipal and private institutions, reflecting the composition of Chile's education system. Average class sizes range from approximately 18 to 25 students, with subsidized schools exhibiting the largest classes and private schools the smallest. Overall, the structure of the sample closely mirrors the national distribution of school types and grade sizes.

Table 2 reports descriptive statistics on hospitalizations and cancer-related admissions for the overall sample and separately for mothers and fathers of students, and Figures A.5 and A.6 show the distribution of mothers’ and fathers’ ages in the year of the shock, overall and by the treatment status of their child. In 65% of cases the mother is the affected parent, in the remaining 35% the father; 76.2% of treated students experience a low-severity shock.

Cancer frequency, mortality, the distribution of cancer types, and the duration of the health event all differ by parental gender. On average, mothers are hospitalized less often than fathers (1.8 versus 2.2 admissions) and spend fewer days in the hospital (9.0 versus 16.5 days), and high-severity cases are somewhat less common among mothers (22.4 versus 26.4%). For mothers, the most frequent diagnoses are breast cancer (C50; 26.4%), in situ malignant neoplasms (D00–D09; 16.0%), cancers of the female genital organs (C51–C58; 15.6%), endocrine glands (C73–C75; 15.5%), and digestive organs (C15–C26; 10.9%). For fathers, the most frequent diagnoses are cancers of the digestive organs (C15–C26; 29.8%), male genital organs (C60–C63; 20.2%), the lymphatic system (C81–C97; 10.6%), and the urinary tract (C64–C68; 8.5%) (Table 2).

3 Main Results

3.1 Impacts on Parental Health

We begin by validating the timing and salience of the parental health shock used in our empirical design. Figure 1 and Appendix Table A.1 report difference-in-differences estimates of the impact of a first cancer hospitalization on parental health outcomes: the number of hospitalizations (Panels (a) and (c), for any cause and cancer-related), days hospitalized (Panels (b) and (d)), and mortality (Panel (e)) around the event. All three outcomes exhibit a sharp and discrete increase at $t = 0$, consistent with the interpretation that the first cancer hospitalization captures a medically significant and unexpected event. In the year of the event, parental mortality increases by 4.7 percentage points, hospital days rise by 5.6 days, and the number of hospitalizations increases by 0.9 admissions relative to $t = -2$. Mortality continues to rise after the event, reaching 8.4 percentage points at $t = 1$ and 10.2 percentage points at $t = 2$, while hospitalization outcomes peak at $t = 0$ and decline thereafter. Hospital days and admissions also show small positive deviations at $t = -1$ (0.2 days and 0.03 admissions), consistent with diagnostic activity and related health problems shortly preceding the first cancer hospitalization and with our choice of $t = -2$ as the reference period. The magnitude and discontinuity of these changes indicate that the first cancer hospitalization approximates well the timing of the health shock.

The severity gradient is substantial. At $t = 0$, high-severity cases increase hospital days by 11.0 days and hospitalizations by 1.7 admissions, compared with 4.0 days and 0.6 admissions for low-severity cases. Mortality also rises much more among high-severity cases: by 7.6 percentage points at $t = 0$, 14.1 percentage points at $t = 1$, and 16.6 percentage points at $t = 2$, compared with 3.8, 6.7, and 8.2 percentage points for low-severity cases. These differences are informative for mechanisms, as high-severity shocks are more likely to involve intensive treatment, greater caregiving and time-use demands, and a higher risk of parental death.

This empirical pattern supports our identification strategy, which relies on quasi-random variation in the occurrence and timing of the health shock during the child’s school years. The sharp jump in hospitalization outcomes at the event time reduces concerns that the shock reflects pre-existing differences in parental health trajectories, and confirms that our treatment captures the onset of an acute health episode that plausibly reconfigures family dynamics and caregiving burdens.

3.2 Impacts on Educational Trajectories

Figure 2 and Appendix Table A.2 report the event-study estimates from Equation 1 for the three educational outcomes: enrollment, the attendance rate, and chronic absenteeism (annual attendance below 85%). Estimates are expressed as percentage-point deviations from the reference period $t = -2$, where $t = 0$ denotes the year of the first parental cancer hospitalization. Table 3 reports the corresponding aggregated difference-in-differences estimates from Equation 2.

Across the three outcomes, the estimates show a clear break in educational trajectories at the time of the parental health shock. Some pre-period coefficients are statistically different from zero, most notably at $t = -1$ for enrollment and attendance, but their magnitudes are small relative to the post-shock changes. The deviations at $t = -1$ are best read as partial treatment rather than differential pre-trends, mirroring the pattern in parental hospital use at $t = -1$ (Section 3.1). Following the shock, enrollment, attendance, and chronic absenteeism all deteriorate sharply. The effects are largest in the year of the first parental cancer hospitalization; enrollment and attendance remain statistically significantly lower through four years after the shock, and chronic absenteeism remains significantly elevated for three.

Parental health shocks reduce enrollment by 0.5 percentage points on average in the post-shock period (Table 3). The dynamic estimates show that enrollment falls by 0.6 percentage points in the year of the shock and remains 0.3 to 0.5 percentage points lower

over the following four years (Appendix Table A.2). Because enrollment measures presence in any school in the national system, these declines reflect exits from the school system rather than transfers across schools. From a baseline above 99% (Table 3), an effect of this size is comparable in percentage points to the dropout effects of parental job loss documented in middle-income settings (Britto et al., 2022).

The attendance rate also declines after the parental health shock, by 0.8 percentage points on average in the post-shock period (Table 3). The dynamic estimates show a decline of 1.1 percentage points in the year of the shock, with declines of 0.5 to 0.9 percentage points persisting over the following four years. Given that the academic year in Chile lasts roughly 170 days, the effect in the year of the shock corresponds to approximately 1.9 fewer school days, lost time that existing estimates link to lower achievement and educational attainment (Carlsson et al., 2015; Liu et al., 2021).

The results for chronic absenteeism indicate that parental health shocks also move students toward a more severe margin of educational disengagement. On average, the shock increases chronic absenteeism by 1.3 percentage points (Table 3), an 18% increase relative to the control mean of 7.1%. The event-study estimates show an increase of 2.2 percentage points in the year of the shock (a 30% increase relative to the control mean), with increases of 1.0 to 1.2 percentage points persisting through the third year; the effect becomes small and statistically insignificant by $t = 4$ (Appendix Table A.2).

3.2.1 By Severity of the Shock

We next examine whether the impact of parental cancer varies with the severity of the health shock, as defined in Section 2.2. Figure 4, together with Table 4 and Appendix Table A.3, reports the estimated effects separately for low- and high-severity shocks.

Severity matters little for enrollment: the average effects are -0.5 percentage points for both groups, with similar post-shock dynamics. For the attendance rate and chronic absenteeism, by contrast, severity matters substantially. The average effect on attendance is nearly twice as large for high-severity as for low-severity cases, at -1.3 compared with -0.7 percentage points. In the year of the shock, attendance falls by 1.7 percentage points for high-severity cases and by 0.9 percentage points for low-severity cases. The severity gradient is even more pronounced for chronic absenteeism: high-severity shocks increase chronic absenteeism by 2.6 percentage points on average, compared with 0.9 percentage points for low-severity shocks, increases of 38% and 12% relative to the respective control means. In the year of the shock, the corresponding increases are 4.1 and 1.6 percentage points. The differential estimates in Figure 4 show that the severity gap is statistically significant in the year of the shock and remains so through the following year for the attendance rate and

through the second year for chronic absenteeism. These results point to a clear dose-response pattern: more severe parental illness generates larger and more persistent disruptions in school participation, particularly on the margins of attendance and chronic absenteeism.

3.2.2 By Student Gender

Figure 5, together with Table 5 and Appendix Table A.4, presents estimates from Equations 1 and 2 interacted with student gender. We find no meaningful gender differences in enrollment effects. The average effects are negative for both girls and boys, at -0.5 percentage points each, and the difference is small and not statistically significant. The dynamic estimates similarly show enrollment declines for both groups, with no robust evidence that the effect differs by gender.

In contrast, the effects on the attendance rate and chronic absenteeism are substantially larger for girls. The static estimates show that attendance falls by 1.2 percentage points for girls, compared with 0.4 percentage points for boys, a statistically significant gender gap of 0.8 percentage points. The event-study estimates show that this gap opens in the year of the shock and remains statistically significant in every post-shock year, though only at the 10% level at $t = 3$. At $t = 0$, attendance falls by 1.4 percentage points for girls and by 0.9 percentage points for boys; by $t = 1$, the corresponding declines are 1.4 and 0.5 percentage points.

The gender gradient is even more pronounced for chronic absenteeism. Parental health shocks increase chronic absenteeism by 2.3 percentage points for girls, compared with a statistically insignificant 0.3 percentage points for boys, a difference of 2.0 percentage points. In the event-study estimates, chronic absenteeism rises by 2.8 percentage points for girls and 1.5 percentage points for boys in the year of the shock, and the female-male difference remains statistically significant through $t = 4$. Parental illness therefore affects boys and girls similarly on the enrollment margin, but generates larger and more persistent disruptions in girls' school engagement, a pattern consistent with the caregiving channel described in Section 1, under which household and care responsibilities fall disproportionately on girls.

3.2.3 Other Dimensions of Heterogeneity

Grade at exposure. Figure 3 reports difference-in-differences estimates by the student's grade at the time of the parental cancer hospitalization. The effects on enrollment are negative across all grades, indicating that parental health shocks reduce school enrollment throughout the 7th–12th grade window.

For the attendance rate and chronic absenteeism, point estimates tend to be larger for

students exposed in later grades, particularly from 9th to 12th grade. The confidence intervals for adjacent grades overlap substantially, however, so the grade gradient should be read with caution; the clearest contrast is for chronic absenteeism, where the point estimate for students exposed in 12th grade is roughly five times as large as that for students exposed in 7th grade. This pattern is consistent with older adolescents being more able to take on responses to the shock, such as market work to compensate for lost household income, caregiving, or household responsibilities.

Affected parent. A large body of work highlights that mothers and fathers contribute differently to children’s human capital formation (Thomas, 1990; Del Boca et al., 2014; Fiorini and Keane, 2014), raising the question of whether the gender of the sick parent shapes the effects of health shocks. To investigate this, we estimate models interacted with whether the cancer affected the mother or the father. The results, presented in Figure 6, Table 6, and Appendix Table A.5, show limited evidence that effects differ by parental gender for enrollment or attendance. The average enrollment estimates are -0.6 percentage points for maternal hospitalizations and -0.4 percentage points for paternal hospitalizations, with a marginally significant difference. For attendance, the estimates are nearly identical, at -0.8 percentage points each. The clearest difference emerges for chronic absenteeism: paternal hospitalizations increase chronic absenteeism by 1.7 percentage points, compared with 1.1 percentage points for maternal diagnoses, and the difference is statistically significant. The dynamic estimates indicate that this difference is concentrated in the year of the shock, when chronic absenteeism rises by 2.6 percentage points following the paternal health shock and by 1.9 percentage points following maternal shocks. Part of this gap likely reflects differences in the severity of the underlying shock rather than the identity of the sick parent: paternal cancers are more severe on average, with more admissions (2.2 versus 1.8), more hospital days (16.5 versus 9.0), and a larger share classified as high severity (26.4 versus 22.4%; Table 2), and, as shown above, chronic absenteeism is the outcome most responsive to severity. Overall, parental gender does not substantially shape enrollment or attendance responses, while paternal health shocks generate a larger short-run increase in chronic absenteeism.

Household composition. Effects do not differ with the presence of a child aged 0–5 in the household at baseline: the estimated differences are 0.2 percentage points (s.e. = 0.1) for enrollment, 0.3 (s.e. = 0.2) for the attendance rate, and 0.0 (s.e. = 0.4) for chronic absenteeism (Figure A.7).

3.3 Mechanisms

Why does a parental health shock disrupt adolescents’ school trajectories? Section 1 outlines the channels through which the shock can operate and argues that, in the Chilean context, the pecuniary and caregiving channels are likely the most salient. In this section, we present the evidence our data allow on these channels: the shock’s effect on the affected parent’s own labor supply, heterogeneity by households’ pre-shock exposure to labor income risk, and the shock’s effect on the children’s hospitalizations, which bears on the child-health margin of the psychological channel. The remaining channels are unobserved in our data, and throughout we read this evidence as suggestive.

The shock reduces the affected parent’s formal employment. We first estimate Equations 1 and 2 using the parents of treated and control students as the units of analysis and their formal labor market outcomes as dependent variables. The estimation sample is restricted to the same sub-experiments and event-time window as the student panel, and each affected parent is compared with control-classmate parents of the same sex: mothers with cancer against control mothers, fathers with cancer against control fathers. Figure 7 and Table 7 report the results. In the post-shock period, the probability that an affected mother is formally employed falls by 3.3 percentage points (s.e. = 0.3), a 9.4% decline relative to the pre-shock control mean of 35.2%, and her months of formal employment fall by 0.31 (s.e. = 0.03), or 9.8% of the control mean of 3.2 months. For affected fathers, formal employment falls by 2.3 percentage points (s.e. = 0.3), a 4.2% decline on a control mean of 56.4%, and months of formal employment fall by 0.29 (s.e. = 0.04), or 5.2% of the control mean of 5.6 months.¹⁰ The dynamics differ by parent: mothers’ employment losses appear in the year of the shock and grow steadily, reaching 5.2 percentage points four years out, while fathers’ formal employment rises by 2.1 percentage points in the year of the shock and then declines steadily, to 6.9 percentage points below the control group four years out (Figure 7). Pre-period coefficients are small relative to these losses (at most 1.0 percentage point in absolute value), although two of the pre-period estimates for fathers are statistically distinguishable from zero. The labor supply of the non-diagnosed parent, in contrast, shows

¹⁰Formal labor earnings are measured monthly in Chilean pesos at constant 2025 prices; in 2025, USD 1 $\approx$ CLP 950. Earnings include zeros for parents without formal employment. For both parents, average post-shock estimates mask the same dynamic pattern: earnings rise in the year of the shock and fall below the counterfactual thereafter. For affected mothers, earnings rise by CLP 33,500 in the year of the shock (14% of the pre-shock control mean of CLP 234,000) and decline steadily afterward, reaching CLP -33,500 (14%) four years out; the year-of-shock increase and the later declines offset, leaving an average post-shock estimate near zero (CLP -300, s.e. = 3,200). For affected fathers, earnings rise by CLP 54,400 (9% of the control mean of CLP 588,000) in the year of the shock and reach CLP -103,000 (18%) four years out, for an average post-shock decline of CLP 24,000 (s.e. = 6,800), or 4.1%.

no offsetting response.¹¹ These estimates provide direct evidence that the shock generates a persistent household income loss, the first ingredient of the pecuniary channel, and are in line with the large employment costs of own illness documented in high-income countries (García-Gómez et al., 2013; Fadlon and Nielsen, 2021), including for breast cancer specifically, the most common diagnosis among mothers in our sample (Ahammer et al., 2026).

The educational response is flat across the pre-shock income distribution. If the pecuniary channel were the dominant driver of the educational response, disruptions should be concentrated in households least able to buffer an income loss. To test this, we augment Equation 2 with interactions of $Post_{ct} \times Treat_{ic}$ and deciles of the parents' pre-shock position in the formal labor market, measured over the three years ending at the reference period ($t \in [-4, -2]$): deciles of months of formal employment and, separately, deciles of formal labor income, computed within cohort, with the bottom decile (households with no formal labor activity in the window) as the reference group. Stable formal employment in Chile carries unemployment insurance, severance protection, and paid sick leave, so a household's position in this distribution proxies for its insurance against labor income risk. Figure 8 reports the results. The profile is flat: of the 54 interaction coefficients (nine deciles, three outcomes, two classifications), only three are statistically significant at the 5% level, and they follow no consistent pattern. For the reference group, enrollment falls by 0.5 percentage points (s.e. = 0.1), the attendance rate falls by 0.8 percentage points (s.e. = 0.1), and chronic absenteeism rises by 1.2 percentage points (s.e. = 0.3) in the post-shock period, and the estimated differences for higher deciles are small throughout. We find no evidence that stronger pre-shock attachment to formal employment buffers the educational response: the disruption is broad-based across the income distribution.

Children's hospitalizations do not rise. The educational response could in part reflect a deterioration of the children's health, the child-health margin of the psychological channel (Section 1). To test this, we re-estimate Equation 2 with the students' hospitalizations as outcomes, measured from the same hospital discharge records as the parental shocks; the hospitalization panel covers event years -4 through $+4$. Figure 9 and Table 8 report the results. We find no evidence of such a response. If anything, the probability that a treated student is hospitalized in a given year falls slightly (-0.14 percentage points, s.e. = 0.08,

¹¹We compare the mothers of treated students whose father was hospitalized with the mothers of control classmates, and likewise for fathers. None of the post-shock estimates is statistically significant at the 5% level. For mothers, the estimates are $+0.4$ percentage points (s.e. = 0.4) for formal employment, -0.07 months (s.e. = 0.04) for months of formal employment, and CLP $-6,300$ (s.e. = 4,400) for monthly earnings; for fathers, they are -0.03 percentage points (s.e. = 0.2), -0.02 months (s.e. = 0.03), and CLP $-5,900$ (s.e. = 4,700).

relative to a pre-shock control mean of 2.8%). Hospitalizations with a mental-health diagnosis are rare at baseline (0.06% of students in a given year), and the estimate is -0.02 percentage points (s.e. = 0.02); estimates for hospitalizations with depression, mood-disorder, or alcohol- and drug-related diagnoses, and for the number of hospitalizations and days in hospital, are likewise small and statistically indistinguishable from zero. Hospitalization is a severe margin of health care use, so these results do not rule out psychological distress treated in outpatient care or left untreated. They do indicate that the drop in school engagement is not explained by a deterioration in the children’s health severe enough to require hospital care.

Taken together, the mechanism evidence describes a shock that strains households on several margins. The shock durably reduces the affected parent’s formal employment, with no offsetting response by the other parent, so the income loss is real and uninsured within the household. The educational response across the parents’ pre-shock income and employment distribution, however, is flat: no group appears visibly buffered, which suggests that the income loss alone does not determine who is disrupted. The concentration of attendance and absenteeism effects among girls is consistent with a caregiving response within the household, and we find no evidence that the children’s health deteriorates, at least at the hospitalization margin.

4 Conclusion

This paper documents how severe parental health shocks disrupt the educational trajectories of adolescents in Chile. We link administrative records for the universe of school-age children and implement a stacked difference-in-differences design that exploits quasi-random variation in the occurrence and timing of parents’ first cancer hospitalizations. The main response is in school engagement: affected students miss substantially more school, and the share who are chronically absent rises by 2.2 percentage points in the year of the shock, a 30% increase over the control mean, and remains elevated for three years. Complete exits from the school system are rarer but persistent: enrollment falls by 0.6 percentage points from a near-universal baseline and remains depressed through four years after the shock. The disruption scales with the severity of the illness.

The incidence of these effects is informative about mechanisms. The shock persistently reduces the affected parent’s formal employment, and the other parent’s labor supply does not respond, so households bear the income loss directly. Yet, the educational response is flat across the parents’ pre-shock income and employment distribution: students from households with more formal-sector insurance are no less affected. The response is concentrated among girls, consistent with caregiving and household responsibilities falling disproportionately on

them, and we find no evidence of a response of children's hospitalizations.

These findings point to an intergenerational cost of parental illness. The setting we study is representative of much of the low- and middle-income world: safety nets are thin, families absorb the consequences of severe illness, and the burden of disease at working ages is rising. As that burden grows, so will its intergenerational costs: parental illness disrupts children's education at a formative stage, with effects that persist for years and may translate into lasting losses in human capital. Buffering these shocks is therefore a first-order task for social protection in these settings; because the disruption reaches across the income distribution, timely educational and psychosocial support for affected families could mitigate its long-run human capital costs.

References

- Aaskoven, Maiken Skovrider, Trine Kjær, and Dorte Gyrd-Hansen, “Effects of parental health shocks on children’s school achievements: A register-based population study,” *Journal of Health Economics*, 2022, 81, 102573.
- Aguilar-Gomez, Sandra, Eva O. Arceo-Gomez, and Elia De la Cruz Toledo, “Inside the black box of child penalties: Unpaid work and household structure,” *Journal of Development Economics*, 2026, 178, 103554.
- Ahammer, Alexander, Gerald J. Pruckner, and Flora Stifflinger, “The Labor and Health Economics of Breast Cancer,” *Journal of Health Economics*, 2026, 108, 103141.
- Alam, Shamma Adeeb, “Parental health shocks, child labor and educational outcomes: Evidence from Tanzania,” *Journal of Health Economics*, 2015, 44, 161–175.
- Angrist, Joshua D. and Alan B. Krueger, “Does Compulsory School Attendance Affect Schooling and Earnings?,” *The Quarterly Journal of Economics*, 1991, 106 (4), 979–1014.
- Becker, Gary S. and Nigel Tomes, “An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility,” *Journal of Political Economy*, 1979, 87 (6), 1153–1189.
- Boca, Daniela Del, Christopher Flinn, and Matthew Wiswall, “Household Choices and Child Development,” *The Review of Economic Studies*, 2014, 81 (1), 137–185.
- Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, “Revisiting Event-Study Designs: Robust and Efficient Estimation,” *The Review of Economic Studies*, 2024, 91 (6), 3253–3285.
- Bratti, Massimiliano and Mariapia Mendola, “Parental health and child schooling,” *Journal of Health Economics*, 2014, 35, 94–108.
- Bray, Freddie, Mathieu Laversanne, Hyuna Sung, Jacques Ferlay, Rebecca L. Siegel, Isabelle Soerjomataram, and Ahmedin Jemal, “Global Cancer Statistics 2022: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries,” *CA: A Cancer Journal for Clinicians*, 2024, 74 (3), 229–263.
- Brito, Emilia and Dante Contreras, “The Caregiving Penalty: Caring for Sick Parents and the Gender Pay Gap,” 2025. Working Paper.
- Britto, Diogo G. C., Caíque Melo, and Breno Sampaio, “The Kids Aren’t Alright: Parental Job Loss and Children’s Outcomes Within and Beyond Schools,” Discussion Paper 17562, Centre for Economic Policy Research 2022.

- Callaway, Brantly and Pedro H. C. Sant’Anna**, “Difference-in-Differences with Multiple Time Periods,” *Journal of Econometrics*, 2021, 225 (2), 200–230.
- Carlsson, Magnus, Gordon B. Dahl, Björn Öckert, and Dan-Olof Rooth**, “The Effect of Schooling on Cognitive Skills,” *Review of Economics and Statistics*, 2015, 97, 533–547.
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer**, “The Effect of Minimum Wages on Low-Wage Jobs*,” *The Quarterly Journal of Economics*, 05 2019, 134 (3), 1405–1454.
- Cunha, Flavio and James J. Heckman**, “The Technology of Skill Formation,” *American Economic Review*, 2007, 97 (2), 31–47.
- , – , and **Susanne M. Schennach**, “Estimating the Technology of Cognitive and Noncognitive Skill Formation,” *Econometrica*, 2010, 78 (3), 883–931.
- de Chaisemartin, Clément and Xavier D’Haultfœuille**, “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects,” *American Economic Review*, 2020, 110 (9), 2964–2996.
- Deshpande, Manasi and Yue Li**, “Who Is Screened Out? Application Costs and the Targeting of Disability Programs,” *American Economic Journal: Economic Policy*, November 2019, 11 (4), 213–48.
- Dinku, Yonatan, David Fielding, and Murat Genç**, “Health shocks and child time allocation decisions by households: evidence from Ethiopia,” *IZA Journal of Labor Economics*, 2018, 7 (1), 4.
- Eguiguren, A. P., C. Guerrero-Nancuante, I. Abarca, B. Cerda, M. J. Muñoz, C. Bass, C. Romero, and M. L. Garmendia**, “¿Quién paga y cuánto? Gastos de bolsillo en diagnóstico oncológico en redes públicas de Chile (ID 1983),” E-póster, VIII Congreso Chileno de Salud Pública & X Congreso Chileno de Epidemiología 2025. E-póster.
- Elacqua, Gregory**, “The impact of school choice and public policy on segregation: Evidence from Chile,” *International Journal of Educational Development*, 2012, 32 (3), 444–453.
- Fadlon, Itzik and Torben Heien Nielsen**, “Family Labor Supply Responses to Severe Health Shocks: Evidence from Danish Administrative Records,” *American Economic Journal: Applied Economics*, 2021, 13 (3), 1–30.

- Fiorini, Mario and Michael P. Keane**, “How the Allocation of Children’s Time Affects Cognitive and Noncognitive Development,” *Journal of Labor Economics*, 2014, *32* (4), 787–836.
- Frimmel, Wolfgang, Martin Halla, Jörg Paetzold, and Julia Schmieder**, “Health of Parents, Their Children’s Labor Supply, and the Role of Migrant Care Workers,” *Journal of Labor Economics*, 2025, *43* (3), 803–841.
- García-Miralles, Esteban and Miriam Gensowski**, “Are Children’s Socio-Emotional Skills Shaped by Parental Health Shocks?,” *Journal of Human Resources*, 2025, *60* (5), 1560–1596.
- García-Gómez, Pilar, Hans van Kippersluis, Owen O’Donnell, and Eddy van Doorslaer**, “Long-Term and Spillover Effects of Health Shocks on Employment and Income,” *Journal of Human Resources*, 2013, *48* (4), 873–909.
- Gertler, Paul, David I. Levine, and Minnie Ames**, “Schooling and parental death,” *Review of Economics and Statistics*, 2004, *86* (1), 211–225.
- Gimenez, Lea, Shin-Yi Chou, Jin-Tan Liu, and Jin-Long Liu**, “Parental Loss and Children’s Well-Being,” *Journal of Human Resources*, 2013, *48* (4), 1035–1071.
- Glaser, Felix and Gerald J. Pruckner**, “A hard pill to swallow? Parental health shocks and children’s mental health,” *Health Economics*, 2023, *32* (12), 2768–2800.
- Gabiak, Beth R., Catherine M. Bender, and Kathryn R. Puskar**, “The impact of parental cancer on the adolescent: an analysis of the literature,” *Psycho-Oncology*, 2007, *16* (2), 127–137.
- Grossman, Michael**, “On the Concept of Health Capital and the Demand for Health,” *Journal of Political Economy*, 1972, *80* (2), 223–255.
- Heckman, James J.**, “The Economics, Technology, and Neuroscience of Human Capability Formation,” *Proceedings of the National Academy of Sciences*, 2007, *104* (33), 13250–13255.
- Hilger, Nathaniel G.**, “Parental Job Loss and Children’s Long-Term Outcomes: Evidence from 7 Million Fathers’ Layoffs,” *American Economic Journal: Applied Economics*, 2016, *8* (3), 247–283.
- International Labour Organization**, “Care Work and Care Jobs for the Future of Decent Work,” Technical Report, International Labour Office, Geneva 2018.

- Joergensen, Anne Cathrine, Stine Kjaer Urhoj, and Anne-Marie Nybo Andersen**, “Primary school achievement and socioeconomic attainment in individuals affected by parental cancer in childhood or adolescence: a Danish nationwide register-based study,” *Journal of Epidemiology and Community Health*, 2018, 72 (11), 982–989.
- Kristiansen, Ida Lykke**, “Consequences of serious parental health events on child mental health and educational outcomes,” *Health Economics*, 2021, 30 (8), 1772–1817.
- Liu, Jing, Monica Lee, and Seth Gershenson**, “The Short- and Long-Run Impacts of Secondary School Absences,” *Journal of Public Economics*, 2021, 199, 104441.
- Loken, Katrine V., Shelly Lundberg, and Julie Riise**, “Lifting the Burden: Formal Care of the Elderly and Labor Supply of Adult Children,” *Journal of Human Resources*, 2017, 52 (1), 247–271.
- Luca, Dara Lee and David E. Bloom**, “The Returns to Parental Health: Evidence from Indonesia,” Working Paper 25304, National Bureau of Economic Research November 2018.
- Mendolia, Silvia, Nga Nguyen, and Oleg Yerokhin**, “The impact of parental illness on children’s schooling and labour force participation: evidence from Vietnam,” *Review of Economics of the Household*, 2019, 17 (2), 469–492.
- Ministerio de Desarrollo Social**, “Síntesis de Resultados: Salud, Encuesta CASEN 2017,” Technical Report, Observatorio Social, Ministerio de Desarrollo Social, Gobierno de Chile 2018.
- Ministerio de Educación, Centro de Estudios**, “Apuntes N.º62: Reporte nacional de asistencia de julio de los años 2018, 2023 y 2024,” Technical Report, Ministerio de Educación de Chile, Santiago, Chile September 2024.
- , “Reporte nacional de asistencia de marzo a diciembre de los años 2018, 2023 y 2024,” Technical Report, Ministerio de Educación de Chile, Santiago, Chile 2025.
- Ministerio de Educación de Chile**, “Mineduc presenta las cifras oficiales de asistencia y desvinculación 2023,” Centro de Estudios, Ministerio de Educación de Chile November 2023.
- Oreopoulos, Philip**, “Estimating Average and Local Average Treatment Effects of Education when Compulsion Matters,” *American Economic Review*, 2006, 96 (1), 152–175.
- , **Marianne Page, and Ann Huff Stevens**, “The Intergenerational Effects of Worker Displacement,” *Journal of Labor Economics*, 2008, 26 (3), 455–483.

- Persson, Petra and Maya Rossin-Slater**, “Family Ruptures, Stress, and the Mental Health of the Next Generation,” *American Economic Review*, 2018, 108 (4-5), 1214–1252.
- Rambachan, Ashesh and Jonathan Roth**, “A More Credible Approach to Parallel Trends,” *The Review of Economic Studies*, 2023, 90 (5), 2555–2591.
- Rege, Mari, Kjetil Telle, and Mark Votruba**, “Parental Job Loss and Children’s School Performance,” *The Review of Economic Studies*, 2011, 78 (4), 1462–1489.
- Rellstab, Sara, Pieter Bakx, Pilar García-Gómez, and Eddy van Doorslaer**, “The kids are alright - labour market effects of unexpected parental hospitalisations in the Netherlands,” *Journal of Health Economics*, 2020, 69, 102275.
- Roth, Jonathan, Pedro H. C. Sant’Anna, Alyssa Bilinski, and John Poe**, “What’s trending in difference-in-differences? A synthesis of the recent econometrics literature,” *Journal of Econometrics*, 2023, 235 (2), 2218–2244.
- Sun, Ang and Yang Yao**, “Health Shocks and Children’s School Attainments in Rural China,” *Economics of Education Review*, 2010, 29 (3), 387–395.
- Sun, Liyang and Sarah Abraham**, “Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects,” *Journal of Econometrics*, 2021, 225 (2), 175–199.
- Superintendencia de Salud**, “Garantías explícitas en salud (GES),” Web page 2026. Retrieved January 2026.
- Thomas, Duncan**, “Intra-Household Resource Allocation: An Inferential Approach,” *Journal of Human Resources*, 1990, 25 (4), 635–664.
- Wen, Jiayi and Haili Huang**, “Parental health penalty on adult children’s employment: Gender differences and long-term consequences,” *Journal of Health Economics*, 2024, 95, 102886.
- Wing, Coady, Madeline Yozwiak, Alex Hollingsworth, Seth Freedman, and Kosali Simon**, “Designing Difference-in-Difference Studies with Staggered Treatment Adoption: Key Concepts and Practical Guidelines,” *Annual Review of Public Health*, 2024, 45, 485–505.
- , **Seth M. Freedman, and Alex Hollingsworth**, “Stacked Difference-in-Differences,” Working Paper 32054, National Bureau of Economic Research January 2024.

World Bank, “School Enrollment, Secondary (% Net) — Chile,” World Development Indicators, indicator SE.SEC.NENR 2017.

World Health Organization, “Noncommunicable Diseases,” Fact sheet, World Health Organization 2025.

Zeltzer, Dan, Liran Einav, Amy Finkelstein, Tzvi Shir, Salomon M. Stemmer, and Ran D. Balicer, “Why Is End-of-Life Spending So High? Evidence from Cancer Patients,” *Review of Economics and Statistics*, 2023, 105 (3), 511–527.

Zheng, Zhiyuan, Jingxuan Zhao, Leticia Nogueira, Xuesong Han, Qinjin Fan, and K. Robin Yabroff, “Associations of Parental Cancer with School Absenteeism, Medical Care Unaffordability, Health Care Use, and Mental Health Among Children,” *JAMA Pediatrics*, 2022, 176 (6), 593–601.

Figures and Tables

Table 1: Summary statistics by treatment status

	Treated		Control		Balance		
	Mean	SE	Mean	SE	p-value	Diff.	Std. Diff.
Child characteristics							
Male	0.496	0.003	0.483	0.000	< 0.001	0.013	0.018
Age of the child when shocked	15.236	0.004	15.234	0.000	0.664	0.002	0.001
First born	0.348	0.003	0.429	0.000	< 0.001	-0.080	-0.117
Second born	0.330	0.003	0.318	0.000	< 0.001	0.012	0.018
Third born	0.198	0.002	0.164	0.000	< 0.001	0.034	0.063
Fourth born or higher	0.124	0.002	0.089	0.000	< 0.001	0.034	0.078
Single birth	0.990	0.001	0.983	0.000	< 0.001	0.007	0.043
0 siblings	0.098	0.002	0.090	0.000	< 0.001	0.008	0.019
1 sibling	0.355	0.003	0.355	0.000	0.972	0.000	0.000
2 siblings	0.321	0.003	0.336	0.000	< 0.001	-0.015	-0.023
3 siblings	0.145	0.002	0.145	0.000	0.920	0.000	0.000
4 siblings	0.052	0.001	0.047	0.000	< 0.001	0.005	0.015
5 or more siblings	0.030	0.001	0.027	0.000	0.005	0.003	0.012
Mother characteristics							
Mother's years of education	11.611	0.017	11.649	0.001	0.036	-0.039	-0.008
Mother's age at birth 10–19	0.085	0.002	0.134	0.000	< 0.001	-0.049	-0.112
Mother's age at birth 20–29	0.418	0.003	0.507	0.000	< 0.001	-0.089	-0.127
Mother's age at birth 30–39	0.439	0.003	0.330	0.000	< 0.001	0.109	0.160
Mother's age at birth 40+	0.058	0.001	0.029	0.000	< 0.001	0.029	0.102
No schooling (mother)	0.008	0.001	0.007	0.000	0.041	0.001	0.009
Incomplete primary (mother)	0.106	0.002	0.100	0.000	< 0.001	0.006	0.014
Complete primary (mother)	0.108	0.002	0.111	0.000	0.094	-0.003	-0.007
Incomplete secondary (mother)	0.117	0.002	0.117	0.000	0.968	0.000	0.000
Complete secondary (mother)	0.336	0.003	0.338	0.000	0.523	-0.002	-0.003
Incomplete university (mother)	0.306	0.002	0.309	0.000	0.297	-0.003	-0.004
Complete university (mother)	0.019	0.001	0.019	0.000	0.532	0.001	0.003
Postgraduate (mother)	0.000	0.000	0.000	0.000	0.002	0.000	-0.005
Father characteristics							
Father's years of education	11.710	0.019	11.680	0.001	0.132	0.030	0.006
Father's age at birth 10–19	0.030	0.001	0.050	0.000	< 0.001	-0.020	-0.073
Father's age at birth 20–29	0.339	0.003	0.454	0.000	< 0.001	-0.115	-0.168
Father's age at birth 30–39	0.430	0.003	0.396	0.000	< 0.001	0.035	0.050
Father's age at birth 40+	0.201	0.002	0.101	0.000	< 0.001	0.101	0.201
No schooling (father)	0.008	0.001	0.007	0.000	0.155	0.001	0.007
Incomplete primary (father)	0.111	0.002	0.102	0.000	< 0.001	0.009	0.020
Complete primary (father)	0.119	0.002	0.130	0.000	< 0.001	-0.011	-0.024
Incomplete secondary (father)	0.091	0.002	0.094	0.000	0.071	-0.003	-0.008
Complete secondary (father)	0.320	0.003	0.321	0.000	0.931	0.000	0.000
Incomplete university (father)	0.312	0.003	0.310	0.000	0.429	0.002	0.003
Complete university (father)	0.040	0.001	0.036	0.000	0.010	0.003	0.011
Postgraduate (father)	0.000	0.000	0.000	0.000	< 0.001	0.000	-0.007
Observations	32,098		505,768				

Notes: This table shows summary statistics for treated and control students in the analysis sample. Means and standard errors are reported separately for each group. “Diff.” is the raw difference in means between treated and control students, and “Std. Diff.” is the standardized mean difference. P-values below 0.001 are reported as < 0.001.

Table 2: Summary statistics of hospitalizations and cancer-related admissions by family member

	Total		Mother		Father	
	Mean	N	Mean	N	Mean	N
General hospitalizations						
N of hospitalizations (all causes)	1.930	32,098	1.808	20,890	2.157	11,208
Days in hospital (all causes)	11.663	32,098	9.043	20,890	16.546	11,208
Cancer hospitalizations						
N of cancer hospitalizations	1.444	32,098	1.387	20,890	1.551	11,208
Days in hospital (cancer)	9.043	32,098	7.012	20,890	12.829	11,208
Cancer types (ICD-10 categories)						
1. Lip, oral cavity and pharynx (C00–C14)	0.013	428	0.009	181	0.022	247
2. Digestive organs (C15–C26)	0.175	5,621	0.109	2,282	0.298	3,339
3. Respiratory organs (C30–C39)	0.030	951	0.016	332	0.055	619
4. Bones and articular cartilage (C40–C41)	0.008	246	0.005	112	0.012	134
5. Skin melanoma and other cancers (C43–C44)	0.033	1,061	0.025	513	0.049	548
6. Breast (C50)	0.173	5,551	0.264	5,517	0.003	34
7. Female genital organs (C51–C58)	0.102	3,258	0.156	3,257	*	*
8. Male genital organs (C60–C63)	0.071	2,263	*	*	0.202	2,260
9. Urinary tract (C64–C68)	0.040	1,295	0.017	346	0.085	949
10. Central nervous system (C69–C72)	0.017	536	0.012	245	0.026	291
11. Endocrine glands (C73–C75)	0.121	3,892	0.155	3,240	0.058	652
12. Multiple malignant neoplasms (C76–C80)	0.034	1,102	0.027	558	0.049	544
13. Lymphatic system (C81–C97)	0.062	1,975	0.037	782	0.106	1,193
14. In situ malignant neoplasms (D00–D09)	0.111	3,556	0.160	3,348	0.019	208
15. Soft tissue and mesothelial neoplasms (C45–C49)	0.011	363	0.008	174	0.017	189
Severity categories						
Low severity	0.762	24,462	0.776	16,209	0.736	8,253
High severity	0.238	7,636	0.224	4,681	0.264	2,955

Notes: This table reports descriptive statistics for all-cause hospitalizations and cancer-related admissions, separately for the full sample, mothers, and fathers. Low severity indicates a single parental hospital admission in the year of the shock, and high severity two or more admissions. Asterisks (*) indicate suppressed values due to small cell counts.

Table 3: Average effect of a parental health shock on educational outcomes

	(1) Enrollment	(2) Attendance	(3) Chronic Absenteeism
$Post_{ct} \times Treat_{ic}$	-0.502*** (0.053)	-0.825*** (0.070)	1.302*** (0.142)
Observations	4,469,494	4,469,494	4,469,494
Control mean	99.50	92.44	7.12

Notes: This table reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2 for each outcome. Column (1) reports the effect on school enrollment, column (2) on the attendance rate and column (3) on chronic absenteeism (defined as annual attendance < 85%). Control mean is the mean of the outcome among control students at $t = -2$. Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Average effect of a parental health shock by cancer severity

	(1)	(2)	(3)	(4)	(5)	(6)
	Enrollment		Attendance		Chronic Absenteeism	
	Low Severity	High Severity	Low Severity	High Severity	Low Severity	High Severity
$Post_{ct} \times Treat_{ic}$	-0.488*** (0.061)	-0.546*** (0.109)	-0.685*** (0.080)	-1.271*** (0.145)	0.892*** (0.162)	2.614*** (0.298)
Observations	3,409,350	1,060,144	3,409,350	1,060,144	3,409,350	1,060,144
Control mean	99.49	99.53	92.42	92.51	7.20	6.86

Notes: This table reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2 on school enrollment, the attendance rate, and chronic absenteeism (defined as annual attendance < 85%), separately for low- and high-severity shocks. Low severity is proxied by a single cancer-related hospital admission in the year of the shock, and high severity by two or more. Control mean is the mean of the outcome among control students at $t = -2$. Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Average effect of a parental health shock by student gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Enrollment			Attendance			Chronic Absenteeism		
	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
$Post_{ct} \times Treat_{ic}$	-0.463*** (0.074)	-0.541*** (0.076)	0.078 (0.106)	-1.245*** (0.098)	-0.402*** (0.100)	-0.843*** (0.140)	2.297*** (0.205)	0.301 (0.196)	1.996*** (0.284)
Observations	4,469,494			4,469,494			4,469,494		

Notes: This table reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, allowing it to vary by student gender. The outcome is school enrollment in columns (1)–(3), the attendance rate in columns (4)–(6), and chronic absenteeism (defined as annual attendance < 85%) in columns (7)–(9). For each outcome, the first column reports the effect for female students, the second for male students, and the third the difference between the two (female minus male). Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Average effect of a parental health shock by gender of the affected parent

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Enrollment			Attendance			Chronic Absenteeism		
	Mother	Father	Diff	Mother	Father	Diff	Mother	Father	Diff
$Post_{ct} \times Treat_{ic}$	-0.566*** (0.066)	-0.380*** (0.088)	-0.186* (0.110)	-0.827*** (0.087)	-0.819*** (0.117)	-0.008 (0.146)	1.096*** (0.177)	1.690*** (0.239)	-0.593** (0.297)
Observations	4,469,494			4,469,494			4,469,494		

Notes: This table reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, allowing it to vary by which parent was hospitalized. The outcome is school enrollment in columns (1)–(3), the attendance rate in columns (4)–(6), and chronic absenteeism (defined as annual attendance < 85%) in columns (7)–(9). For each outcome, the first column reports the effect when the mother is hospitalized, the second when the father is hospitalized, and the third the difference between the two (mother minus father). Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of a parental health shock on parent formal employment

	(1)	(2)	(3)	(4)
	Formal employment		Months in formal employment	
	Mothers	Fathers	Mothers	Fathers
$Post_{ct} \times Treat_{ic}$	-3.301*** (0.262)	-2.341*** (0.327)	-0.312*** (0.025)	-0.289*** (0.035)
Observations	2,570,330	1,341,128	2,570,330	1,341,128
Control mean	35.16	56.37	3.20	5.58

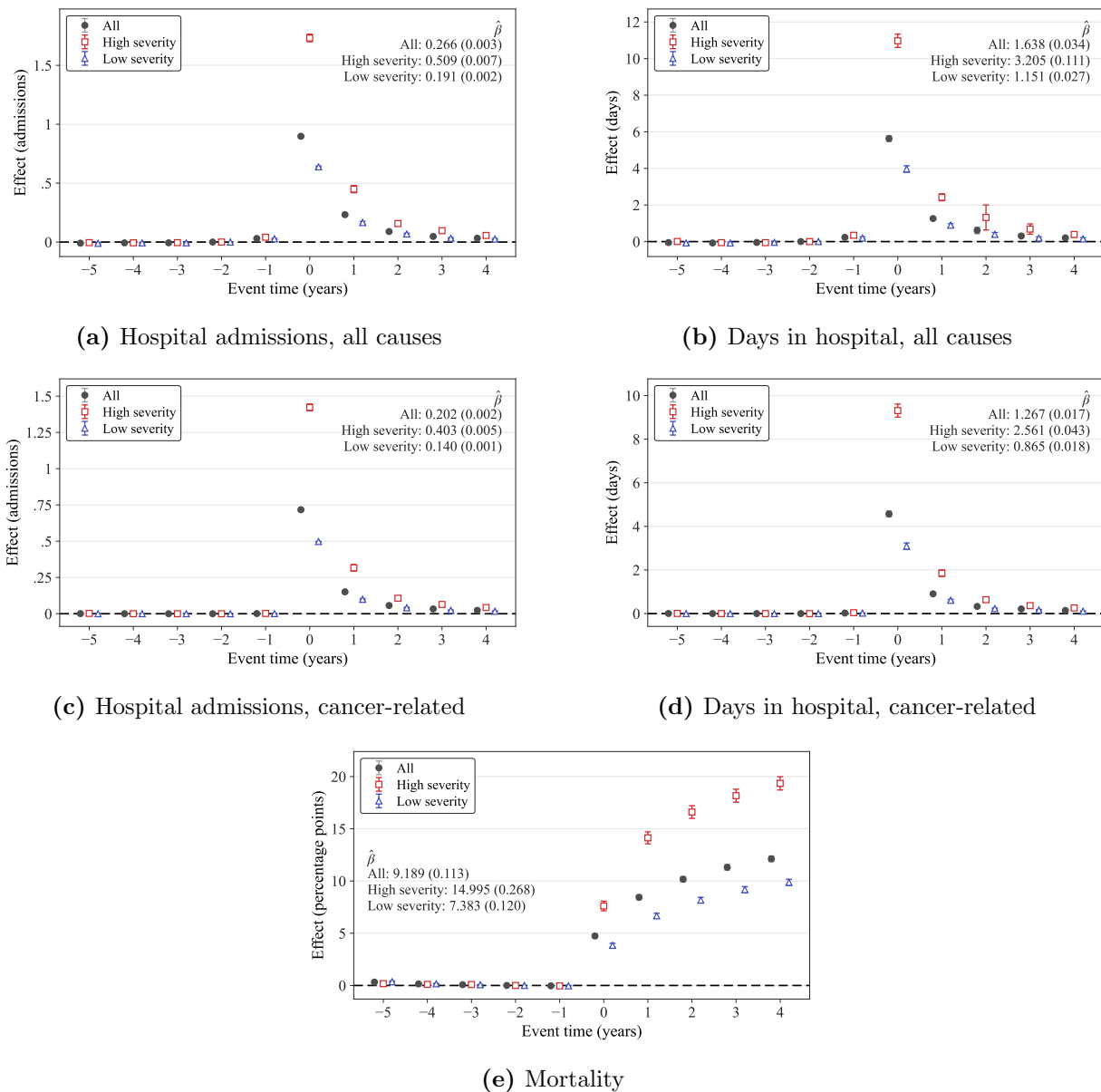
Notes: This table reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2 estimated on the parents of treated and control students, restricting the sample to the same sub-experiments and event-time window as the student panel. The outcome in columns (1) and (2) is an indicator (in percentage points) for any formal employment during the year, measured from unemployment insurance and pension contribution records; the outcome in columns (3) and (4) is the number of months with formal employment during the year. Each affected parent is compared with control-classmate parents of the same sex: columns (1) and (3) compare mothers with cancer to the mothers of control classmates, and columns (2) and (4) compare fathers with cancer to the fathers of control classmates. Control mean is the mean of the outcome among control parents at $t = -2$. Standard errors in parentheses are clustered at the parent level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of a parental health shock on children’s hospitalizations

	(1)	(2)	(3)	(4)	(5)
	Any hospitalization	Mental-health diagnosis	Alcohol, drug, or mood disorder	Number of hospitalizations	Days in hospital
$Post_{ct} \times Treat_{ic}$	-0.136* (0.083)	-0.020 (0.016)	-0.001 (0.012)	-0.0011 (0.0012)	-0.0005 (0.0083)
Observations	3,931,620	3,931,620	3,931,620	3,931,620	3,931,620
Control mean	2.78	0.060	0.030	0.0334	0.1117

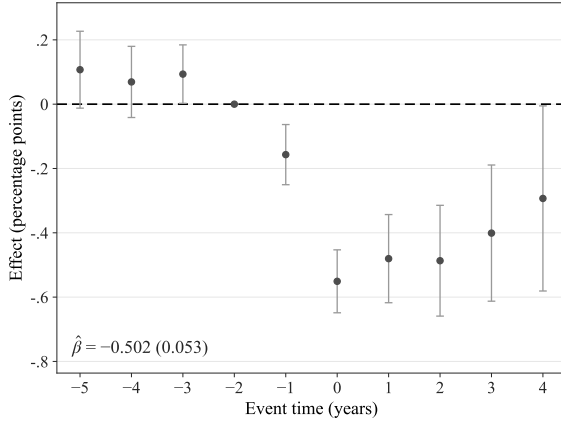
Notes: This table reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2 estimated on the treated and control students’ hospitalizations, measured from the Ministry of Health hospital discharge records; the sample covers the sub-experiments of the student panel over event years -4 through $+4$. The outcomes in columns (1)–(3) are indicators (in percentage points) for any hospital discharge of the student during the year: for any cause (1); with a mental or behavioral diagnosis, ICD-10 chapter F (2); and with an alcohol- (F10), drug- (F11–F16, F18–F19), or mood-disorder-related (F30–F39) diagnosis (3). Column (4) is the number of hospitalizations and column (5) the number of days in hospital during the year. Control mean is the mean of the outcome among control students at $t = -2$. Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Effect of a parental health shock on parental health outcomes, overall and by severity

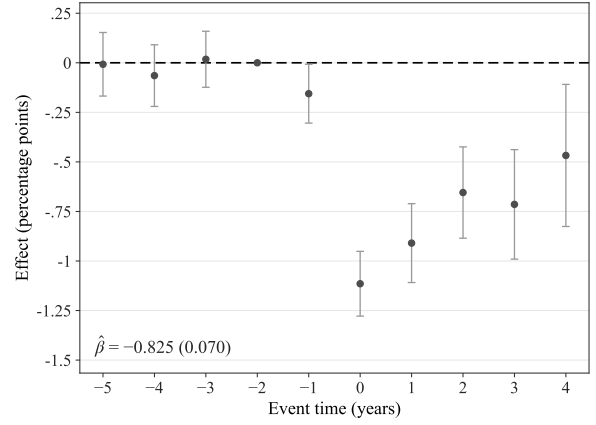


Notes: This figure plots the event-study coefficients from Equation 1 for the impact of a first parental cancer hospitalization on parental health outcomes, for all parents and separately for high and low severity shocks (two or more versus a single hospital admission in the year of the shock). Panels (a) and (b) report effects on the number of hospital admissions and days spent in the hospital for any cause; Panels (c) and (d) restrict them to cancer-related admissions, which are zero before the first cancer hospitalization by construction; Panel (e) reports effects on parental mortality. The reference period is $t = -2$, and coefficients are expressed as deviations (admissions, days, and percentage points, respectively) from that period. The text in each panel reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2 for each group, with its standard error. Control means at $t = -2$ for all parents: 0.077 admissions, 0.316 days, and a mortality rate of 1.312. The sample consists of mothers and fathers of treated and control students in the analysis sample: students exposed to a first parental cancer hospitalization between 2010 and 2018 and their untreated classmates in the same school, grade, and cohort. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the student level.

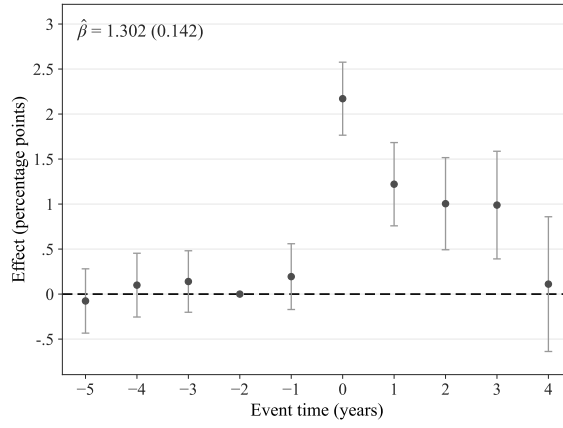
Figure 2: Effect of a parental health shock on educational outcomes



(a) Enrollment



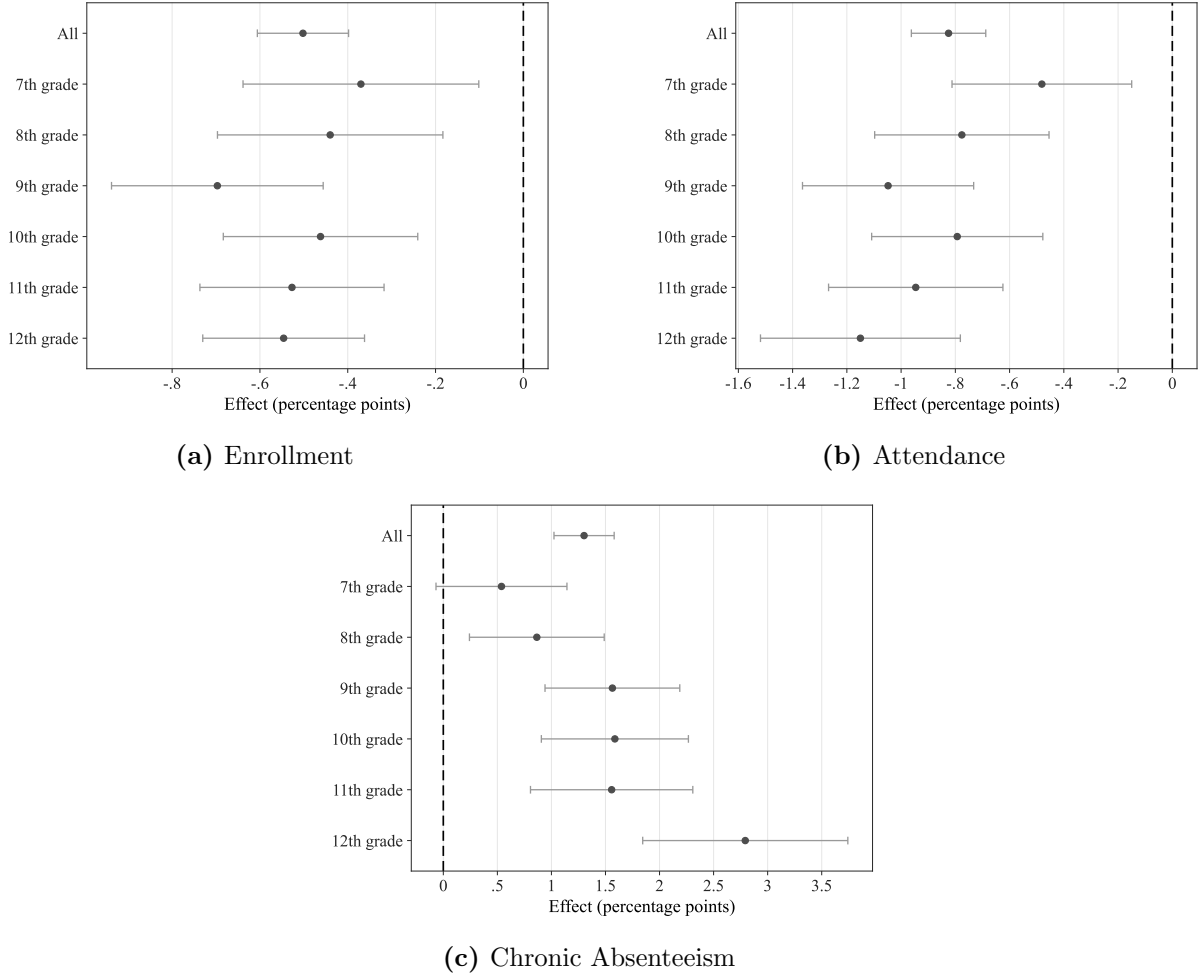
(b) Attendance



(c) Chronic Absenteeism

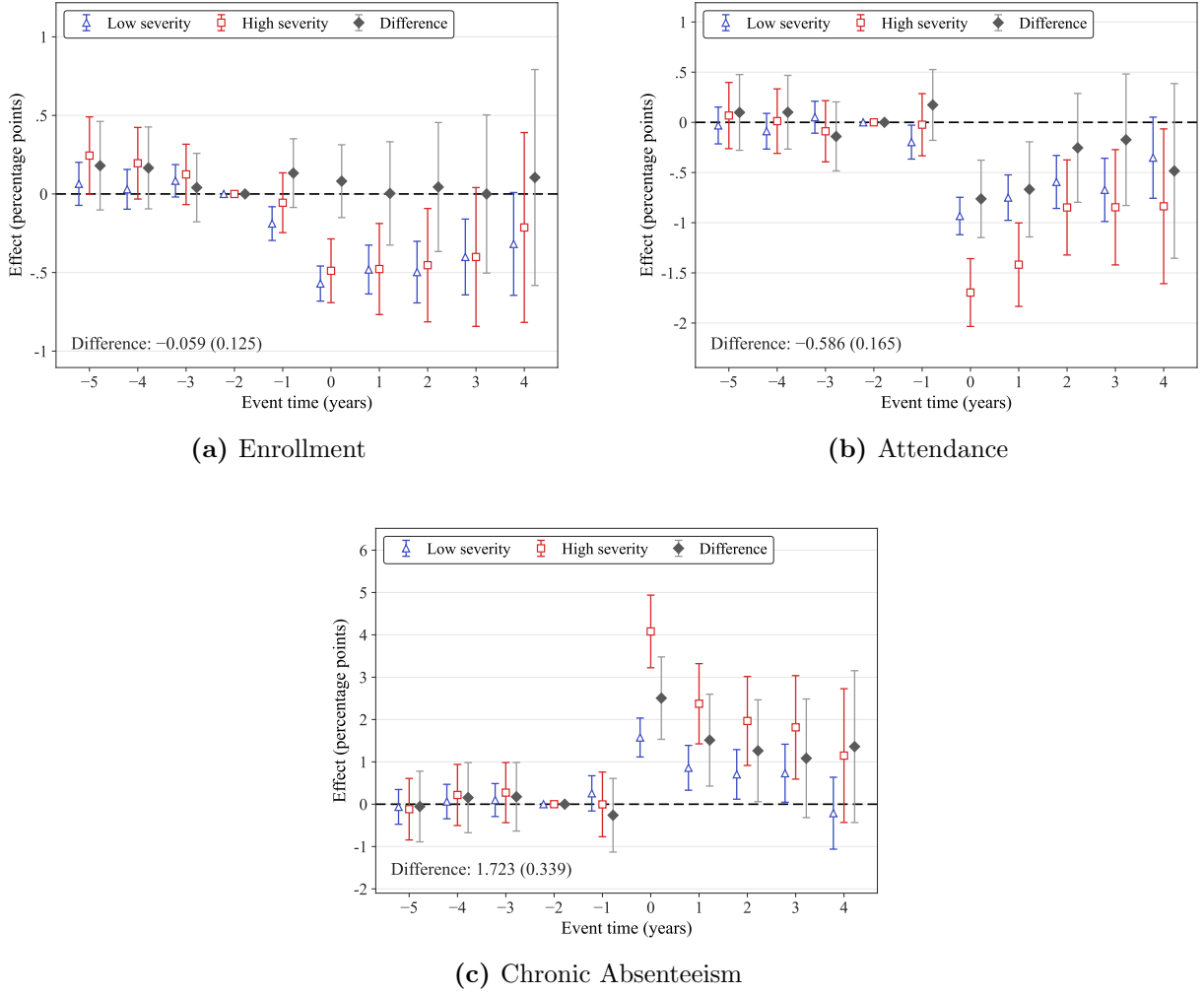
Notes: This figure plots the estimated coefficients from Equation 1 for school enrollment (Panel a), attendance rate (Panel b), and chronic absenteeism (defined as annual attendance < 85%, Panel c). The reference period is $t = -2$, and coefficients are expressed as percentage-point deviations from that period. The text in each panel reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, with its standard error. Control means at $t = -2$: 99.50 (enrollment), 92.44 (attendance), and 7.12 (chronic absenteeism). Vertical lines represent 95% confidence intervals. Standard errors are clustered at the student level.

Figure 3: Average effect of a parental health shock by student grade



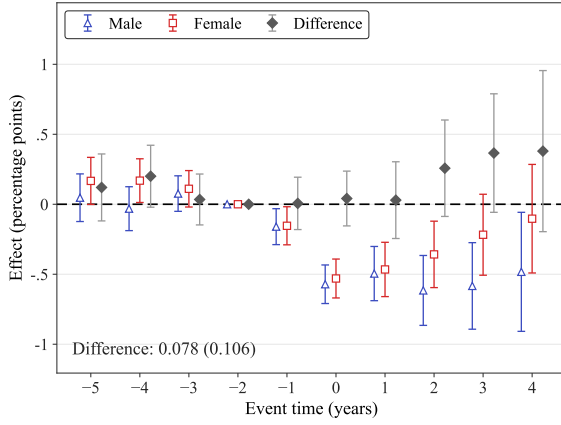
Notes: This figure plots the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2 for school enrollment (Panel a), the attendance rate (Panel b), and chronic absenteeism (defined as annual attendance $< 85\%$, Panel c), in percentage points. The top point in each panel shows the overall effect, followed by grade-specific estimates based on the student's grade at the time of the parental health shock. Control means at $t = -2$: 99.50 (enrollment), 92.44 (attendance), and 7.12 (chronic absenteeism). Dots represent point estimates, and horizontal bars denote 95% confidence intervals. Standard errors are clustered at the student level.

Figure 4: Effect of a parental health shock by cancer severity

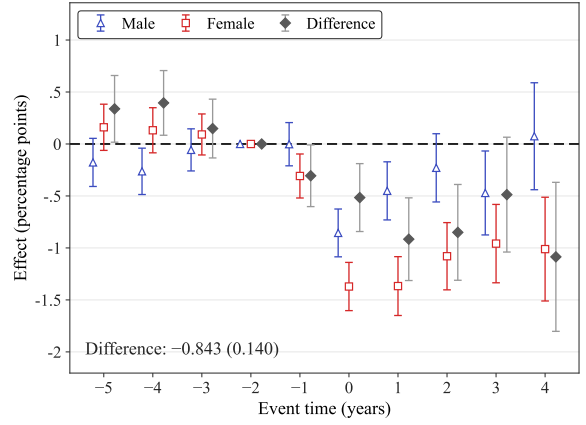


Notes: This figure plots the estimated coefficients from Equation 1, allowing the coefficients to vary by cancer severity (high severity: two or more parental hospital admissions in the year of the shock; low severity: a single admission). The figure reports estimates separately for high- and low-severity parental health shocks, as well as the difference between the two (high minus low), for school enrollment (Panel a), attendance rate (Panel b), and chronic absenteeism (defined as annual attendance $< 85\%$, Panel c). The reference period is $t = -2$, and coefficients are expressed as percentage-point deviations from that period. The text in each panel reports the difference in the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, with its standard error. Control means at $t = -2$, low and high severity: 99.49 and 99.53 (enrollment), 92.42 and 92.51 (attendance), and 7.20 and 6.86 (chronic absenteeism). Vertical lines represent 95% confidence intervals. Standard errors are clustered at the student level.

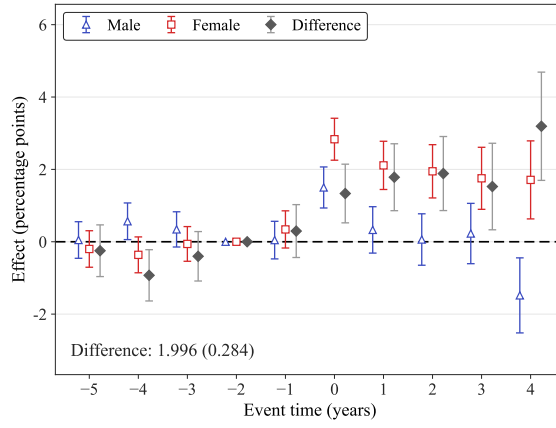
Figure 5: Effect of a parental health shock by student gender



(a) Enrollment



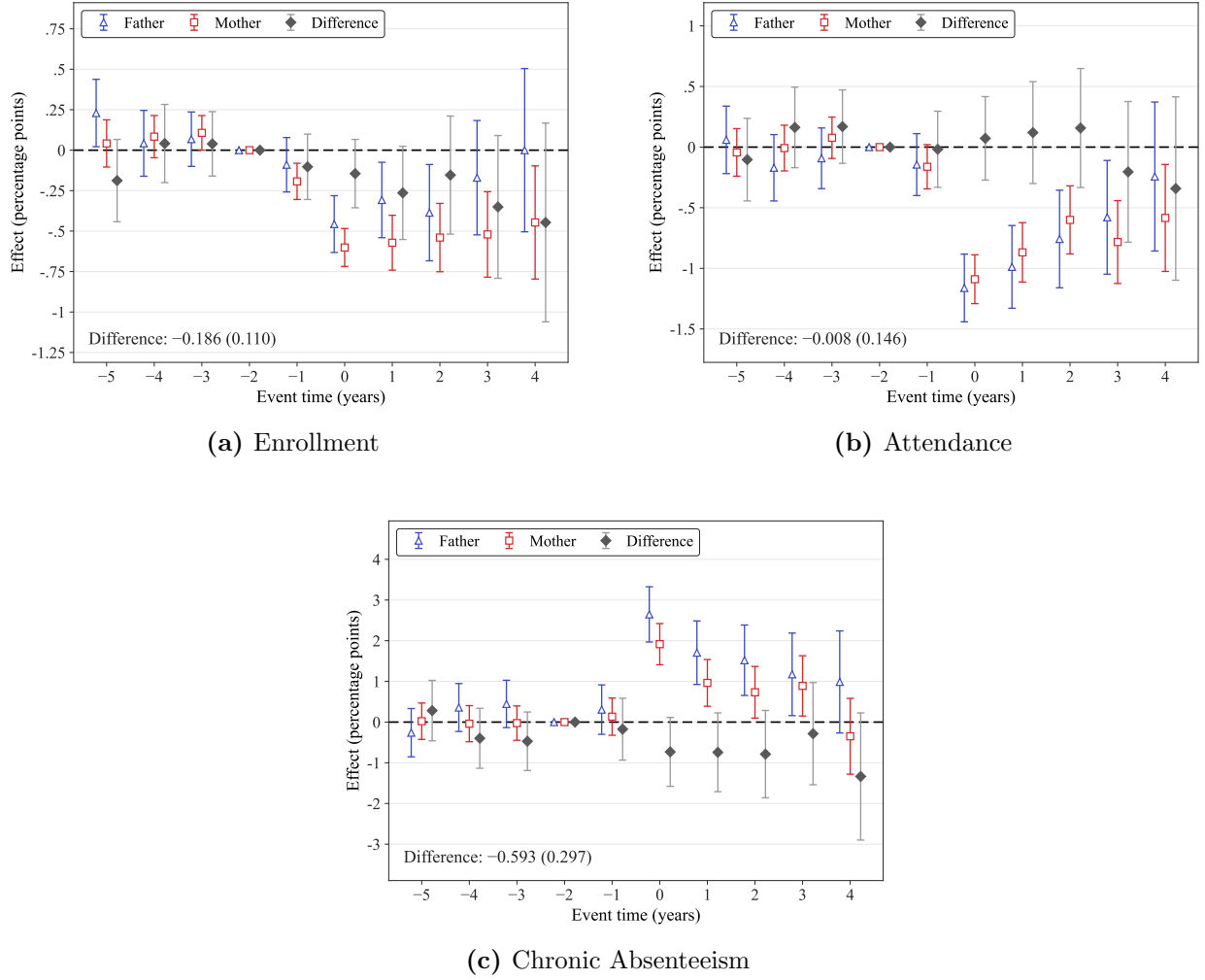
(b) Attendance



(c) Chronic Absenteeism

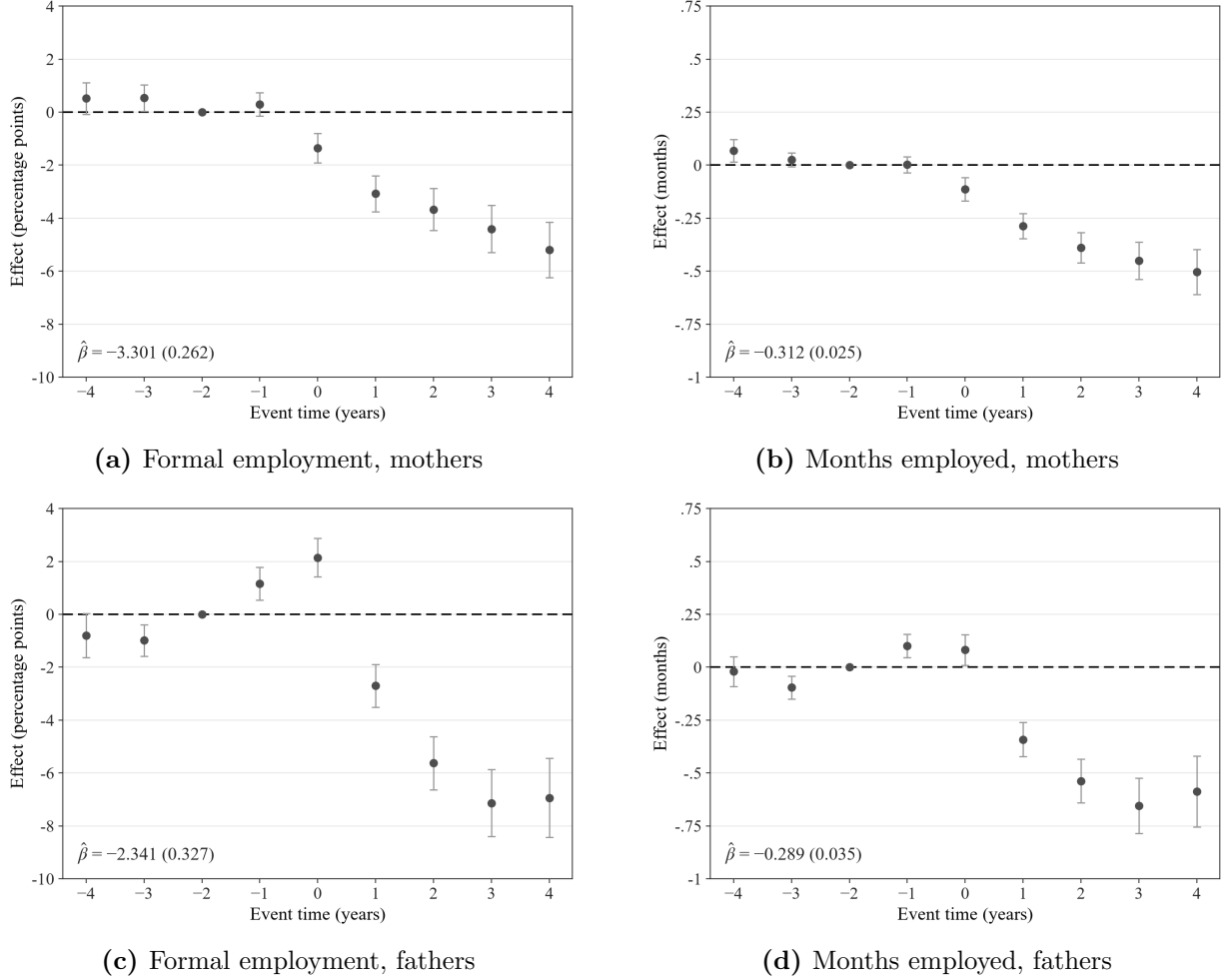
Notes: This figure plots the estimated coefficients from Equation 1, allowing the coefficients to vary by student gender. The figure reports estimates separately for female and male students, as well as the difference between the two (female minus male), for school enrollment (Panel a), attendance rate (Panel b), and chronic absenteeism (defined as annual attendance < 85%, Panel c). The reference period is $t = -2$, and coefficients are expressed as percentage-point deviations from that period. The text in each panel reports the difference in the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, with its standard error. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the student level.

Figure 6: Effect of a parental health shock by gender of the affected parent



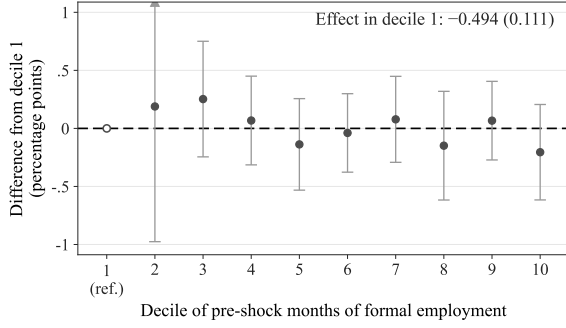
Notes: This figure plots the estimated coefficients from Equation 1, allowing the coefficients to vary by the gender of the hospitalized parent. The figure reports estimates separately for students whose mother or father was hospitalized, as well as the difference between the two (mother minus father), for school enrollment (Panel a), attendance rate (Panel b), and chronic absenteeism (defined as annual attendance < 85%, Panel c). The reference period is $t = -2$, and coefficients are expressed as percentage-point deviations from that period. The text in each panel reports the difference in the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, with its standard error. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the student level.

Figure 7: Effect of a parental health shock on parent formal employment, mothers and fathers

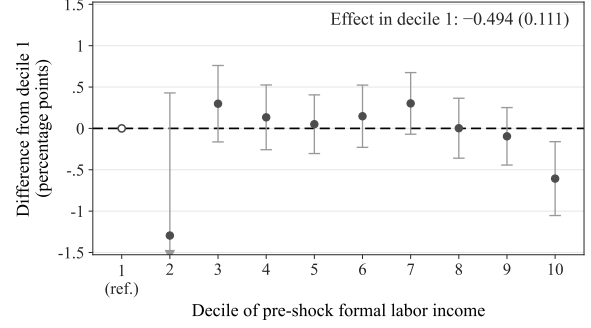


Notes: This figure plots the event-study coefficients from Equation 1 estimated on the parents of treated and control students, restricting the sample to the same sub-experiments as the student panel, over event years -4 through $+4$. Each hospitalized parent is compared with control-classmate parents of the same sex: Panels (a) and (b) compare mothers with cancer to the mothers of control classmates, and Panels (c) and (d) compare fathers with cancer to the fathers of control classmates. Panels (a) and (c) report effects on an indicator for any formal employment during the year (in percentage points), and Panels (b) and (d) on the number of months with formal employment during the year, both measured from unemployment insurance and pension contribution records. The reference period is $t = -2$. The text in each panel reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, with its standard error. Control means at $t = -2$: 35.16% employed and 3.20 months for mothers, and 56.37% employed and 5.58 months for fathers. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the parent level.

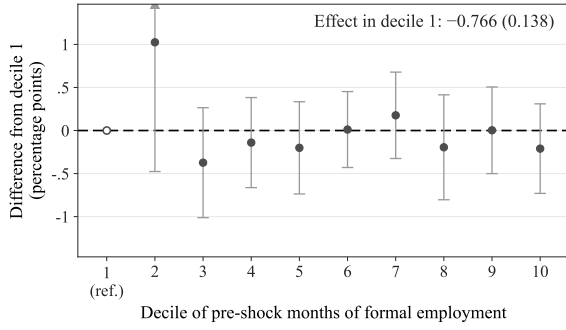
Figure 8: Effect of a parental health shock on educational outcomes by deciles of the parents' pre-shock labor-market position



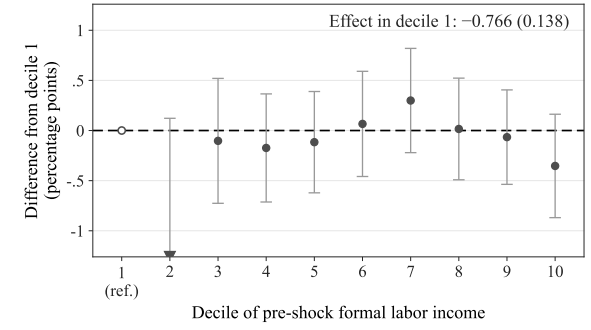
(a) Enrollment: employment deciles



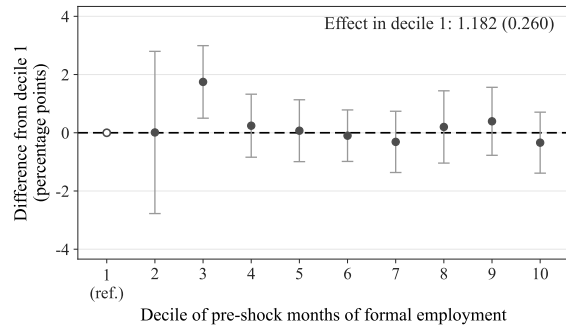
(b) Enrollment: income deciles



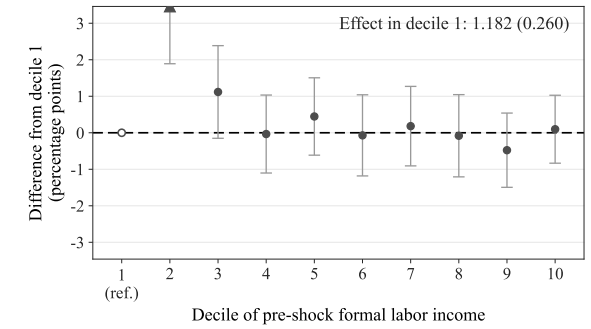
(c) Attendance: employment deciles



(d) Attendance: income deciles



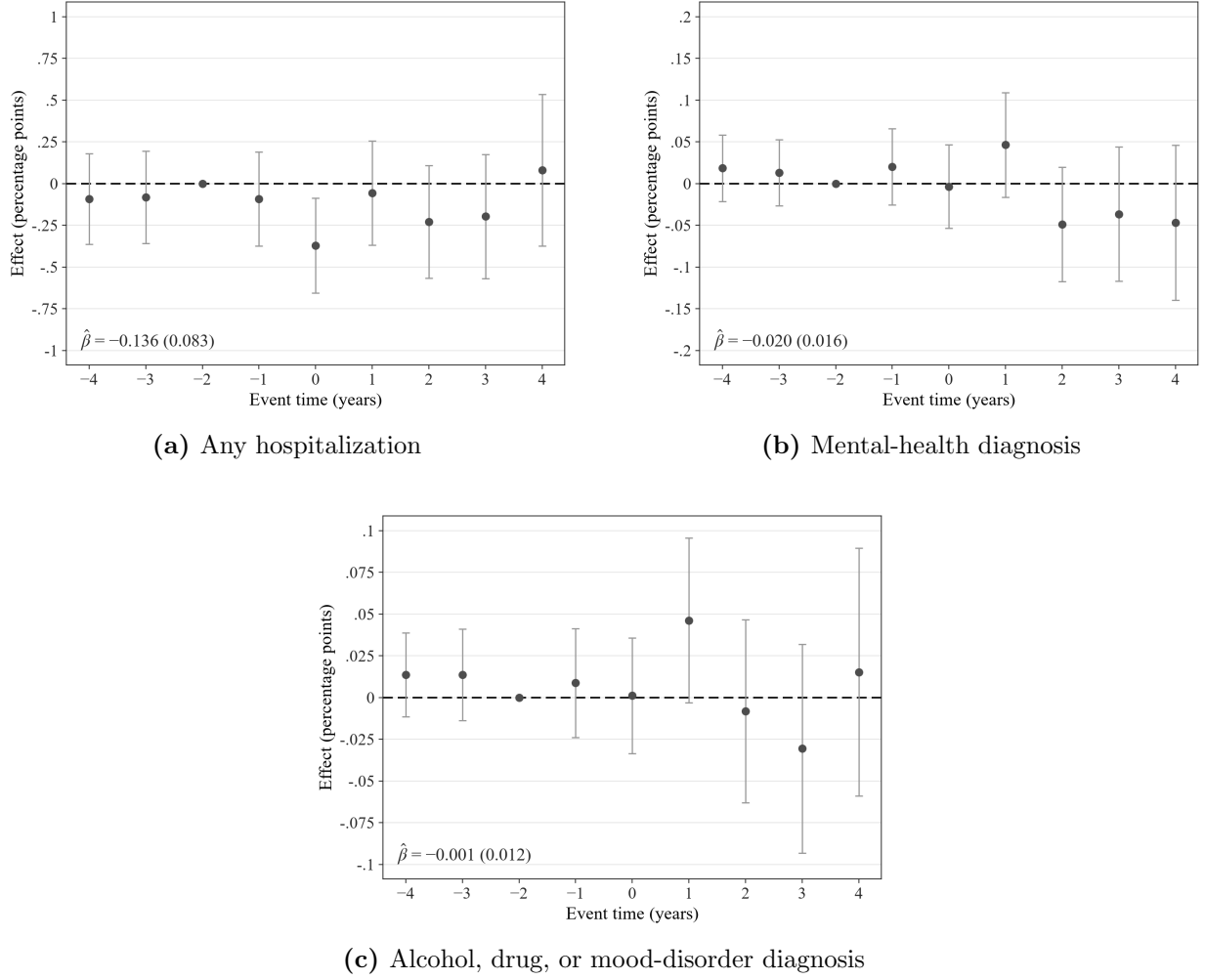
(e) Chronic Absenteeism: employment deciles



(f) Chronic Absenteeism: income deciles

Notes: This figure plots the coefficients on the interaction of $Post_{ct} \times Treat_{ic}$ with deciles of the parents' pre-shock position in the formal labor market, from Equation 2 augmented with these interactions. Deciles are computed within cohort over the three years ending at the reference period ($t \in [-4, -2]$), for months of formal employment (left column) and formal labor income (right column), measured from unemployment insurance and pension contribution records; households with no observed formal labor activity in the window are in the bottom decile, which serves as the reference group. Each point is the difference from the reference group, in percentage points; vertical lines represent 95% confidence intervals. The text in each panel reports the estimated post-shock effect for the reference group, with its standard error. The vertical axis is scaled to deciles 3–10; where the estimate or confidence interval for decile 2 extends beyond it, an arrow marks the edge. Standard errors are clustered at the student level.

Figure 9: Effect of a parental health shock on children's hospitalizations



Notes: This figure plots the event-study coefficients from Equation 1 estimated on the treated and control students' hospitalizations, measured from the Ministry of Health hospital discharge records, on the student panel used for the educational outcomes (event years -4 through $+4$). The outcome in Panel (a) is an indicator (in percentage points) for any hospital discharge of the student during the year; in Panel (b), for a discharge with a mental or behavioral diagnosis (ICD-10 chapter F); and in Panel (c), for a discharge with an alcohol- (F10), drug- (F11–F16, F18–F19), or mood-disorder-related (F30–F39) diagnosis. The reference period is $t = -2$. Vertical lines represent 95% confidence intervals. The text in each panel reports the estimated coefficient on $Post_{ct} \times Treat_{ic}$ from Equation 2, with its standard error. Control means at $t = -2$, in percent: 2.78 (any hospitalization), 0.060 (mental-health hospitalizations), and 0.030 (alcohol, drug, or mood-disorder hospitalizations). Standard errors are clustered at the student level.

A Additional Figures and Tables

Table A.1: Effect of a parental health shock on parental health outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All			Low Severity			High Severity		
	Mortality	Days	N. Hosp.	Mortality	Days	N. Hosp.	Mortality	Days	N. Hosp.
-5	0.322*** (0.033)	-0.053** (0.022)	-0.009*** (0.002)	0.355*** (0.036)	-0.075*** (0.026)	-0.011*** (0.003)	0.177** (0.074)	0.005 (0.045)	-0.005 (0.005)
-4	0.147*** (0.017)	-0.075*** (0.021)	-0.007*** (0.002)	0.159*** (0.019)	-0.080*** (0.025)	-0.007*** (0.003)	0.103*** (0.040)	-0.059* (0.034)	-0.007 (0.004)
-3	0.073*** (0.011)	-0.047** (0.023)	-0.006*** (0.002)	0.068*** (0.014)	-0.044 (0.028)	-0.007*** (0.002)	0.090*** (0.021)	-0.058 (0.036)	-0.005 (0.005)
-1	-0.038*** (0.014)	0.231*** (0.026)	0.030*** (0.002)	-0.036** (0.016)	0.195*** (0.031)	0.027*** (0.003)	-0.043 (0.028)	0.346*** (0.048)	0.041*** (0.005)
0	4.737*** (0.094)	5.630*** (0.083)	0.898*** (0.006)	3.842*** (0.099)	3.966*** (0.090)	0.638*** (0.004)	7.611*** (0.235)	10.973*** (0.184)	1.732*** (0.016)
1	8.442*** (0.120)	1.258*** (0.040)	0.233*** (0.005)	6.670*** (0.126)	0.897*** (0.042)	0.165*** (0.005)	14.132*** (0.293)	2.420*** (0.097)	0.449*** (0.016)
2	10.171*** (0.130)	0.613*** (0.092)	0.089*** (0.004)	8.167*** (0.137)	0.393*** (0.053)	0.068*** (0.004)	16.604*** (0.308)	1.317*** (0.349)	0.157*** (0.011)
3	11.311*** (0.136)	0.307*** (0.043)	0.048*** (0.003)	9.174*** (0.145)	0.190*** (0.034)	0.032*** (0.003)	18.168*** (0.317)	0.684*** (0.144)	0.097*** (0.009)
4	12.124*** (0.140)	0.203*** (0.033)	0.033*** (0.003)	9.873*** (0.150)	0.145*** (0.035)	0.026*** (0.003)	19.351*** (0.324)	0.389*** (0.076)	0.056*** (0.007)
Observations	7,377,144	7,377,144	7,377,144	5,629,696	5,629,696	5,629,696	1,747,448	1,747,448	1,747,448
Control mean	1.312	0.316	0.077	1.316	0.316	0.077	1.297	0.314	0.077

Notes: Event-study estimates from Equation 1 for parental hospitalization outcomes in period t . The reference period is $t = -2$. Columns (1)–(3) include all shocks, columns (4)–(6) low-severity shocks, and columns (7)–(9) high-severity shocks (a single versus two or more hospital admissions in the year of the shock). Within each group, the outcomes are the parental mortality rate (columns (1), (4), and (7)), the number of days spent in the hospital (columns (2), (5), and (8)), and the number of hospitalizations (columns (3), (6), and (9)). Control mean is the mean of the outcome among control parents at $t = -2$. Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Effect of a parental health shock on educational outcomes: event-study estimates

	(1) Enrollment	(2) Attendance	(3) Chronic Absenteeism
-5	0.107* (0.061)	-0.008 (0.082)	-0.077 (0.182)
-4	0.069 (0.056)	-0.065 (0.079)	0.100 (0.181)
-3	0.093** (0.046)	0.018 (0.072)	0.140 (0.174)
-1	-0.157*** (0.048)	-0.156** (0.076)	0.194 (0.186)
0	-0.551*** (0.050)	-1.115*** (0.083)	2.171*** (0.207)
1	-0.480*** (0.070)	-0.910*** (0.102)	1.221*** (0.236)
2	-0.487*** (0.088)	-0.655*** (0.118)	1.004*** (0.261)
3	-0.401*** (0.108)	-0.714*** (0.141)	0.989*** (0.305)
4	-0.293** (0.147)	-0.467** (0.183)	0.111 (0.382)
Observations	4,469,494	4,469,494	4,469,494
Control mean	99.50	92.44	7.12

Notes: This table shows the estimated coefficients from Equation 1. The reference period is $t = -2$. Column (1) reports the effect on school enrollment, column (2) on the attendance rate, and column (3) on chronic absenteeism (defined as annual attendance $< 85\%$). Control mean is the mean of the outcome among control students at $t = -2$. Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Effect of a parental health shock by cancer severity: event-study estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Enrollment		Attendance		Chronic Absenteeism	
	Low Severity	High Severity	Low Severity	High Severity	Low Severity	High Severity
-5	0.064 (0.070)	0.244* (0.126)	-0.031 (0.094)	0.068 (0.168)	-0.064 (0.209)	-0.118 (0.371)
-4	0.030 (0.065)	0.196* (0.116)	-0.089 (0.091)	0.012 (0.164)	0.063 (0.207)	0.218 (0.368)
-3	0.084 (0.053)	0.125 (0.098)	0.051 (0.081)	-0.089 (0.155)	0.098 (0.199)	0.274 (0.362)
-1	-0.188*** (0.055)	-0.056 (0.097)	-0.197** (0.086)	-0.024 (0.158)	0.256 (0.212)	-0.005 (0.390)
0	-0.570*** (0.057)	-0.489*** (0.104)	-0.933*** (0.095)	-1.696*** (0.172)	1.575*** (0.235)	4.080*** (0.438)
1	-0.481*** (0.079)	-0.478*** (0.148)	-0.750*** (0.116)	-1.418*** (0.212)	0.859*** (0.270)	2.373*** (0.483)
2	-0.497*** (0.100)	-0.453** (0.184)	-0.594*** (0.135)	-0.848*** (0.242)	0.704** (0.299)	1.966*** (0.536)
3	-0.401*** (0.123)	-0.401* (0.225)	-0.673*** (0.161)	-0.846*** (0.293)	0.731** (0.350)	1.815*** (0.624)
4	-0.318* (0.167)	-0.213 (0.308)	-0.352* (0.206)	-0.837** (0.393)	-0.213 (0.433)	1.148 (0.806)
Observations	3,409,350	1,060,144	3,409,350	1,060,144	3,409,350	1,060,144
Control mean	99.49	99.53	92.42	92.51	7.20	6.86

Notes: This table shows the estimated coefficients from Equation 1, estimated separately for low- and high-severity shocks. The reference period is $t = -2$. The outcome is school enrollment in columns (1) and (2), the attendance rate in columns (3) and (4), and chronic absenteeism (defined as annual attendance $< 85\%$) in columns (5) and (6). Odd-numbered columns report low-severity shocks and even-numbered columns high-severity shocks. Low severity is proxied by a single cancer-related hospital admission, and high severity by two or more. Control mean is the mean of the outcome among control students at $t = -2$. Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Effect of a parental health shock by student gender: event-study estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Enrollment			Attendance			Chronic Absenteeism		
	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
-5	0.167*	0.047	0.120	0.160	-0.177	0.338**	-0.200	0.048	-0.248
	(0.086)	(0.087)	(0.122)	(0.113)	(0.118)	(0.164)	(0.257)	(0.258)	(0.364)
-4	0.169**	-0.032	0.200*	0.132	-0.263**	0.395**	-0.362	0.566**	-0.928**
	(0.080)	(0.080)	(0.113)	(0.111)	(0.114)	(0.159)	(0.253)	(0.258)	(0.362)
-3	0.110*	0.076	0.034	0.092	-0.057	0.148	-0.060	0.342	-0.402
	(0.066)	(0.065)	(0.093)	(0.101)	(0.103)	(0.144)	(0.245)	(0.248)	(0.349)
-1	-0.154**	-0.160**	0.006	-0.308***	-0.002	-0.306**	0.341	0.046	0.295
	(0.069)	(0.065)	(0.095)	(0.108)	(0.106)	(0.151)	(0.262)	(0.265)	(0.373)
0	-0.530***	-0.572***	0.041	-1.371***	-0.856***	-0.516***	2.834***	1.500***	1.333***
	(0.071)	(0.070)	(0.100)	(0.118)	(0.117)	(0.167)	(0.296)	(0.289)	(0.414)
1	-0.466***	-0.495***	0.029	-1.367***	-0.451***	-0.916***	2.111***	0.328	1.783***
	(0.099)	(0.099)	(0.140)	(0.144)	(0.143)	(0.203)	(0.340)	(0.327)	(0.472)
2	-0.358***	-0.616***	0.257	-1.080***	-0.230	-0.850***	1.947***	0.062	1.885***
	(0.121)	(0.127)	(0.176)	(0.165)	(0.167)	(0.235)	(0.376)	(0.363)	(0.522)
3	-0.218	-0.584***	0.366*	-0.958***	-0.471**	-0.487*	1.754***	0.227	1.526**
	(0.148)	(0.158)	(0.216)	(0.192)	(0.206)	(0.282)	(0.437)	(0.425)	(0.610)
4	-0.103	-0.483**	0.380	-1.011***	0.074	-1.086***	1.710***	-1.482***	3.192***
	(0.198)	(0.217)	(0.294)	(0.255)	(0.262)	(0.366)	(0.550)	(0.529)	(0.763)
Observations	4,469,494			4,469,494			4,469,494		

Notes: This table reports the estimated coefficients from Equation 1, allowing them to vary by student gender. The reference period is $t = -2$. The outcome is school enrollment in columns (1)–(3), the attendance rate in columns (4)–(6), and chronic absenteeism (defined as annual attendance $< 85\%$) in columns (7)–(9). For each outcome, the first column reports the effect for female students, the second for male students, and the third the difference between the two (female minus male). Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Effect of a parental health shock by gender of the affected parent: event-study estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Enrollment			Attendance			Chronic Absenteeism		
	Mother	Father	Diff	Mother	Father	Diff	Mother	Father	Diff
-5	0.042 (0.074)	0.229** (0.106)	-0.188 (0.130)	-0.044 (0.100)	0.060 (0.142)	-0.103 (0.174)	0.022 (0.228)	-0.260 (0.303)	0.282 (0.379)
-4	0.084 (0.067)	0.042 (0.104)	0.041 (0.123)	-0.008 (0.096)	-0.170 (0.140)	0.162 (0.170)	-0.039 (0.226)	0.358 (0.300)	-0.397 (0.376)
-3	0.107** (0.054)	0.068 (0.086)	0.039 (0.102)	0.077 (0.087)	-0.092 (0.128)	0.169 (0.155)	-0.025 (0.215)	0.446 (0.297)	-0.471 (0.367)
-1	-0.193*** (0.057)	-0.090 (0.086)	-0.103 (0.103)	-0.162* (0.093)	-0.144 (0.130)	-0.018 (0.160)	0.133 (0.233)	0.307 (0.310)	-0.174 (0.388)
0	-0.601*** (0.060)	-0.457*** (0.089)	-0.145 (0.108)	-1.090*** (0.103)	-1.162*** (0.143)	0.072 (0.176)	1.915*** (0.258)	2.647*** (0.346)	-0.732* (0.432)
1	-0.572*** (0.086)	-0.308*** (0.119)	-0.264* (0.147)	-0.868*** (0.125)	-0.988*** (0.174)	0.120 (0.214)	0.963*** (0.293)	1.706*** (0.398)	-0.742 (0.494)
2	-0.540*** (0.108)	-0.386** (0.152)	-0.154 (0.186)	-0.600*** (0.143)	-0.758*** (0.205)	0.157 (0.250)	0.733** (0.324)	1.520*** (0.441)	-0.788 (0.547)
3	-0.521*** (0.135)	-0.170 (0.180)	-0.351 (0.225)	-0.783*** (0.174)	-0.579** (0.239)	-0.204 (0.296)	0.889** (0.378)	1.173** (0.517)	-0.284 (0.641)
4	-0.447** (0.179)	0.000 (0.257)	-0.447 (0.313)	-0.584*** (0.225)	-0.243 (0.313)	-0.342 (0.386)	-0.349 (0.476)	0.987 (0.640)	-1.336* (0.797)
Observations	4,469,494			4,469,494			4,469,494		

Notes: This table reports the estimated coefficients from Equation 1, allowing them to vary by which parent was hospitalized. The reference period is $t = -2$. The outcome is school enrollment in columns (1)–(3), the attendance rate in columns (4)–(6), and chronic absenteeism (defined as annual attendance $< 85\%$) in columns (7)–(9). For each outcome, the first column reports the effect when the mother is hospitalized, the second when the father is hospitalized, and the third the difference between the two (mother minus father). Standard errors in parentheses are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Number of classes by grade and school type

Grade	Total	%	Municipal/Public	%	Subsidized	%	Private	%
7th	4,971	15.49	1,737	15.32	2,545	15.52	689	15.80
8th	4,965	15.47	1,741	15.36	2,480	15.12	744	17.06
9th	5,561	17.33	1,866	16.46	2,941	17.93	754	17.29
10th	5,546	17.28	1,902	16.78	2,880	17.56	764	17.52
11th	5,735	17.87	2,080	18.35	2,904	17.71	751	17.22
12th	5,320	16.57	2,012	17.75	2,650	16.16	658	15.09
Total	32,098	—	11,338	—	16,400	—	4,360	—

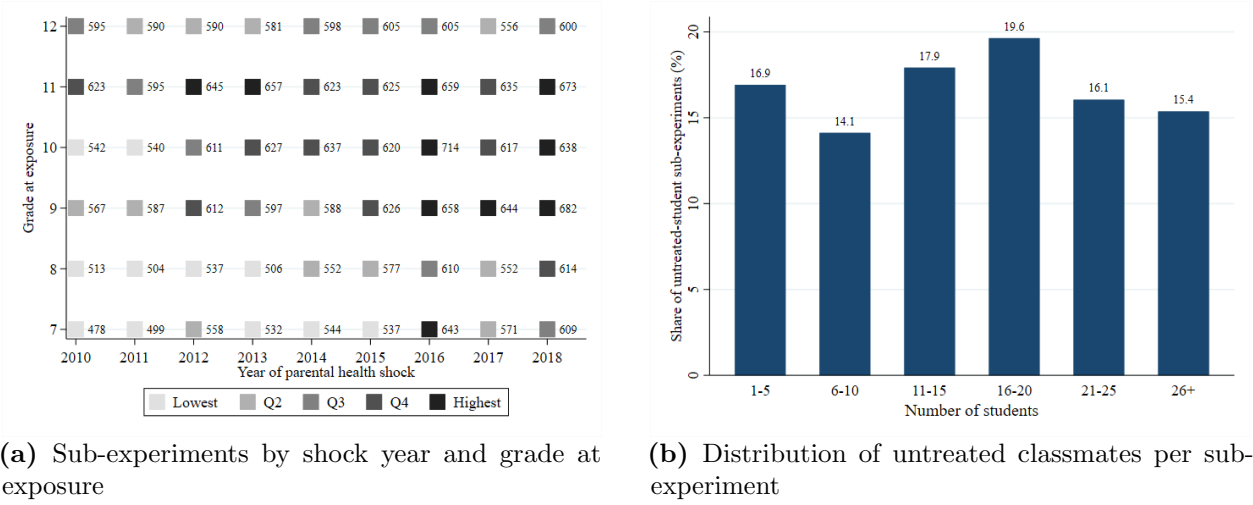
Notes: This table reports the distribution of classes by grade and school type. “%” in the second column is the grade’s share of all classes; “%” in the remaining columns indicates the share of each school type occurring in that grade. All values rounded to at most three decimals.

Table A.7: Average students per class by grade and school type

Grade	Total	Municipal/Public	Subsidized	Private
7th	23.1	20.5	25.3	19.8
8th	22.4	20.1	24.5	18.7
9th	21.3	20.0	22.6	18.5
10th	21.2	20.4	22.3	18.3
11th	20.6	19.8	21.6	17.6
12th	21.4	20.9	22.4	17.6
Total	21.6	20.3	23.1	18.45

Notes: This table reports the mean number of enrolled students per class for each grade and school type.

Figure A.1: Identifying variation in the stacked difference-in-differences design



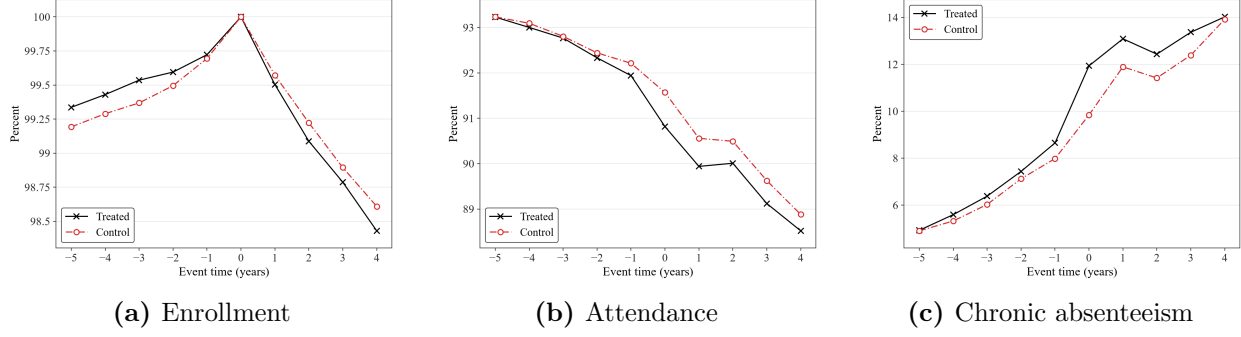
Notes: This figure describes the identifying variation used in the stacked difference-in-differences design. Panel (a) reports the number of treated-student sub-experiments by year of the parental health shock and grade at exposure. Darker markers indicate cells with a larger number of sub-experiments, with quintiles defined over the distribution of shock-year-by-grade cells. The number next to each marker reports the number of treated-student sub-experiments in that shock-year-by-grade cell. Panel (b) reports the distribution of the number of untreated classmates available within each treated-student sub-experiment. Each sub-experiment is centered on a treated student whose parent experienced a first cancer hospitalization, and the comparison group consists of untreated classmates in the same school-grade-cohort who satisfy the same sample restrictions and parental-linkage requirements.

Table A.8: Composition of treated-student sub-experiments by shock year

Characteristic	Year of parental health shock									Total
	2010	2011	2012	2013	2014	2015	2016	2017	2018	
<i>Affected parent</i>										
Father affected	35.20	35.44	34.03	33.37	35.69	35.24	33.56	34.88	36.87	34.92
Mother affected	64.80	64.56	65.97	66.63	64.31	64.76	66.44	65.12	63.13	65.08
<i>Student gender</i>										
Female student	50.06	50.71	50.63	50.77	49.80	48.75	50.71	51.05	49.95	50.27
Male student	49.94	49.29	49.37	49.23	50.20	51.25	49.29	48.95	50.05	49.73
<i>Grade at exposure</i>										
Grade 7	14.41	15.05	15.71	15.20	15.36	14.96	16.53	15.97	15.96	15.49
Grade 8	15.46	15.20	15.11	14.46	15.58	16.07	15.69	15.44	16.09	15.47
Grade 9	17.09	17.71	17.22	17.06	16.60	17.44	16.92	18.01	17.87	17.33
Grade 10	16.34	16.29	17.20	17.91	17.98	17.27	18.36	17.26	16.72	17.28
Grade 11	18.78	17.95	18.15	18.77	17.59	17.41	16.95	17.76	17.64	17.87
Grade 12	17.93	17.80	16.61	16.60	16.88	16.85	15.56	15.55	15.72	16.57
<i>Severity of parental health shock</i>										
Low-severity shock	75.02	75.72	74.67	76.86	75.27	77.52	76.78	76.87	76.97	76.21
High-severity shock	24.98	24.28	25.33	23.14	24.73	22.48	23.22	23.13	23.03	23.79
<i>School type</i>										
Municipal/Public school	39.45	36.02	35.18	34.60	34.61	35.32	32.99	34.52	35.72	35.32
Subsidized private school	47.86	50.53	51.31	50.31	51.78	52.42	53.59	51.75	49.87	51.09
Private school	12.69	13.45	13.51	15.09	13.61	12.26	13.42	13.73	14.41	13.58
Number of sub-experiments (N)	3,318	3,315	3,553	3,500	3,542	3,590	3,889	3,575	3,816	32,098

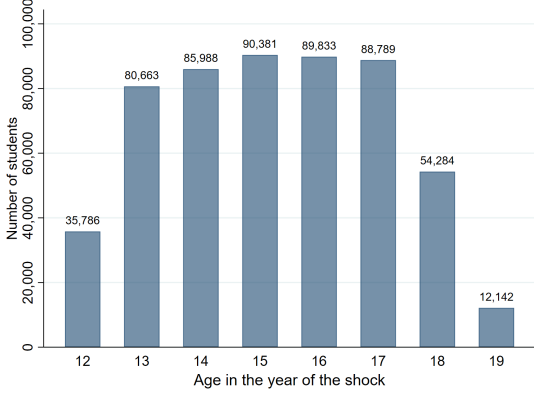
Notes: This table reports the composition of treated-student sub-experiments by year of parental health shock. Each column reports the share of treated-student sub-experiments in a given shock year accounted for by each characteristic. The final column reports the corresponding share in the full analysis sample. Characteristics are measured at baseline or at the time of exposure, before post-shock educational outcomes are realized. Low- and high-severity shocks are defined using the number of parental cancer-related hospitalizations. The last row reports the number of treated-student sub-experiments in each shock year.

Figure A.2: Raw trends in educational outcomes by treatment status

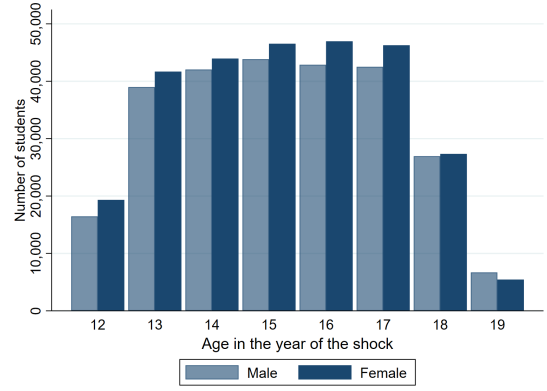


Notes: This figure plots raw mean outcomes for treated students and untreated classmates by event time relative to the first parental cancer hospitalization. Panel (a) reports enrollment, Panel (b) reports attendance, and Panel (c) reports chronic absenteeism. Event time is measured in years, with $t = 0$ corresponding to the year of the parental health shock. Treated students are those whose parent experiences a first cancer hospitalization, while controls are untreated classmates in the same school-grade-cohort who satisfy the same sample restrictions and parental-linkage requirements. These descriptive trends complement the event-study estimates by showing the evolution of treated and control students before and after the parental health shock.

Figure A.3: Students' age in the year of the parental health shock



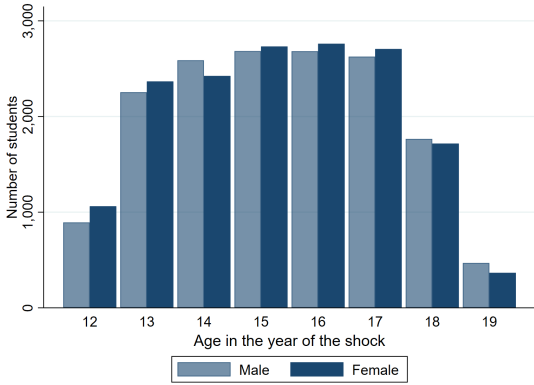
(a) Overall distribution



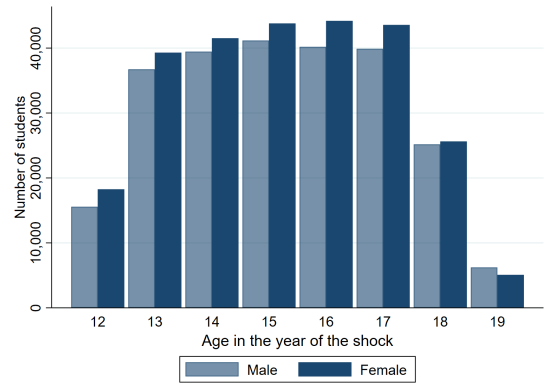
(b) Distribution by gender

Notes: This figure shows the age distribution of students in the analysis sample, treated and control, in the year of the parental cancer hospitalization. For control students, age is measured in the year of the shock of the treated student in their sub-experiment. Students aged 11 are grouped with age 12, and those aged 20 or older with age 19. Panel (a) presents the overall distribution. Panel (b) reports it separately for boys and girls.

Figure A.4: Students' age in the year of the parental health shock: treated vs. control students



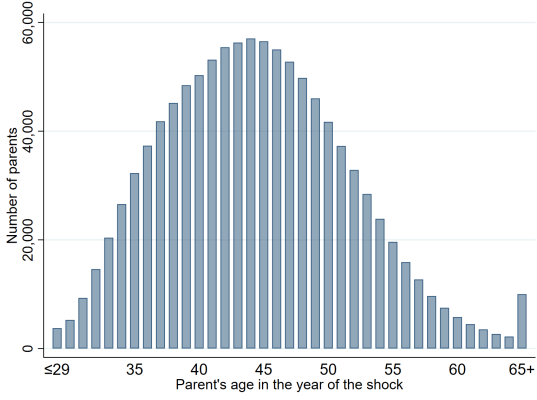
(a) Treated students



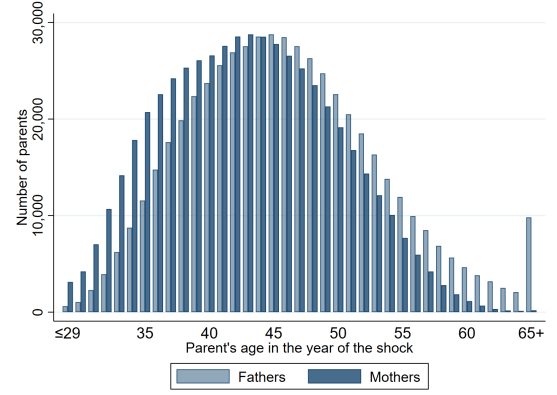
(b) Control students

Notes: This figure compares the distribution of students' ages in the year of the parental cancer hospitalization for the treated and control groups, by student gender. Panel (a) shows the age distribution for treated students. Panel (b) shows the distribution for control students (untreated classmates in the same school, grade, and cohort) measured in the year of the shock of the treated student in their sub-experiment. Age groups as in Figure A.3.

Figure A.5: Parents' age in the year of the parental health shock



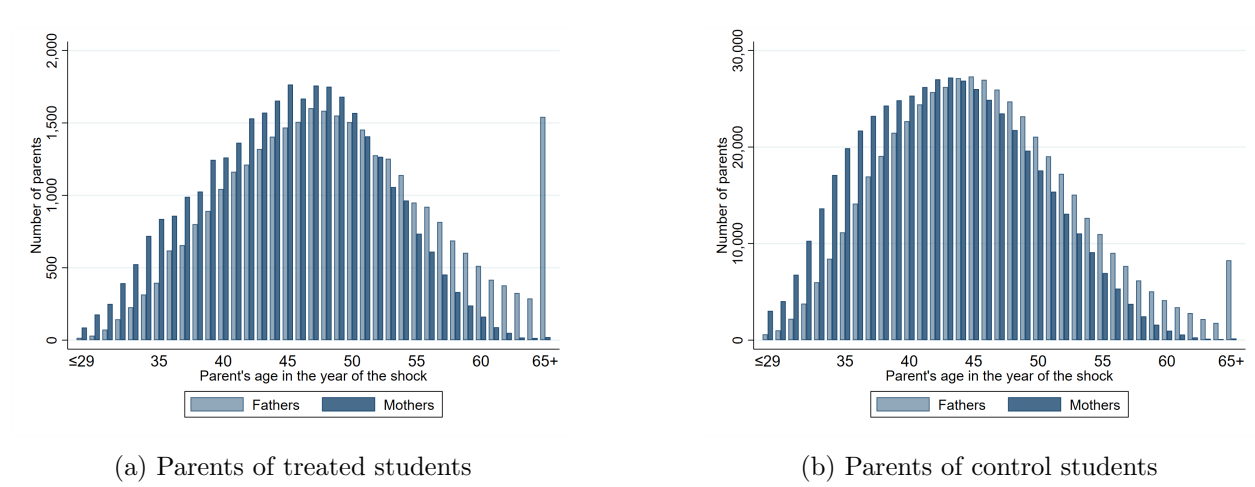
(a) Overall distribution



(b) Distribution by parent's gender

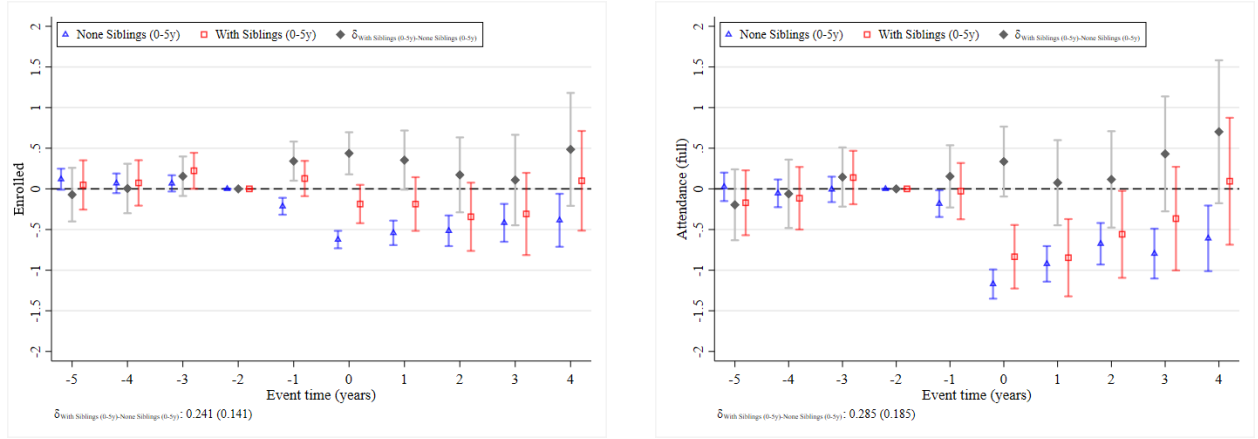
Notes: This figure shows the age distribution of the mothers and fathers of students in the analysis sample in the year of the shock. It includes both the parent hospitalized with cancer and the other parent, as well as the parents of control students, whose age is measured in the year of the shock of the treated student in their sub-experiment. Each parent is counted once for each of their children in the sample. Ages 29 or younger and 65 or older are grouped. Panel (a) pools mothers and fathers. Panel (b) shows fathers and mothers separately.

Figure A.6: Parents' age in the year of the parental health shock: parents of treated vs. control students



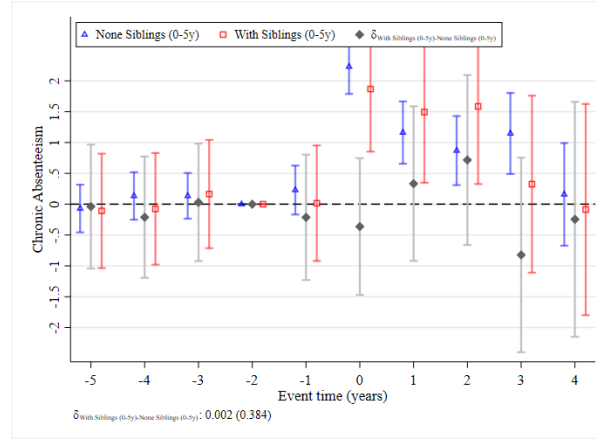
Notes: This figure shows the age distribution of mothers and fathers in the year of the shock, by the treatment status of their child. Panel (a) shows the parents of treated students, including the parent who was not hospitalized. Panel (b) shows the parents of control students (untreated classmates in the same school, grade, and cohort), measured in the year of the shock of the treated student in their sub-experiment. Age groups as in Figure A.5.

Figure A.7: Effect of a parental health shock by presence of a young child (0–5) in the household



(a) Enrollment

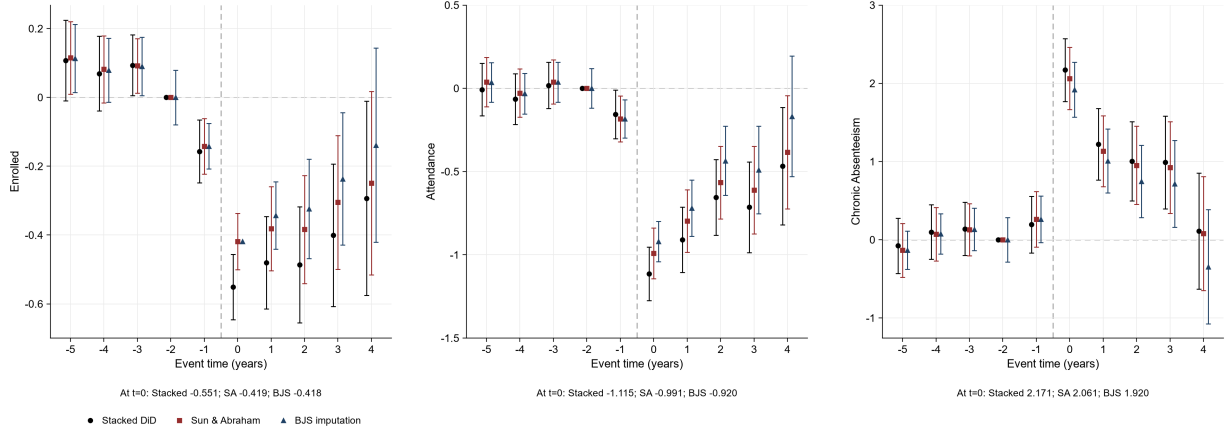
(b) Attendance



(c) Chronic Absenteeism

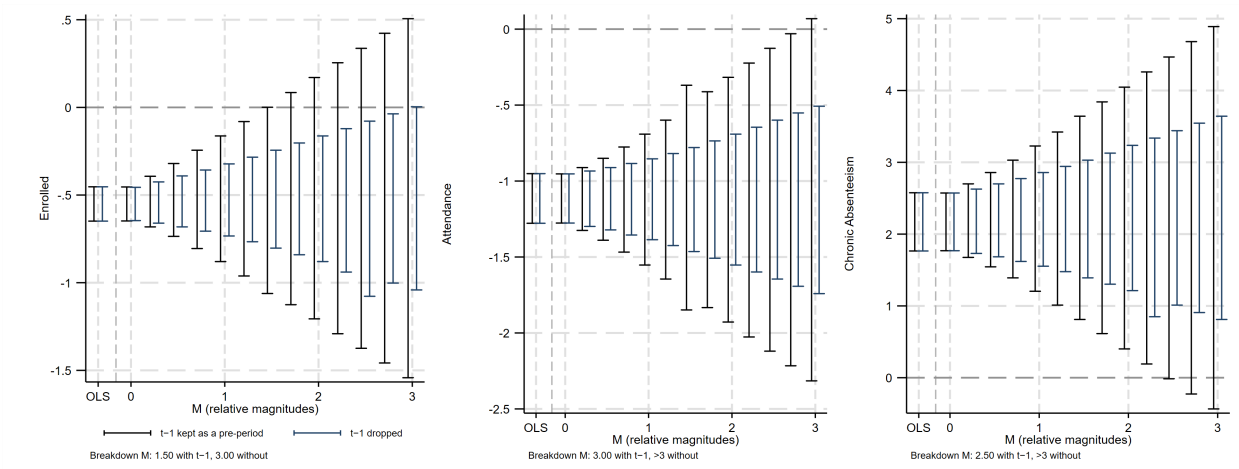
Notes: This figure plots the estimated coefficients from Equation 1, allowing the coefficients to vary by whether a child aged 0–5 was present in the student’s household at baseline. The figure reports estimates separately for students with and without a young child at home, as well as the difference between the two, for school enrollment (Panel a), attendance rate (Panel b), and chronic absenteeism (defined as annual attendance < 85%, Panel c). The reference period is $t = -2$, and coefficients are expressed as percentage-point deviations from that period. Vertical lines represent 95% confidence intervals.

Figure A.8: Robustness of the main educational results to alternative estimators



Notes: This figure compares the event-study estimates of Equation 1 (Stacked DiD) with two alternative estimators: the interaction-weighted estimator of Sun and Abraham (2021) and the imputation estimator of Borusyak et al. (2024) (BJS). Outcomes are school enrollment, the attendance rate, and chronic absenteeism (defined as annual attendance $< 85\%$), in percentage points. The reference period is $t = -2$ for all series. The note below each panel reports the three estimates at $t = 0$. For enrollment, the BJS routine normalizes the effect path at $t = 0$, so no confidence interval is available for that coefficient after re-anchoring; its point estimate is shown without one. Vertical lines represent 95% confidence intervals.

Figure A.9: Sensitivity of the year-of-shock effects to violations of parallel trends



Notes: This figure reports robust 95% confidence sets for the effect in the year of the shock ($t = 0$) under the relative-magnitudes restriction of Rambachan and Roth (2023), which allows post-shock violations of parallel trends up to $\bar{M}$ times the largest pre-shock violation. “OLS” denotes the unrestricted confidence interval. Black intervals treat $t = -1$ as a pre-period; blue intervals drop it, treating it as partially treated. The note below each panel reports the breakdown value, the smallest $\bar{M}$ at which the confidence set includes zero: with $t = -1$ kept as a pre-period, 1.5 for enrollment, 3.0 for the attendance rate, and 2.5 for chronic absenteeism; with $t = -1$ dropped, 3.0 for enrollment and above 3 for the attendance rate and chronic absenteeism.

B Data Construction and Cleaning Procedures

Student Performance Database

We begin with the national student performance records, which provide annual information for all enrolled students from 2002 to 2023. The raw dataset contains 58,415,243 observations corresponding to 7,750,247 unique students, with an average of approximately 2.5 million students per year.

To focus on regular school trajectories, we restrict the sample to primary education and secondary programs for children and youth, including basic education, academic (humanistic–scientific) secondary education, and the main technical–professional modalities (commercial, industrial, technical, agricultural, maritime, and artistic tracks). We exclude all adult education programs, evening education, and prison-schooling modalities, which removes 11,791,340 observations (equivalent to 1,882,519 students, or roughly 536,000 per year).

We drop observations with invalid grade-point averages (GPAs) outside the 1–7 scale or missing GPA values (158 students). To avoid ambiguous course–year assignments, we also remove students who transferred schools during the same academic year.

Cancer Shock Database

We use the universe of hospital discharge records from the Ministry of Health for the years 2007–2022; first cancer hospitalizations (the health shocks) are identified between 2010 and 2018. Diagnoses follow the ICD-10 classification. We identify cancer-related hospitalizations using codes beginning with “C” (968 distinct cancer diagnoses) and “D” (899 benign and in situ tumor diagnoses).

Out of all hospital discharges in this period, 3,037,946 correspond to a diagnosis starting with C or D, representing 53% of all hospitalizations. For each parent, we retain only the *first* hospitalization associated with a cancer diagnosis, yielding 527,120 unique parental cancer shocks.

Construction of Treated Students and Classmates

We merge the cleaned performance database with parental identifiers. Treated students are defined as those who were enrolled at any point between 2002 and 2023 and experienced a parental cancer shock during an academic year in which they were actively enrolled. We identify 111,394 such students.

For each course–year, we construct a list of treated students. When multiple treated students are present, we create up to four treatment slots (treated IDs) per classroom. We

then return to the full performance database and merge in all classmates of these treated students. We retain only course–years containing at least one treated student.

A student may appear multiple times (up to nine course–year observations), either as a control in multiple classrooms or as both treated and control across different years.

Next, we reshape the dataset so that treated IDs move from columns to rows, duplicating the corresponding course information as needed. We clean implausible student ages, restricting age to be within three years above or below the modal age for each grade. We also remove a small number of sequencing errors in the longitudinal course assignments (less than 1% of observations).¹²

The resulting dataset is organized such that each row corresponds to a student–course pair. Classrooms may contain up to four treated students, and each student may serve as a control in up to ten course–years. We attach additional information indicating all courses in which a student served as a control.

Expanding the Panel

We expand the dataset to include all years in which each student was enrolled in the school system. To reduce computational load, we partition the dataset into up to 21 stacked blocks per student. After this procedure, the panel contains 1,218,663 observations and 110,486 treated students, since treated students may also appear as controls in later years. The resulting dataset includes 105,043 course–year cells.

We then remove string variables from wide-format control specifications and merge in birth dates from the vital statistics records. Among controls, 51,184 students had missing birth dates; we recover most of these using Ministry of Education records and drop the remaining 17,512 observations (less than 1% of the sample, equivalent to 117,748 rows).

We reshape the course-level dataset from long to wide format (stacking control-course information downward), resulting in 110,486 treated students and 2,131,956 controls. We remove duplicated courses (affecting 75,776 students), drop courses without treated or control students (187,153 observations without controls and 1,432 without treated), and remove 80,134 controls who later received a cancer shock. Additionally, we drop 321,825 control observations that appeared multiple times as classmates of different treated students.

After these steps, the final counts are 110,352 treated students, 2,072,672 controls, and 104,127 course–year cells.

¹²All data-cleaning adjustments for which no explicit numerical counts are reported correspond to fewer than 1% of total observations and do not affect the results.

Balanced Panel and Final Sample Restrictions

We construct a balanced panel such that each student is observed for all years between 2002 and 2023, or from age 7 until completing grade 12 (4th year of secondary education), or until turning 18 if they do not finish secondary school.

For the final analysis sample, we retain only students enrolled between 7th grade and 12th grade. We restrict to shocks occurring between 2010 and 2018 and keep students whose parental information is complete for both mother and father. Students are excluded if both parents experienced a shock; we require exactly one affected parent. Finally, we exclude school-grade-cohort cells in which more than one student experiences a parental first cancer hospitalization in the same calendar year so that each sub-experiment in the final analysis sample contains exactly one treated student, and we remove control students who experience a parental cancer shock at any point. The intermediate steps described above, in which classrooms may contain up to four treated students and a student may appear as a control in several course-years, therefore apply to the construction of the raw stacked panel, not to the final analysis sample, which comprises 32,098 treated students and 505,768 untreated classmates.