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RESEARCH ARTICLE

The subjective treatment effects of COVID-19 on child well-being: evidence from Luxembourg

Francesco Andreoli[1,2] · Claudine Kirsch[3] · Eugenio Peluso[2,4] · Vincenzo Prete[5]

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Abstract
Estimating the impact of COVID-19 on the multiple dimensions of child well-being requires quasi-random variation in exposure to it, which is unlikely to occur during a pandemic. Recent developments in econometrics have highlighted the relevance of subjective evaluations of treatment effects in the absence of randomization. This paper delivers new evidence, based on primary data collected in Luxembourg in Spring 2021 about their subjective appraisal of the effects of COVID-19 on multiple dimensions of children's well-being. Effects are recovered through specific survey questions, asking children to compare actual outcomes with counterfactual ones, that they believe would have occurred in the absence of COVID-19. Children report negative effects of COVID-19 on subjective health and on schooling outcomes, as well as disruptions on the time used to interact with the family. The paper explores the sources of heterogeneity behind these results.

Keywords Subjective treatment effects · COVID-19 · Well-being · Children · Family · Luxembourg

JEL Classification D60 · I31 · J13

1 Introduction

In March 2020, the dramatic consequences of the worldwide outbreak of COVID-19 led many countries to adopt quarantine measures and social distance policies to contain the spread of the virus. Although inevitable in the absence of a vaccine, quarantine measures produced drastic changes in everyday life with high economic and social costs. School closures have impacted the lives of children (and their families) the most, exposing them to home-learning and increasing demand for parental care, whereas in-person interactions with peers have drastically reduced.

While an expanding literature has brought about evidence of the educational performances and the subjective well-being of children during or after the pandemic

Extended author information available on the last page of the article

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across Europe (e.g., see Engel de Abreu et al. 2021; Kirsch et al. 2021a, 2022; Kirsch and Vaiouli 2023), little is known about the *causal* impact of the pandemic on adolescents. This paper provides new evidence in this direction, using innovative survey data about children's subjective evaluations of the effect of COVID-19 on many dimensions concerning their lives at home, at school and with peers.

The implied estimates contribute to the literature addressing the consequences of COVID-19 on children, which has so far widely relied on comparisons of outcomes observed before and after the pandemic. Recent evidence shows that such changes are associated with negative emotions, e.g., anxiety disorders, stress, and depression (Golberstein et al. 2020; Waselewski et al. 2020; Rogers et al. 2021; Viner et al. 2021), with some groups more vulnerable than others. Significant risk factors are the existence of special educational needs, excessive media exposure, and the presence of mental illness. Female and older adolescents are also at higher risk of suffering from mental health problems (Gilsbach et al. 2021; Panchal et al. 2021), as well as adolescents from disadvantaged backgrounds or ethnic minority groups receiving mental health services exclusively in school environments (Golberstein et al. 2020). The COVID-19 has impacted learning outcomes through schooling disruptions. Evidence is that learning losses were less intense for children from wealthier families (Andrew et al. 2020; Aucejo et al. 2020; Chetty et al. 2020; Bacher-Hicks et al. 2021; Kirsch et al. 2021a; Maldonado and De Witte 2021), where parents are on average better educated and have more opportunities to spend time with their children by helping them with homework or engaging them in physical activities (Bonal and Gonzalez 2020).

The before-after estimators of COVID-19 effects may lead to biased estimates of the true effect, which is confounded by changes in many dimensions of the life of the children that occurred during the pandemic period but that are not correlated with, or part of, the pandemic itself (such as, for instance, parents' divorce). Addressing the effect of COVID-19 requires instead comparing the actual level of outcomes to a *counterfactual* level, which would have been observed in the absence of the pandemic, holding all other factors (which may vary over time) as fixed. Counterfactuals are difficult to identify empirically when the underlying treatment, the COVID-19 shock, is common to all units.

In this paper, we have followed a different and innovative strategy, which consists of asking children directly about the relevant counterfactual outcome in the absence of COVID-19. We collect primary data through an innovative survey on children. The survey took place in Luxembourg in June and July 2021 and invited children aged 12–16 to participate. The children were asked to provide information on demographics and family resources. Moreover, children have been asked to infer their subjective evaluation of the treatment effect of COVID-19 on a large array of dimensions of well-being, concerning their relations with parents, social media, school, sports, and healthy habits. For each dimension, children were asked whether their outcome would have been more/better, less/worse, or about the same if COVID-19 had not taken place. Whether reported subjective treatment effects have a causal content depends crucially on two assumptions: first, that counterfactual outcomes are measured without error and, second, that survey respondents have well-formed knowledge of counterfactual scenarios. The survey questionnaire has been constructed in a way that it minimizes the risk of failing these assumptions, although such risk cannot be eliminated. Therefore, our estimates are a step closer to estimating the causal effect of COVID-19 on children but cannot be claimed causal unless the assumptions are fully validated.

Our empirical approach to elicit treatment effects from exposure to the COVID-19 pandemic is inspired by a surging literature that uses subjective expectations to understand decision-making under uncertainty. The subjective expectations approach, pioneered by Manski (1990), has been recently used in human capital models by Manski (2018), Arcidiacono et al. (2020), Wiswall and Zafar (2021). Giustinelli and Shapiro (2019) have investigated how survey questions eliciting potential outcomes in counterfactual situations prove useful in identifying subjective treatment effects of health shocks and policies. The contribution closer to ours is Aucejo et al. (2020), which investigates subjective treatment effects of the COVID-19 treatment for bachelor students on outcomes such as their GPA, the probability of completing or delaying graduation, and expectations about employment and earnings. Estimating subjective treatment effects requires eliciting subjective expectations about counterfactual outcomes that would have been realized in the absence of COVID-19 within a survey experiment. In the experiment, every unit is both in the treatment (observed realizations with COVID-19) and in the control group (hypothetical realizations in the absence of COVID-19). The outcomes prevailing in the control group are elicited through the survey questionnaire.

This paper follows the approach of Aucejo et al. (2020) and recovers the subjective appraisal of the COVID-19 treatment effect on children's well-being, thereby leading to novel estimates of the subjective treatment effects of COVID-19. Such estimates are elicited through a survey questionnaire and are specific to each respondent. We are hence capable of depicting heterogeneity in the distribution of effects and relate this heterogeneity to the characteristics of the respondents. Children report negative effects of COVID-19 on subjective health and on schooling outcomes, which are important dimensions of their well-being (see also Sandner et al. 2023). We also find that COVID-19 has produced disruptions in time used to interact within the family as well as for socialization and learning purposes (and therefore opportunities for investments in human capital) only for children with low-educated mothers (see also Grewenig et al. 2021). Such estimates reveal potential channels through which COVID-19 has impacted actual and future well-being opportunities of children.

2 Empirical framework

2.1 Context and the survey instrument

The first case of COVID-19 was reported in Luxembourg in March 2020. The government called more or less immediately for a lockdown owing to the raising infection rates in Europe. Schools closed from 16th March 2020 to May 2020 and students worked from home. Thereafter, they gradually returned to school with strict social and physical prevention measures in place. From September 2020 to July

2021, they could attend school apart from two weeks owing to a second lockdown in Winter 2020. Teachers offered distance education for those unable to attend. From January 2021, social and physical distancing measures were gradually lifted.

Data used in this paper come from an original survey developed at the University of Luxembourg for the COVID-Kids II project. The project COVID-Kids II was advertised extensively on social media platforms (e.g., Facebook, Instagram, WhatsApp). Convenient sampling of parents/guardians and educators was used to recruit secondary school-age children in state and private schools to participate in the project. Diversity was sought in terms of school type and socio-economic status (based on the International Standard Classification of Occupations ISCO 08 and the International Socio-Economic Index of Occupational Status ISEI-08). While the survey was advertised on social media, the second author also approached 14 head teachers of private schools and asked them to invite their students to complete either the online questionnaire or a pen-and-paper version (if students preferred) at home (see Kirsch and Vaiouli 2023). Seven head teachers asked students to complete the online questionnaires and two distributed the pen-and-paper questionnaires. Participants could complete it in a language of their choice (Luxembourgish, German, French, English, Portuguese) upon their parents' informed consent. The data was collected between 7th June and 15th July 2021 and 365 adolescents aged 12–16 took part. Of these, 83% attended private schools, and 17% state schools. 36 students from two private schools completed the pen-and-paper questionnaires (for more details see Bebić-Crestany et al. 2023).

The self-report questionnaire used in COVID-Kids II included items relevant to children's life satisfaction, subjective well-being, and school performance that came from validated screening tools on children's subjective well-being (e.g., Rees and Main 2016) and from the PISA data. The translations into Luxembourgish, German, French, English, and Portuguese were developed and validated through back-translations by four multilingual members of the COVID-Kids II team. The COVID-Kids II survey comprised 64 questions divided into three sections. In the first section, children report their (and their parents') socio-demographic characteristics (age, gender, household composition, parents' employment status, parents' educational attainment) as well as dwelling characteristics (type of dwelling, existence of outdoor space). The second section collects information on children's subjective well-being, attitudes and preferences, leisure activities, and learning experiences at home and school. We collect information about 15 outcomes that are investigated in this study (more below). Each outcome is elicited through a battery of survey questions, whose response scale varies between a minimum (indicating little quantity/poor quality/low intensity) to a maximum (indicating high quantity/high quality/high intensity). For instance, one of the outcomes is "General Health" which is captured by a question investigating the actual self-assessed level of health at the time of the survey. The response ranges between poor health (1) to good health (5). We resort to the responses to these questions to assess measures of the levels of the outcomes of interest. The final part of the survey addresses children's subjective estimates of the pandemic treatment effects on a variety of dimensions of well-being (e.g., health, sociality, school, and family). To this end, the survey asks questions about what life would have been like without COVID-19. To the extent that such responses vary across children, the survey is thus capable of addressing heterogeneity in subjective treatment effects. The questionnaire and the description of the data are presented by Kirsch et al. (2021b).

2.2 Assessing subjective treatment effects

In causal inference literature, the treatment effect is the difference between realized and counterfactual outcomes, which would have been observed in the absence of a given event or intervention, holding all the rest as fixed (for a review, see Imbens and Wooldridge 2009). Counterfactual outcomes are seldom observable, making the problem of causal inference one of missing information.

In our setting, the main treatment is the insurgence of COVID-19 and the disruptions that behavioural and policy responses to the pandemic have brought about. The potential outcome of child i in the presence of COVID-19, denoted $Y_i(COVID-19)$ is observable in Spring 2021 for an array of 15 relevant dimensions of children's well-being. This outcome can be measured on a qualitative ordinal scale or in terms of the probability of achieving the best outcome. We define $Y_i(w/out\,COVID-19)$ as the counterfactual outcome that would have been achieved in the absence of COVID-19, all other factors being equal. This outcome is not observable. The individual treatment effect, denoted

$$TE_i = Y_i(COVID-19) - Y_i(w/outCOVID-19),$$

measures the change in outcomes of child i that is attributable to COVID-19. The effect TE_i is also unobservable.

One can adopt econometric techniques to produce estimates of *moments* of the distribution of TE_i, such as its average $E[TE_i]$. Identifying such moments is not an easy task, as all children were exposed to COVID-19 at the same time, and implementing (quasi-)randomization strategies is difficult. Before-after estimators also fail to capture treatment effects in the presence of time-varying confounders related to pandemic. Furthermore, aggregate estimators of treatment effects would neglect the heterogeneity of responses in the data, focusing on one or a few moments of interest in the distribution of TE_i. It is likely that exposure to COVID-19 led to highly heterogeneous responses among children along some lines that are not observable or revealed by the data.

We explore an alternative strategy. Within the survey, we elicited the children's subjective appraisal of the COVID-19 impact on the relevant outcomes. Each child is requested to evaluate her/his own counterfactual outcome in the absence of COVID-19 and then report her/his subjective assessment of the treatment effect (TE). The wording of the key question, in Sect. 8 of the survey, is:

> *We now ask you to imagine yourself and your family in a different world where COVID-19 and all related changes have not happened. What would your life look like without COVID-19 now? Without COVID-19,…*

Respondents are then provided with a list of 15 items, each concerning a relevant dimension of their well-being. The children are asked to assess whether outcomes in any specific dimension are *more/better*, *about the same* or *less/worse* had COVID-19 not happened, compared to the actual situation in June–July 2021. The within-person estimate of the COVID-19 effect has the advantage of being less plagues (as opposed to comparing average scores across treatment and control groups) by issues related to quantitative assessments of outcomes (see Bond and Lang 2019).

To reduce the cognitive burden on the children, the survey question asks them to report how their actual performance would have changed if COVID-19 had not occurred. The children's responses, therefore, refer to the outcome they would have expected to achieve after removing the effect of COVID-19. If the effect of COVID-19 is a negative effect on some outcomes, children would report more/better outcomes in the absence of COVID-19. To simplify the exposition of treatment effects, we recode answers to directly measure the sign of such effect that children are asked to remove, thereby yielding an estimate of the *subjective treatment effect* of COVID-19. Such an effect is bound to compare the post-pandemic outcomes to counterfactual outcomes that would have been realized had COVID-19 not taken place. We measure treatment effects on a discrete scale taking three values: (i) value "-1" when outcomes deteriorate due to COVID-19, that is, the respondent reports that her/his actual outcomes are *worse/less* than they would have been in the absence of COVID-19; (ii) value "0" if the outcomes are *about the same* with or without COVID-19; (iii) value "+1" when outcomes improve due to COVID-19, that is the respondent reports that her/his actual outcomes are *better/more* than they would have been in the absence of COVID-19. We, thus, obtain a treatment indicator $\widehat{TE}_i \in \{-1, 0, 1\}$ that captures improvement or deterioration in outcomes due to COVID-19. The scale of this indicator is arbitrary. Averaging $\widehat{TE}_i$ across observations provides a metric of the direction of changes. We can also obtain alternative estimates of the features of the treatment effects which do not rely on the specific choice of cardinalization of the measurement scale of treatment effects, such as the probability the treatment effects are positive (i.e., $\Pr\left[\widehat{TE}_i = 1\right]$) or the probability that the treatment effects are negative as the average of an indicator (i.e., $\Pr\left[\widehat{TE}_i = -1\right]$) or the probability that treatment effects are zero (i.e., $\Pr\left[\widehat{TE}_i = 0\right]$).

The treatment effects that we recover can be interpreted in subjective terms. Students, in fact, are asked to evaluate realized outcomes in the presence of COVID-19, to which everybody has been exposed (albeit to a different extent), and a counterfactual situation of which nobody in the sample has a direct experience. The counterfactual situation is, hence, replaced with a subjective evaluation of the prevailing outcome that the respondent would have expected to achieve in 2021 had COVID-19 treatment not existed. Treatment effects are identified under two key assumptions. First, there is no measurement error in the outcomes that we recover through the survey instrument. The robustness of this assumption depends on the type of outcome. Many outcomes refer to subjective evaluations of children's conditions when the survey is made (such as their well-being, general health, and so on). These outcomes may be measured with error due to subjective biases in evaluation and reporting on an arbitrary measurement scale. However, the implied measurement error is less of a concern for treatment effect subjective evaluations, provided that the sources of potential biases have an equal impact on actual and counterfactual subjective evaluations that cancel out in evaluations of changes in the outcome of individuals measured by the indicator TE_i. Furthermore, in our data, the subjective treatment effect TE_i is measured through an ordinal scale, which is bound to capture directions of changes (improvement or deterioration) without requesting respondents to quantify such changes, thereby avoiding reporting biases. The remaining outcomes, concerning aspects of time use within the family or measures of school performances, have been collected through carefully designed questions validated in previous studies (Kirsch et al. 2021a). The risk that measurement error affects the measurement of these dimensions is minimal.

The second assumption is that respondents have well-formed expectations regarding counterfactual outcomes that would have prevailed in 2021 in the absence of COVID-19. This assumption is challenging. It is very likely that children have a clear knowledge of how their situation was one year ahead (pre-pandemic) and use this knowledge to project how that situation would have evolved in the absence of the pandemic. Identification of the subjective treatment effect requires children one additional effort compared to merely reporting pre-pandemic outcomes, that is, to disentangle those changes in outcomes that are attributable to pandemic-related factors from those factors that are time-varying, correlated with outcomes but unrelated to the treatment. The wording of the questionnaire has been explicitly designed to clarify this point to the respondents by asking them to focus on all changes in their lives and those of their relatives that they believe could be attributed to the pandemic, while leaving any other aspect as fixed in the comparison.

The latter assumption is difficult to validate in the data without knowledge of the pre-pandemic outcomes of respondents. If violated, the treatment effect would recover a before-after estimate. The estimate would be nonetheless interesting per se for at least two reasons. First, the estimate would be specific to the individual, thereby representing beliefs upon which children and/or their families may act. Second, the estimates would recover direct (for instance, effects related to school closures and reduced in-person socialization) and mediated effects (for instance, effects related to increased exposure to social media) combined, thereby increasing sources of heterogeneity of COVID-19 treatment effects. We study in a regression framework the extent to which heterogeneous effects are related to demographics, family and housing resources, and school experience observed in the survey. The regression results are descriptive in nature and bear no causal content, as heterogeneity in subjective treatment effects may depend on unobservable traits that are correlated with potential outcomes and with the treatment.

2.3 The data

Data have been collected with an online questionnaire for a sample of $N = 365$ children enrolled in secondary education in Luxembourg. The final sample excludes those outside the age range 12–16 (with some exceptions of students aged 11 but attending the same grade as 12-years-old peers), those who spent less than 8 min on the online questionnaire, missed more than 50% of the answers in the entire questionnaire, and omitted to answer questions on school satisfaction and performance.

The using sample shrinks to 332 children. A large majority of sampled children (83%) was enrolled in 6 of the 18 private schools in Luxembourg. Private schools in Luxembourg can follow either National or independent curricula and can be tuition-free or charge substantial fees. Importantly, these schools attract students with different educational and linguistic needs, aspirations, and socio-economic backgrounds. As noted by Kirsch et al (2022), it is estimated that 75% of children aged 6–16 attended one of the private schools selected in this project. The using sample consists of 4% of this particular school population. To mitigate issues on data representativeness, several actions were undertaken, including extensive communication of the survey to schools, teachers, and students, offering multiple modes of response to the survey, and making questionnaires available in multiple languages.

Some caveats to the sampling strategy are worth mentioning. While there are no statistical differences in parental (occupational) characteristics between children across private and public schools in the survey (see Bebić-Crestany et al. 2023), our sampling design does not allow to avoid self-selection of respondents within each school. Selection may occur along the lines of unobservable traits, such as the willingness of parents and children to engage in responding to online surveys, that could affect the representativeness of the samples and limit the external validity of our estimates.

Table 1 reports summary statistics of the sample, which includes a majority of girls (70%), aged on average 14.14 years and living in a village (58%). The description based on SES shows a high fraction of children whose mother holds a university degree (62%) and is employed (85%). Most of the respondents attended childcare when aged 0–2 (73%) and are enrolled in a private school (83%).

Table 2 provides descriptive statistics for the 15 dimensions of child well-being (see also Kirsch et al. 2022). Columns (1–4) report statistics about the well-being indicators as observed at the time of the survey. In column (5) we focus on the probability that a child responds with a positive or strongly positive response item to a question eliciting one of the 15 dimensions of well-being. About 58% of children are in *Good health*, whereas less than 50% of the participants report healthy habits: 45% are *Doing sports* often, and 34% are *Eating unhealthy food*. During the pandemic, 22% of children declare spending *Time with parents* (for instance, playing games), 83% spend time *Dining with parents* (indicating proximity to the family), and 42% of children spend time *Talking with parents* (indicating quality time). The questionnaire elicits information about the use of connected devices. Nearly 65% of children report an *Intense use of pc or tablet*, and 38% are *Playing video games*. The survey goes on to collect information about experiences with school. About 75% of children are currently *Satisfied with school*, 50% have an *Interest in school*, 75% of children are satisfied with their *Average school marks*, whereas 17% experience *Difficulties at school*. Lastly, we observe that 75% of children are often *Using social networks*, whereas only a minority is currently spending a considerable amount of time *Using the internet.*

We employ a logit regression to assess the partial correlations of the demographics, family and housing resources, and school experience on the *probability* of reporting a positive or strongly positive response to any of the 15 outcomes of well-being indicators.

Table 1 Descriptive statistics of covariates

	Mean	Standard deviation	Min	Max	N
	(1)	(2)	(3)	(4)	(5)
Demographics					
Age	14.14	1.42	11	16	332
Female (1 = yes)	0.70	0.46	0	1	331
Living in a city (1 = yes)	0.42	0.49	0	1	321
Healthy weight (1 = yes)	0.74	0.44	0	1	304
Family environment					
Family size	3.30	1.05	1	5	331
High-educated mother (1 = yes)	0.62	0.49	0	1	253
Non-working mother (1 = yes)	0.15	0.36	0	1	301
High-income family (1 = yes)	0.17	0.37	0	1	327
Home resources					
House with garden (1 = yes)	0.75	0.43	0	1	329
Many books at home (1 = yes)	0.60	0.49	0	1	329
Owning a computer (1 = yes)	0.67	0.47	0	1	328
Owning a tablet (1 = yes)	0.66	0.47	0	1	327
School experience					
Childcare (1 = yes)	0.73	0.45	0	1	326
State school (1 = yes)	0.17	0.37	0	1	330
Special educational needs (1 = yes)	0.09	0.29	0	1	329

We report the marginal effects of each regressor in the Appendix (Fig. 2). Overall, we find evidence that gender, age, living in a city, family resources captured by ownership of a computer, the number of books available to children at home, and the presence of quiet space to work are significant predictors of levels of well-being reported by the surveyed children.

In the following section, we analyze the distribution of subjective treatment effects of COVID-19 for each of these 15 dimensions of well-being highlighted above.

3 Results about subjective treatment effects

Table 3 reports estimates of the subjective treatment effects. In columns (1)–(3), we provide estimates of the probability that in our sample outcomes are better/more, about the same or worse/less compared to what they would have been without COVID-19. These categories are mutually exclusive and allow to understand whether positive or negative treatment effects are dominating each well-being dimension. We also report in column (4) the average value of $\widehat{TE}_i$ in the sample for each well-being dimension. This estimate is useful to depict the sign and significance of the subjective treatment effects. Column (4) provides evidence that

Table 2 Outcome levels and reference scale

Well-being dimension (Y):	Measurement scale			Descriptive statistics	
	Min	Max	Reference level (R)	Mean	Prob[Y ≥ R]
	(1)	(2)	(3)	(4)	(5)
General health	1 (very bad)	5 (very good)	4 (good)	3.71	0.58
Doing sports	1 (almost never)	4 (very often)	3(often)	2.44	0.45
Eating unhealthy food	1 (never/almost never)	4 (almost every day/every day)	3 (often/once/twice a week)	2.23	0.34
Time with parents	1 (almost never)	4 (very often)	3 (often)	1.98	0.22
Dining with parents	1 (never/almost never)	4 (almost every day/every day)	3 (often/once/twice a week)	3.53	0.83
Talking with parents	1 (never/almost never)	4 (almost every day/every day)	3 (often/once/twice a week)	2.37	0.42
Intense use of pc or tablet	1 (strongly disagree)	4 (strongly agree)	3 (agree)	2.77	0.63
Playing video game	1 (almost never)	4 (very often)	3 (often)	2.22	0.38
Satisfied with school	1 (very dissatisfied)	4 (very satisfied)	3 (satisfied)	2.87	0.75
Interest in school	1 (almost never)	4 (almost every day/every day)	3 (once/twice a week)	2.41	0.50
Average school marks	1 (unsatisfactory)	4 (very good/excellent)	3 (good)	3.00	0.75
Difficulties at school	1 (better than peers)	4 (rather bad)	3 (not so good)	1.82	0.17
Worries for school	1 (almost never)	4 (very often)	3 (often)	2.42	0.46
Using social networks	1 almost never)	4 (almost every day/every day)	3 (often)	3.10	0.75
Using internet weekday	1 (not at all)	5 (more than 6 h.)	4 (4–6 h)	3.46	0.45

The range of the measurement scale (min–max) are reported in columns (1)–(2). The reference level R in column (3) refers to the category that we use as a reference for dichotomizing the ordered scale of well-being. R is specific to each well-being dimension. Column (4) corresponds to the average level reported in the min–max scale, whereas column (5) report the fraction of respondents reporting a well-being level larger or equal than the reference level

Table 3 Subjective treatment effects $\widehat{TE}$ (cardinal scale), full sample and by by sub-group

Well-being dimensions	Descriptive statistics				By gender		Δ	By high-educated mother		Δ	By childcare attendance		Δ
	$\widehat{TE}=-1$	$\widehat{TE}=0$	$\widehat{TE}=1$	Mean $\widehat{TE}$	Male	Female	(5)–(6)	Yes	No	(8)–(9)	Yes	No	(11)–(12)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
General health	0.27	0.68	0.04	−0.23***	−0.20***	−0.25***	0.06	−0.19***	−0.25***	0.06	−0.28***	−0.11**	−0.17***
				(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.07)	(0.03)	(0.05)	(0.06)
Doing sports	0.37	0.53	0.10	−0.26***	−0.37***	−0.21***	−0.15*	−0.33***	−0.26***	−0.07	−0.32***	−0.12*	−0.20**
				(0.04)	(0.07)	(0.04)	(0.08)	(0.05)	(0.07)	(0.08)	(0.04)	(0.07)	(0.08)
Eating unhealthy food	0.12	0.74	0.14	0.02	0.03	0.01	0.02	0.07	0.01	0.06	0.03	0.00	0.03
				(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)	(0.07)	(0.04)	(0.05)	(0.06)
Time with parents	0.21	0.63	0.17	−0.04	0.07	−0.10**	0.17**	0.11**	−0.18***	0.29***	−0.05	−0.05	0.00
				(0.03)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)	(0.08)	(0.04)	(0.07)	(0.08)
Dining with parents	0.17	0.76	0.07	−0.10***	−0.02	−0.14***	0.12**	0.02	−0.22***	0.24***	−0.10***	−0.15***	0.05
				(0.03)	(0.05)	(0.03)	(0.06)	(0.03)	(0.05)	(0.06)	(0.03)	(0.05)	(0.06)
Talking with parents	0.12	0.74	0.14	0.02	−0.01	0.04	−0.05	0.03	−0.01	0.04	0.03	0.01	0.02
				(0.03)	(0.04)	(0.04)	(0.06)	(0.03)	(0.06)	(0.07)	(0.03)	(0.05)	(0.06)
Intense use of pc	0.14	0.54	0.32	0.18***	0.18***	0.18***	−0.00	0.30***	0.11	0.18**	0.22***	0.08	0.13*
				(0.04)	(0.07)	(0.05)	(0.08)	(0.05)	(0.07)	(0.09)	(0.05)	(0.06)	(0.08)
Playing video games	0.09	0.62	0.29	0.20***	0.15**	0.22***	−0.08	0.20***	0.26***	−0.06	0.18***	0.25***	−0.07
				(0.03)	(0.06)	(0.04)	(0.08)	(0.05)	(0.06)	(0.08)	(0.04)	(0.05)	(0.07)
Satisfied with school	0.32	0.60	0.09	−0.23***	−0.27***	−0.22***	−0.05	−0.24***	−0.26***	0.02	−0.28***	−0.11*	−0.17**
				(0.03)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)	(0.08)	(0.04)	(0.06)	(0.07)
Interest in school	0.24	0.68	0.08	−0.16***	−0.17***	−0.16***	−0.01	−0.17***	−0.21***	0.04	−0.20***	−0.07	−0.13**
				(0.03)	(0.06)	(0.04)	(0.07)	(0.04)	(0.06)	(0.07)	(0.04)	(0.05)	(0.06)

Table 3 (continued)

Well-being dimensions	Descriptive statistics				By gender		Δ	By high-educated mother		Δ	By childcare attendance		Δ
	$\widehat{TE}=-1$	$\widehat{TE}=0$	$\widehat{TE}=1$	Mean $\widehat{TE}$	Male	Female	(5)–(6)	Yes	No	(8)–(9)	Yes	No	(11)–(12)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Average school marks	0.28	0.63	0.09	−0.19***	−0.15**	−0.21***	0.06	−0.17***	−0.20***	0.03	−0.22***	−0.10	−0.13*
				(0.03)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)	(0.08)	(0.04)	(0.06)	(0.07)
Difficulties at school	0.09	0.70	0.21	0.13***	0.12**	0.13***	−0.02	0.14***	0.17***	−0.03	0.09**	0.23***	−0.15**
				(0.03)	(0.06)	(0.04)	(0.07)	(0.04)	(0.06)	(0.07)	(0.04)	(0.05)	(0.07)
Worries for school	0.12	0.64	0.24	0.11***	0.10*	0.12***	−0.02	0.16***	0.04	0.11	0.08*	0.21***	−0.14*
				(0.03)	(0.06)	(0.04)	(0.07)	(0.05)	(0.07)	(0.08)	(0.04)	(0.06)	(0.07)
Using social networks	0.16	0.60	0.24	0.07**	0.08	0.07	0.02	0.27***	−0.10	0.37***	0.09**	0.05	0.04
				(0.04)	(0.06)	(0.04)	(0.08)	(0.05)	(0.06)	(0.08)	(0.04)	(0.06)	(0.08)
Using internet	0.16	0.60	0.24	0.09**	0.12*	0.07	0.05	0.27***	−0.09	0.36***	0.11**	0.02	0.09
				(0.04)	(0.06)	(0.04)	(0.08)	(0.05)	(0.06)	(0.08)	(0.04)	(0.06)	(0.08)

Columns (1)–(3) report the proportion of cases with $\widehat{TE}=-1$ for "worse/less", $\widehat{TE}=0$ for "about the same" and $\widehat{TE}=1$ for "better/more" in the data. Column (4) is the sample average of subjective treatment effects based on the scale $\widehat{TE}=\{-1,0,+1\}$. Columns (5)–(13) report average subjective treatment effects by sub-group. SE in parenthesis. Significance levels $*$ ($p<10\%$), $**$ ($p<5\%$) or $***$ ($p<1\%$).

treatment effects are largely significant across many dimensions except for unhealthy food consumption and for variables measuring the time spent with parents. In these cases, the subjective average effect is indistinguishable from zero.

Treatment effects estimates are available at the individual level. We can study heterogeneity in the distribution of these effects within a regression framework for each well-being dimension separately. We run a multiple logit regression for the $\widehat{TE}_i$ indicator for each well-being dimension separately, following the model:

$$\Pr\left[\widehat{TE}_i = k|X, WB\right] = f\left(\alpha_k + \beta_k X_i + \delta_k WB_i\right), \quad k \in \{-1, 0, 1\}, \tag{1}$$

where X_i is a vector of individual observables including demographics, family and home resources, and school experience variables. All controls are dummy variables and are featured in Table 1. The model also controls for the level of the reference outcome, denoted WB_i. In this way, we disentangle effects related to the extent of well-being registered by any indicator from the effect of observable heterogeneity. f is the logistic function. The parameters are specific to each outcome. We derive marginal treatment effects only for categories $k = -1$ (worse/less) and $k = 1$ (better/more), which correspond to the change in probability that a positive or negative treatment effect is observed in correspondence to the fact that a certain driver of heterogeneity is observed or not, leaving all the other drivers as fixed. Figure 1 reports marginal effects of covariates on the probability of reporting positive or negative subjective evaluations of COVID-19 effects, alongside the 95% CI. Each panel of the figure corresponds to an outcome (and hence a different dependent variable). Control variables are on the vertical axis, while the magnitude of the marginal effects for the probability of worse/less or better/more treatment effects is on the horizontal axis.

We now discuss patterns of treatment effects from Table 3 and the role of drivers of heterogeneity (as captured by marginal treatment effects in Fig. 1) for each dimension of well-being separately.

General health A large majority of children (about 70%) report zero treatment effect of COVID-19 on their general health. The rest of the children report, in large majority, negative treatment effects. The average effect (column 4) turns out to be negative and significant. We find that home resources, as measured by the presence of books at home, significantly correlate with a reduced risk of negative impacts of COVID-19 on general health. Attending early childcare (when aged 1–5) and owning a computer, instead, correlates with rising the probability of achieving better health outcomes due to COVID-19, even after holding family resources as fixed.

Doing sports Almost 40% of children declare a reduction in their sports activity due to COVID-19 restrictions. We find weak evidence that family resources, as measured by the probability of owning a PC or a tablet, correlate with rising sports activities due to COVID-19. Treatment effects do not vary along other dimensions.

Eating unhealthy food We do not detect significant changes in unhealthy diet due to COVID-19. Only a small fraction of children, about 14%, report an increase in unhealthy food consumption due to COVID-19, while a similar proportion reports a reduction in the consumption of unhealthy food. The two changes counterbalance each other.

Time with parents, talking with parents, dining with parents Table 3 shows that a substantial proportion of children report that the time they spent with parents on different

Fig. 1 **Average marginal effect of covariates on subjective treatment effect**. The figure reports marginal treatment effects issued from estimating Eq. (1) with 95% CI. Each model estimated separately on 15 child well-being outcomes. Effects are reported for response items $\{-1, 1\}$, that is for treatment effect items "worse/less" (in black, solid line), and "better/more" (in red, dashed line)

activities has not varied by the effect of COVID-19, providing evidence that the pandemic did not alter the habits of most children as reported in the second year of the pandemic when children were back at school. A share of 17% of children report that the time spent with parents increased, while 14% of children report an increase of the time talking with parents on account of COVID-19. At the same time, similar shares of children reported a reduction in these two activities due to COVID-19. These estimates hint that COVID-19 had, on average, no impact on time and quality of the time children spent with their parents in 2021, as reported by children. However, subjective estimates of treatment effects also uncover substantial heterogeneity at the individual level about the direction of the effects of COVID-19, which would compensate on average. We find, instead, evidence that COVID-19 has deteriorated opportunities to dine with parents (a moment in which all members of the family interact and exchange), while the effect is positive only for a share of 7%, leading to an average negative effect on the sample. Heterogeneity analysis confirms that maternal education has a positive impact on subjective treatment effects. Children with highly-educated mothers tend to display higher chances that COVID-19 has increased their time spent alone with parents or dining with family. However, the effect of maternal education on the probability that COVID-19 subjective effects are negative is non-significant. Complementarity between the quality of mothers and the time spent with children is likely due to the higher use of smart working for this group of women.

Using computer, playing video games A large proportion of children, about 30%, report that the time they spend using a computer and playing videogames has increased due to COVID-19. Only less than 15% report a negative impact of COVID-19 on these dimensions. Heterogeneity analysis reveals interesting patterns. Owning a computer does not significantly affect the probability that the child increases (or decreases) the use of that computer due to COVID-19. We find, instead, an impact on playing video games. Children who own a computer (as opposed to those who share a computer at home or only own a video game platform, about one-third of the sample) are more (less) likely to report that, due to COVID-19, they have decreased (increased) the time they spend on video games. Owning a computer offers more working/leisure opportunities to children besides playing video games which, combined with the increased stimuli from school and peers during COVID-19 times, contribute to reducing time on video games. Home resources availability and attendance of childcare seem to produce significant positive effects, both by rising the probability of increasing the use of computer and reducing the chances that more of the time on computer is spent on video games.

Satisfaction with school, interest in school, average school marks, difficulties at school COVID-19 significantly reduces satisfaction and interest in school, as well as average marks, while increasing difficulties in school. We do not detect significant differences attributable to the drivers we consider, with some exceptions. Children in larger families tend to report more dissatisfaction and difficulties at school. Children who attended a day-care centre or had a nanny when they were aged 1 to 3 are also found to report a decrease in satisfaction with school, as well as an increase in difficulties at school due to COVID-19.

Using internet, using social networks The two dimensions are entangled. There has been a small, yet significant, positive effect of COVID-19 on the use of the internet and social networks among children. We find evidence that this effect is channelled by mothers' education, holding all the rest as fixed. Such heterogeneity may be related to differences in parenting styles based on parental education.

Regression analysis reveals that maternal education and early childcare attendance are persistent drivers of COVID-19 treatment effects heterogeneity (see Fig. 3 in the Appendix). Housing resources and demographics, particularly gender, which explain heterogeneity in levels, have little role in explaining heterogeneity in subjective treatment effects. Columns (5)–(13) of Table 3 recover heterogeneity across relevant sub-groups of the population. We measure $\widehat{TE}_i$ for each sub-group.

Subjective treatment effects largely coincide across genders (columns 5–7). Girls spend significantly less time with parents than boys, with no differences in the quality of time use. Mother's education seems to have an insurance role against the negative effects of COVID-19 (columns 8–10). We distinguish between the highly educated mothers (those with a tertiary education, 62% in the sample) and mothers with lower qualifications (with at most a high-school degree). Children with high-educated mothers are less likely to reduce interactions with parents. Compared to those with low-qualified mothers, they also spend more time on the internet and social media, indicating a larger ability to cope with socialization shocks.

Early childcare attendance is increasingly seen as a substitute for parental investments in early skills formation, especially for less well-off families. Compared to non-attending children, those who recalled attending a daycare centre or having a nanny, report significantly stronger negative effects of COVID-19 on health, sports practice, satisfaction, and performance at school (columns 11–13). Early childcare attendance or the use of nannies facilitates the labour market attachment of mothers, thereby expanding the income capacity of the family of origin and improving investments in their children. As a result, such children are exposed to better resources at home due to the mediating impact on maternal employment, leading to better outcomes and wider chances to see achievements being reduced in dimensions (such as health, sport, and school experience) affected by COVID-19. Early childcare attendance can have effects that manifest primarily through non-cognitive dimensions of children's abilities (Morando and Platt 2022). Consistently with this evidence, we find that children attending early childcare report having more opportunities for socializing with peers through social media and facing fewer difficulties at school due to COVID-19 compared to other children.

4 Discussion

Subjective treatment effects of COVID-19 have been elicited for a sample of children aged 12–16 living in Luxembourg. Effects refer to dimensions of well-being that have already materialized for children when they participate in the survey. We make use of these data to deliver three contributions to the literature. First, we deliver evidence about the size and magnitude of subjective treatment effects about a well-known and commonly understood phenomenon elicited among young respondents. Differently from recent literature addressing students' earning expectations (Arcidiacono et al. 2020; Diaz-Serrano and Nilsson 2022), our interest is on outcomes for which children have a direct, personal, and daily experience, both before and during the pandemic. Second, we contribute knowledge about the impact of COVID-19 on the well-being of younger people, largely affected by school closures and increased pandemic-related uncertainty. Children report lower health and reduced ability to practice sports due to COVID-19. They also report increased use of connected devices and social networks. Satisfaction and performance at school have also been affected by COVID-19, with effects going in the expected direction. Third, we leverage the fact that subjective treatment effects are reported at the individual level to study their heterogeneity. We document substantial heterogeneity along the lines of resources available to the children, including the mother's education, housing characteristics, and early educational investments. In contrast, differences based on gender and family composition (which correlate instead with the outcomes levels registered in Spring 2021) are not relevant drivers of treatment effects heterogeneity.

The survey collects information about key covariates, which we use to explain the drivers of heterogeneity. We assess how covariates explain treatment effects heterogeneity rather than measuring the impact of covariates on the average effects. Our analysis confirms that demographics have little role in explaining heterogeneity. Resources available to the children via their family of origin have a major impact. The indicators for mother education and for early childcare attendance when aged 1–3 (a dimension closely related to mothers' attachment to the labour market, when the child was born, and a proxy for actual attachment to the labour market) are by far the most relevant drivers.

Mother's education has an insurance effect *vis-à-vis* the consequences of the pandemic on well-being dimensions related to socialization within the family (time with parents) and with peers, as well as school experience. Children whose mothers have a university degree (more likely to benefit from smart work arrangements) did not reduce their time (quantity and quality) spent with parents due to the pandemic. By contrast, about 20% of children with less qualified mothers reported spending less time with parents due to the pandemic. Our findings align with those of Bonal and Gonzalez (2020), suggesting that middle- and upper-class families (as captured by parents' education or available resources at home) were better equipped to maintain high education standards during periods of distance learning and enhance their learning and socialization experiences. Arguably, most of these activities are carried out by children and parents together, implying an increased demand for time spent within the family. While adolescents whose mothers had higher education degrees were more likely to report a trend of reduction in time spent with their family over the pandemic period (Bebić-Crestany et al. 2023), the subjective treatment effect estimates are positive, implying that for this group the negative trend could have been even stronger in the absence of the pandemic. Time spent in the family can enhance adolescents' educational and social outcomes (which will become evident only upon school completion). Our results identify a mechanism through which the COVID-19 epidemic has affected the educational outcomes of children unevenly across the population while reinforcing intergenerational persistence of education.

Mothers with a university degree also enjoy high incomes on average, which can be invested in purchasing personal computers and other devices used for distance learning purposes. The pandemic has increased the adoption of such devices only in families with mothers holding a university degree, highlighting another channel through which mothers' education can protect children against learning losses due to school disruptions. Similar results for comparable age groups in Italy are found by Contini et al. (2022), showing that school closures have reduced math skills for children with low-qualified mothers. Lastly, we find that the subjective effects of COVID-19 vary according to attendance at early childcare institutions when the respondent was 1–3 years old. Early childcare attendance does not seem to provide insurance against the effects of COVID-19. Instead, attendance is correlated with more pronounced negative effects of COVID-19. The mechanisms behind these effects are unclear and deserve further investigation.

Appendix

See Figs. 2 and 3.

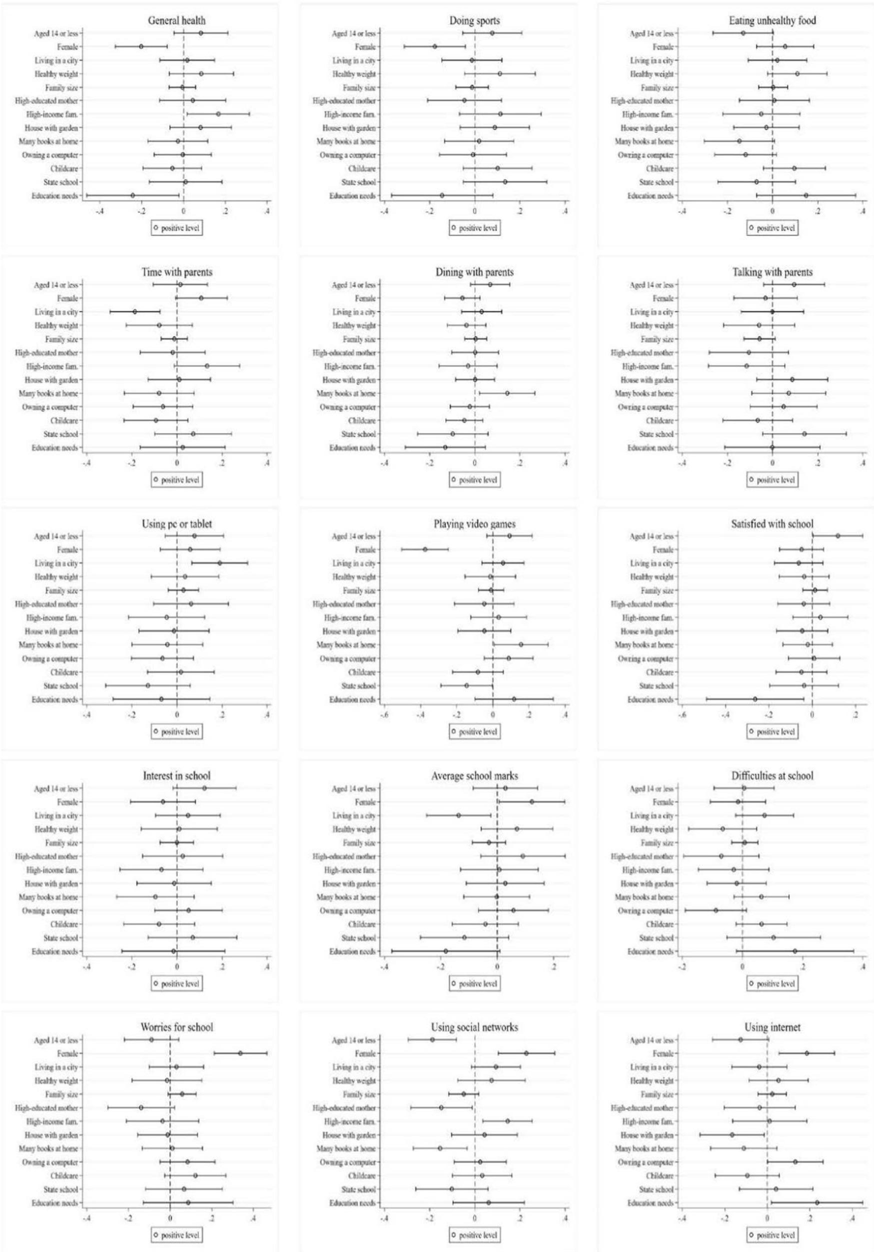

Fig. 2 **Marginal effects of covariates on outcomes** $\mathbf{Y}_i(COVID-19)$. The figure reports Logit coefficients and 95% CI of regression of an indicator taking value 1 if the child reports a positive level of well-being for each of the 15 dimensions separately (and 0 otherwise)

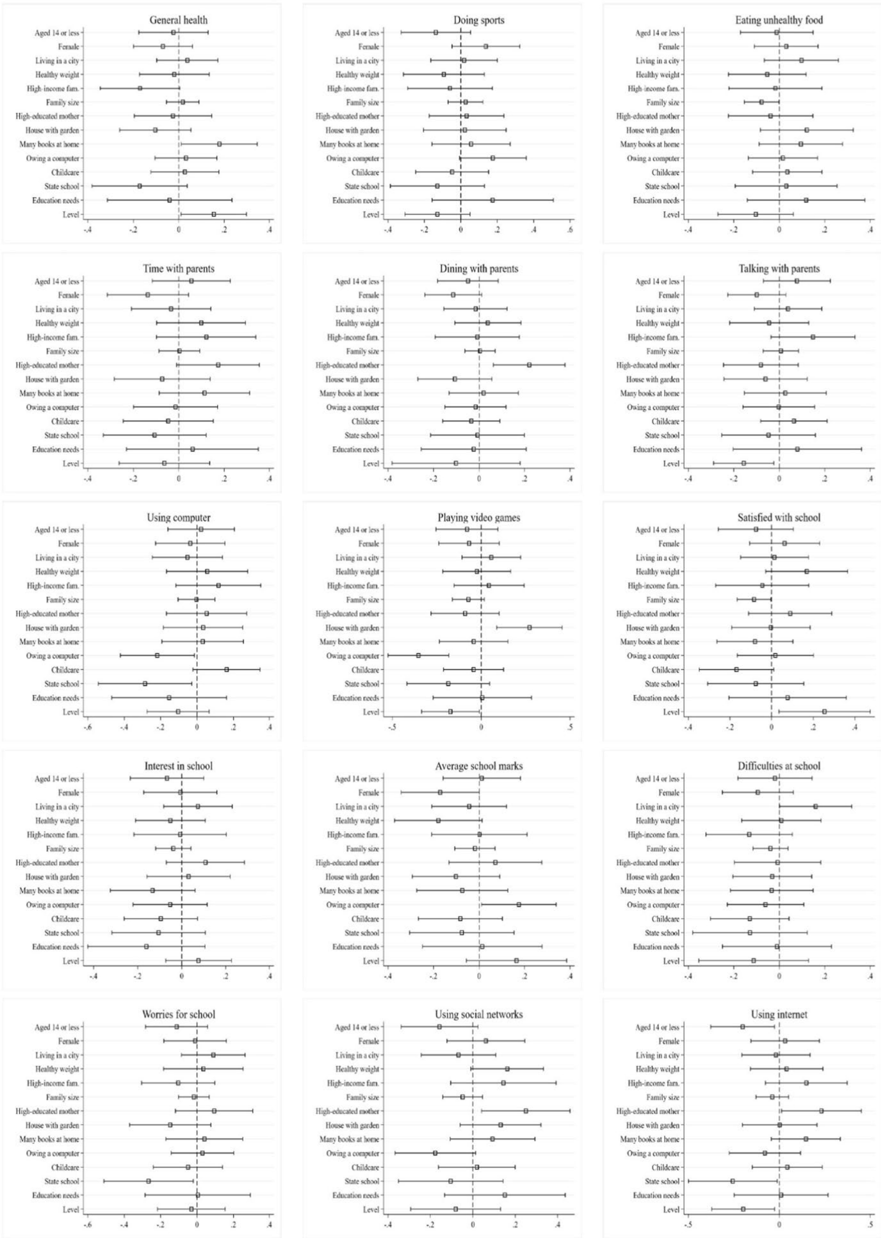

Fig. 3 **Marginal effects of covariates on $\widehat{TE}_i$.** The figure reports OLS coefficients and 95% CI of regression of the subjective treatment effect index $\widehat{TE}_i$ on the list of covariates used in model (1). Marginal treatment effect issued from estimating Eq. (1), with 95% CI

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Declarations

Conflict of interest Author Francesco Andreoli declares that he has no conflict of interest. Author Claudine Kirsch declares that she has no conflict of interest. Author Eugenio Peluso declares that he has no conflict of interest. Author Vincenzo Prete declares that he has no conflict of interest.

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Authors and Affiliations

Francesco Andreoli[1,2] · Claudine Kirsch[3] · Eugenio Peluso[2,4] · Vincenzo Prete[5]

✉ Francesco Andreoli
francesco.andreoli@univr.it

Claudine Kirsch
claudine.kirsch@uni.lu

Eugenio Peluso
eugenio.peluso@liser.lu

Vincenzo Prete
vincenzo.prete@unipa.it

[1] Department of Economics, University of Verona, Via Cantarane 24, 37129 Verona, Italy

[2] Luxembourg Institute of Socio-Economic Research (LISER), MSH, 11 Porte Des Sciences, Belval Campus, 4366 Esch-Sur-Alzette, Luxembourg

[3] Faculty of Humanities, Education and Social Sciences, University of Luxembourg, Esch-Sur-Alzette, Luxembourg

[4] Faculty of Law, Economics and Finance, Department of Economics and Management, University of Luxembourg, Rue Coudenhove-Kalergi, 1359 Esch-Sur-Alzette, Luxembourg

[5] Department of Law, University of Palermo, Piazza Bologni 8, 90134 Palermo, Italy