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Postal Address:
Institut d'Economia de Barcelona
Facultat d'Economia i Empresa
Universitat de Barcelona
C/ John M. Keynes, 1-11
(08034) Barcelona, Spain
Tel.: + 34 93 403 46 46
ieb@ub.edu
http://www.ieb.ub.edu

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ABSTRACT: We use census data on external assessments in primary and secondary school in the Basque Country (Spain) to estimate learning losses due to the COVID-19 pandemic in March 2021, one year after school closures, which lasted from March to June 2020. Differences-in-differences with student and school-by-grade fixed effects show an average learning loss of 0.045 standard deviations, an effect which is smaller than short-run effects estimated by previous papers, and estimated after 6 months of one of the most successful school reopening campaigns among OECD countries. The effect is larger in Mathematics, moderate in Basque language, and none in Spanish language. Controlling for socioeconomic differences, learning losses are especially large in public schools, and also in private schools with a high percentage of low-performing students. On the other hand, we find a regression to the mean within schools, possibly due to a compressed curriculum during the whole period. Finally, we show that students' with higher learning losses self-report significantly worse levels of socio-emotional well- being due to the pandemic.

JEL Codes: I24, I3, H75
Keywords: Education, learning loss, COVID-19, socio-emotional wellbeing

Andreu Arenas
University of Barcelona, IEB and IPErG
E-mail: andreu.arenas@ub.edu

Lucas Gortazar
ESADE EcPol and World Bank
E-mail: lucas.gortazar@esade.edu

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1 Introduction

The COVID-19 outbreak has been a very large and sudden shock, which stopped face-to-face learning through school closures for several weeks or months, all over the world. One of the main concerns about the long-lasting effects of the pandemic is about learning and human capital. For instance, Hanushek and Woessmann (2020) estimate that students in grades 1-12 affected by school closures might expect some 3 percent lower income over their entire lifetimes. For nations, the lower long-term growth related to such losses might yield an average of 1.5 percent lower annual GDP for the remainder of the century. Hence, the extent and the persistence of the effects of the pandemic on students' learning is a relevant question worldwide, and understanding and characterizing these effects, including its implications for inequality, is a crucial step towards designing effective policy responses.

In this paper, we use census data on external assessments in primary and lower secondary school students in the Spanish region of the Basque Country to study the effect of the pandemic on students' learning. We observe students' academic outcomes in primary and lower secondary school for two cohorts. On the one hand, the COVID-19 cohort (affected by school closures), which took the primary school external assessments before the pandemic (in 2017), and the lower secondary school external assessment in March 2021. On the other hand, we observe a control cohort, which took both assessments before the pandemic (in 2015 and 2019). Hence, we estimate the learning effect of the pandemic by differences-in-differences, including student and grade fixed effects.

Our results show significant learning losses by March 2021, one year after the Covid-19 outbreak, and hence, one year after a period of school closures and remote learning of three months (March to June 2020), a summer break (June to September 2020) and six months of successful school reopening (September 2020 to March 2021). For instance, we find a learning loss in Mathematics of around 0.075 standard deviations (s.d.), and in

Basque language, of 0.05 s.d.. The average magnitude of our estimates is equivalent to 13% of the usual learning which would take place in a regular year. This is smaller (50% less) than the loss documented in other countries where learning was measured between June and September 2020, relative to baseline measurements in previous years or cohorts. This could be explained by two reasons: (i) a measurement effect, such that learning losses are over-estimated when measured immediately after a break (as in the summer learning loss, (von Hippel and Hamrock, 2019; Von Hippel, 2019)); (ii) an actual catch-up following the reopening of schools. The learning loss is largest for Mathematics (20% of a regular year learning) and Basque language (11%). We do not find any learning loss in Spanish language. This is interesting because in the Basque Country, education is organized through three language models and the most prevalent model gives a high importance to the Basque language - a difficult language with no similarities with any other European language.

Furthermore, we study what type of students and schools have been most affected by the pandemic. We find that most differences are driven by school effects, as opposed to student effects. For instance, we find that learning losses are significantly larger in public schools, which represent approximately 50% of the school network. On the other hand, the effects are rather small in private schools. In this setting, private schools are publicly funded (although they often charge additional fees to parents) and privately managed, and represent the remaining 50% of the school network.

At the same time, we find that the learning loss varies significantly within private schools. Indeed, we find that overall the pandemic has increased the gap between schools with high and low-performing pupils (based on pre-treatment performance, i.e., in primary school tests), and that this happens mostly within private schools. While high-performing private schools show no learning loss due to the pandemic, low-performing private schools feature significant learning losses. These differences also hold after accounting for students' and schools' socio-economic status, as well as other characteristics (such as gender, language spoken at home or migrant status) which we do not find to be significantly related to learning losses. These results suggest that schools' reaction to the sudden shock has been a crucial moderator of the effect of the pandemic on learning.

While the pandemic increases the gap between schools with previously high and low performing students, we also find a regression to the mean within schools. More precisely, we observe that students with higher scores in primary school are those with the largest learning losses, compared to similar students in the control cohort. This could reflect a compressed curriculum following the COVID-19 outbreak and the school reopening campaign in 2020/21.[1] On average, we do not find significantly different effects of the pandemic by students' socio-economic status.

Finally, we study the relationship between students' attitudes towards school and socio-emotional well-being deterioration due to the pandemic and learning. We retrieve self-reported changes in socio-emotional well-being and attitudes towards school due to the pandemic from a survey completed by all COVID-19 cohort students during the external assessments. We find that the most disadvantaged students (both academically and socio-economically) report larger negative effects of the pandemic on well-being. We also find that students reporting larger well-being deterioration due to the pandemic feature significantly larger learning losses, both unconditionally and within groups (i.e., within schools, socio-economic status, and other characteristics). These results are policy-relevant because they show that students are very much aware of the effects of the pandemics on themselves, and outline the large overlap between educational and socio-emotional well-being challenges due to the COVID-19 pandemic.

[1] A compressed curriculum was one of the measures proposed by UNESCO to deal with the pandemic, for instance (Source).

This paper makes three contributions to the growing literature on the learning and human capital effects of the pandemic, which we further develop below. First, we provide estimates of the learning loss one year after the beginning of the pandemic, using a differences-in-differences within-student design that allows us to address biases from cohort effects, and using validated external assessments to measure learning. Second, we characterize of the learning loss across schools and students, documenting the importance of school effects. This is important to understand the mechanisms behind the learning loss due the pandemic, and necessary to understand what are the best policies to address it. Third, we jointly study the learning loss due to the pandemic and students' socio-emotional well-being deterioration. We show that these problems largely overlap, and that students are aware of it, which is important for targeting policy responses.

1.1 Existing evidence on learning losses due to the Pandemic

As outlined by Werner and Woessmann (2021), the crucial methodological challenge for measuring learning losses due to the pandemic is addressing bias from cohort effects. This requires individual-level longitudinal data, to observe how the students tested after the school closures had performed on tests before the school closures, and to compare them to earlier cohorts. As of October 2021, the only study that had access to that type of data was Engzell *et al.* (2021). They exploit that national assessments take place twice a year in The Netherlands to study outcomes of students just before and after the first nationwide school closures that lasted 8 weeks, and compare progress during this period to the same period in the 3 previous years. They find a learning loss of about 3 percentile points or 0.08 standard deviations. The effect is equivalent to one-fifth of a school year, the same period that schools remained closed, and it is larger among students from less-educated homes. Another important early study by Maldonado and De Witte (2021) uses school-level achievement data in a large sample of Catholic schools in Flanders (Belgium), where full closures continued for two months followed by partial openings. Controlling for a vector of school characteristics, they find large learning losses (0.17 s.d. in Math), and that schools with larger shares of disadvantaged students show larger losses.

An open and important question is whether the learning losses documented immediately after school closures will persist over time. Our first contribution is to provide a design resembling Engzell *et al.* (2021) (i.e., a differences-in-differences design addressing bias from cohort effect) that measures learning outcomes one year after the beginning of the pandemic (i.e., after school closures and remote learning for three months, between March and June 2020), a summer break (June-September 2020), and six months of successful school reopening (September 2020-March 2021). We compare the progress made by students before and during the pandemic between primary and secondary school, and compare such progress with the same period, for the previous cohort. We find significant learning losses, suggesting that this is a persistent effect, although nevertheless smaller in magnitude, implying that there may be room for some catching up over the medium and long run.

Other studies have estimated learning losses at different points in time. Contini *et al.* (2021) designed an exam for 2000 primary school children in Torino, and matched the sample with test scores from a pre-pandemic national standardised assessment. They find a large learning loss in mathematics (-0.19 sd), larger for well-performing children of low-educated parents. This is measured in October 2020, shortly after school closures and the summer break. In Denmark, Birkelund and Karlson (2021) estimate the learning loss in mid-2021, 14 months after the start of the pandemic (and including two school closures and two large re-opening campaigns): they find that compared to the trend implied by pre-covid cohorts and grades, there is no major learning loss nor significant differences according to the economic level of the student. This is interesting because it suggests an attenuation of the learning loss. Our results imply some attenuation, but still some persistence within a similar time frame. Using a differences-in-differences design similar to this paper, they examine heterogeneous effects, finding little evidence of widening learning gaps by family background, as in our results. A report by the UK's Education Department assessing learning throughout 2020/2021 suggests that periods of school closure (March-June 2020, and January-March 2021) display losses, while periods of reopening (Autumn 2020 and Spring 2021) display a catch up.[2]

Other relevant contributions include Schult and Lindner (2021), which compare standardized means across cohorts in Baden-Württemberg; Tomasik *et al.* (2021), which use latent growth models comparing learning in Switzerland in the eight weeks of confinement vs. the previous eight weeks; or Lichand *et al.* (2021), which show a 36% increase in dropout risk and a 0.32 sd declilen in test scores under remote learning in Sao Paulo, finding evidence that school reopenings significantly attenuated the learning loss, consistently with our results.

Other papers have focused on time-use. For instance, Grewenig *et al.* (2021) collect detailed information on students before and during the school closures in a survey of 1099 parents in Germany. They find that students significantly reduced their daily learning time, especially low achievers. This pattern is interesting, because we observe an opposite effect for learning (i.e., a regression to the mean). We find that the regression to the mean is mostly driven by a subset of schools (low-performing and public schools). Hence, this emphasizes the importance of school effects, which may act on top of individual-level time-use effects. Werner and Woessmann (2021) combine a review of the emerging international literature with new evidence from German longitudinal time-use surveys. They find that children's learning time decreased severely during the first school closures, particularly for low-achieving students, and increased only slightly one year later.

[2]Link to the report

1.2 Learning losses and socio-emotional well-being

The study of the effect of the pandemic on children's socio-emotional well-being has received slightly less attention. Newlove-Delgado *et al.* (2021) show a deterioration in the mental health of young people aged 5-16 years in the UK. Likewise, Blanden *et al.* (2021) find significant behavioral and emotional difficulties for children due to the pandemic, using data from the UK Household Longitudinal Study. The magnitude of their effects is at least as large as the immediate impacts of school closures on learning implied by other studies.

Ravens-Sieberer *et al.* (2021a,b) compare mental health and well-being measures of children in the spring of 2020, compared to previous cohorts in Germany, finding significantly lower scores and a further deterioriation in a second wave in early 2021. Again, they document substantial heterogeneity, with children from disadvantaged families experiencing more negative effects. Werner and Woessmann (2021) also present survey evidence that the socio-emotional well-being of students in Germany declined in the short run. Overall, their survey provides a mixed picture. They find a huge psychological burden for many children and families, but that the majority of children eventually proved quite resilient to the situation, with most parents reporting no change in most dimensions of their child's socio-emotional well-being during the school closures and some even reporting improvements. Nevertheless, they find substantial heterogeneity across families, consistent with our results. In Spain, Pizarro-Ruiz and Ordóñez-Camblor (2021) survey 590 confined Spanish children and teenagers between 8 and 18 years old, showing that during confinement, children and adolescents showed emotional and behavioural alterations.

To the best of our knowledge, ours is the first paper that brings together measures of learning loss with socio-emotional well-being problems due to the pandemic, showing their large overlap and outlining students' awareness.

2 Institutional setting and data

2.1 The Basque school system

The Basque school system is self-managed, and financed through its own tax revenues. It is subject to Spanish regulation for key issues regarding the structure of the system and levels, selection and training of the teaching profession, curriculum design, grade promotion or title expedition. The most recent data (2019/2020) show that the system enrolled 376,104 students between kindergarten and upper secondary (both general and vocational) education. Compulsory education consists of 6 years of primary education and 4 grades of lower secondary education.

The system is organized around two distinct school networks of equal size. Both of them are publicly funded, but one is state-owned (public schools), whereas the other is privately owned (private schools), run by religious entities or cooperatives which operate under a non-profit scheme.[3] These networks differ in their budgetary autonomy (private schools are able to use their own resources for personnel and management more freely), student composition (private schools disproportionately enrol native students and students from higher socio-economic backgrounds) and funding formula (the lack of sufficient public funding generates the needs of those schools to obtain alternative sources of funding through voluntary parental co-payments).[4] In addition, the system is organised in three different streams regarding language of instruction. The A model (Spanish is the main language of instruction and Basque is taught as a single subject), the B model (which balances the weight of both languages in terms of hours of instruction) and the D model (Basque being the main language of instruction, and Spanish being taught as a single subject). While about 34% of

[3]Moreover, a minority of 0.8% of students attend privately funded schools, which represents the lowest share among all Spanish Autonomous Communities.

[4]According to EUSTAT (2018), parents paid an average annual fee of €1156.6 for basic education services (without considering complementary activities or services) to private schools (publicly funded) in the Basque education system.

population aged 5-24 has Basque as its mother tongue (some of which share it with Spanish), around 75% of students attend the D language model.[5] Hence, Basque is a language that is largely learnt at school, rather than at home.

2.2 External assessments, data collection, and school selection

The Basque Institute for Research and Evaluation in Education (ISEI-IVEI) is a public agency dependent of the Department for Education of the Basque Country. The ISEI-IVEI is responsible for the design, development and reporting of external assessments; and also in charge of producing and promoting education research knowledge. Since 2009, the ISEI-IVEI has been effectively implementing external diagnosis evaluations (Evaluaciones de Diagnóstico, or EDs), of census nature. These evaluations take place every two years at mid-stage grades in primary (4th grade) and lower secondary (the equivalent to 8th grade), usually at the beginning of the third academic term. This means that in practice, with minor exceptions (students that repeat grade, newcomers or drop-outs), most students from cohorts which participate in the 4th grade test end up participating again 4 years later, in the grade 8 assessment, allowing for a longitudinal analysis. In the last years, these assessments took place in February and March 2015, March 2017, May 2019, and March 2021.

EDs are used for formative purposes: students and their families as well as school principals receive an individualised report about their individual or school performance, contextualised by the student or school socio-economic status. Specific student or school improvement plans are set through the support of schools and teachers (for students) and the inspectorate and teacher training centres (for schools). Student and school results cannot made be public by law, avoiding any sort of rankings or school indicators.

EDs are competency-based assessments where student competency is estimated through Item Response Theory model based on students' response to various items: given the

[5] Source: Basque government.

multiple-choice nature of the test, ISEI-IVEI implements a two-parameter model (Birnbaum, 1968) for dichotomously scored responses and the generalised partial credit model (Muraki, 1992) for items with more than two ordered correct response categories. Common items allowed to scale results to make them comparable to previous years in the same scale.

EDs focus on three key domains which all students have to take: Mathematics, Basque language and Spanish language. Additionally, other competencies are assessed, but not for all students and not necessarily in every year, such as Science, English language competency, Social and Citizen competency or Learning to Learn competency. In our study, we compare the cohort of students mostly born in 2005 (and hence taking the 4th grade assessment in 2015 and the 8th grade assessment in 2019) as the control group with the cohort of students mostly born in 2007 (taking the 4th grade assessment in 2017 and the 8th grade assessment in 2021) as the treated group, that is, the cohort affect by COVID-19.

In Spain, education external assessments are partially transferred to regions (Autonomous Communities), although the Ministry of Education is theoretically responsible to organise national assessments. While other regions in Spain also do run external assessments, the ISEI-IVEI's EDs have three fundamental advantages, especially when it comes to comparability of results and its usage of data for research. First, its aforementioned longitudinal structure. Second, as in PISA, EDs have common items throughout the years to compare students' learning over time and across cohorts. And third, the ISEI-IVEI EDs are the only regional evaluations that are applied by an external party outside the schools and the system, and therefore, the reliability of the data is much higher.

The 2021 edition was conditioned by the circumstances regarding school reopening while COVID-19 pandemic outbreaks were still relevant and the incidence of the virus was prevalent and high. Like all schools in Spain, the Basque Country closed its schools between March 12 up until the end of the school year 2019/2020. During school year 2020/21, all schools reopened successfully, but many school operated in morning shift to reduce the risk of contagion during lunch breaks in indoor spaces. Schools were pressed to provide the regular services in a compressed schedule, whereas at the same time they had to attend individual needs of the students most harmed by the school closures between March and June 2020. OECD data suggests that the Spanish education system was successful regarding the school reopening campaign in 2020/21: while Spain stood 10th among OECD countries with fewer school days lost by December 31st, the system advanced to the 4th position by May 31st.[6]

Data from the Basque Education system shows that the proportion of classes opened in the school year 2020/21 was always above 98.4% and on average near 99%, with the months of January to March (prior to the EDs) witnessing a participation always over 98.6%, even with a COVID-19 outbreak taking place in January 2021.[7] This figure is no different from the national figure in Spain, which stood between 98.6% and 99.7% in January-March 2021. These numbers were similar in the period of September to December 2020.[8]

Given the difficulties faced by schools regarding reopening, ISEI-IVEI allowed, for its first time, that schools would participate in the EDs on a voluntary basis: once schools made their decisions, students within participating schools were not allowed to refuse to participate. Whereas in regular year, the rate of participation of schools and students was consistently in very high numbers (above 95% of schools), the 2021 edition of EDs took place with a reduced sample of schools (130 schools, compared to 326 schools in the control cohort), which enrol around 38% of students.

2.3 Data

We use data on two cohorts of students. The first one, the control cohort, took the primary school exams in 2015, and the secondary school exams in 2019. The second one, which we

[6]Link to source 1 - OECD. “The state of school education: One year into the COVID pandemic”. Link to source 2 - OECD. “The state of Global Education 18 months into the pandemic.”

[7]Link to source (ISEI-IVEI).

[8]Link to source 1 (Spanish Government), link to source 2 (Spanish Government).

name the COVID or Treatment cohort, took the primary school exam in 2017, and the lower secondary school exam in 2021.

We focus on three learning outcomes, namely test scores in Mathematics, Spanish language and Basque language. We observe the students' gender, socio-economic status, language spoken at home, immigrant status and basic school characteristics (including indicators on school ownership - private or public-, language model followed and average socio-economic status of students in the school of attendance). We classify students and schools as of either high (above median) or low (below median) socioeconomic status, following a SES index computed by ISEI-IVEI, which aggregates information from various measures, similarly to PISA (i.e., parental education, occupation, ownership of certain goods, time spent at home, or holidays). For the control cohort, we observe the test scores and individual covariates of all students, both in primary and secondary education. For the COVID cohort, we observe all students in primary education, and all students from participating schools in secondary education. We focus only on students which we observe twice (i.e., in primary and in secondary education).

2.3.1 Selection into exam-taking

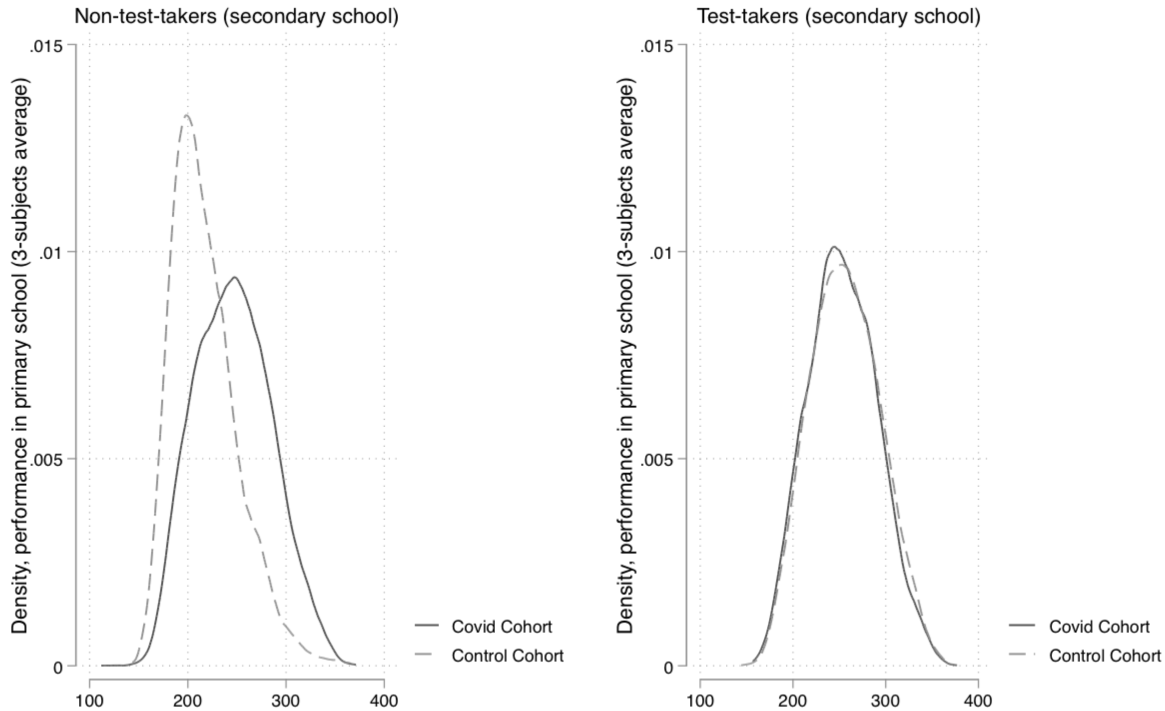
One challenge for identifying the effect of the pandemic is that exam-taking is not compulsory for the COVID cohort. Schools' results cannot made be public by law, to avoid rankings, meaning that schools do not have incentives to participate (or not participate). Nonetheless, this may be a problem if exam-taking decisions are correlated with determinants of test scores. Selection into exam-taking depends on schools, not on individual students' decisions. In schools which agreed to participate, only the classes which were confined at home due to positive COVID-19 case are exempted from taking the tests.

The longitudinal nature of the data allows us to measure and address some selection concerns. The data contain information on primary school performance of all students, both for the COVID cohort (i.e., the cohort taking the secondary school exam in March 2021) and for the control cohort. Hence, we can measure an important dimension of selection into exam-taking by looking at the primary school performance of the COVID cohort, compared to the control cohort.

In regular years, educational factors (i.e., grade repetition) are the main reason for not observing students in the secondary school exam which were observed in the primary school exams. In the COVID cohort, however, many students who would normally participate do not take the secondary school test for new reasons. As a result, we expect the population of non-test-takers in the COVID cohort to have a higher level of past performance than previous cohorts. However, it is less clear whether the population of test-takers in the COVID cohort will be different, on average, compared to a regular year. For instance, if schools which do not take the test in 2021 tend to be high-performing schools, the COVID cohort participating in the 2021 test will be negatively selected. Instead, if schools which do not take exams in 2021 tend to be below-average schools, the COVID cohort will be positively selected.

Figure 1 displays the distribution of primary school test scores (average of Math, Spanish and Basque), comparing students which took and which did not take the secondary school test, for the COVID and the control cohort. The left panel of the figure shows that, as expected, non-takers in the COVID have on average higher performance in primary on average than non-takers from the Control cohort. The right panel, however, shows that test-takers from the COVID cohort are rather similar (in terms of primary school past performance) to test-takers from the control cohort.

Figure 1: School performance in primary school of secondary school exam-takers



Hence, this pattern suggests that schools participating in the secondary school test with the COVID cohort are similar to the average school from the Control cohort. Nevertheless, in all model regressions, we control for grade-by-school fixed effects, which account for any school-specific differences in performance across grades, and also present specifications which control for primary school test outcomes.

3 Effects on learning

We estimate learning losses by differences-in-differences. We use test scores as the outcome variable. As explained in section 2.2., following Item Response Theory, test scores are scaled to the baseline year (2009) average performance using common items (items that are repeated in every wave) for Math, Basque and Spanish: the baseline year distribution of learning outcomes has its mean approximately at 250 points, with a standard deviation of 50 points. ISEI-IVEI experts provided the benchmark of 20 points as the equivalent of what a student learns per year.[9]

We regress the test scores of student i in grade g on individual fixed effects (α_i), grade fixed effects (δ_g) and an interaction between a COVID cohort dummy and a secondary school (2nd of ESO, or 8th grade) dummy. We also control for school-by-grade fixed effects, which allow each school to have a different intercept for primary and secondary school test scores. Hence, the identification assumption is that changes in test scores between primary and secondary education would be constant across cohorts in absence of the pandemic.

$$y_{ig} = \alpha_i + \delta_g + \beta \left(\text{Covid Cohort}_i \times \text{Secondary School}_g\right) + \gamma X_{ig} + \epsilon_{ig}$$

The left panel of figure 2 reports point estimates and 95% confidence intervals of the baseline differences in differences model, where we cluster the standard errors at the student level. We also report point estimates, standard errors, and further descriptives in table A2 in the Appendix. The results show statistically significant learning losses by March 2021, one year after the Covid-19 outbreak, and hence, one year after school closures. The largest learning loss effect is on Mathematics. The magnitude of the estimate (3.8 points in the test scale) corresponds to 0.075 standard deviations (s.d.) and of 20% equivalent of learning in

[9]Other papers use one-third of a standard deviation as an equivalent to one year of learning (Werner and Woessmann, 2021).

a regular school year. We also find sizable effects for Basque by about 2.2 points in the test scale (0.05 s.d. and 11% of the usual learning which would take place in a regular year). Finally, we find no significant learning losses for Spanish. Overall, the average learning loss is of 0.043 standard deviations.

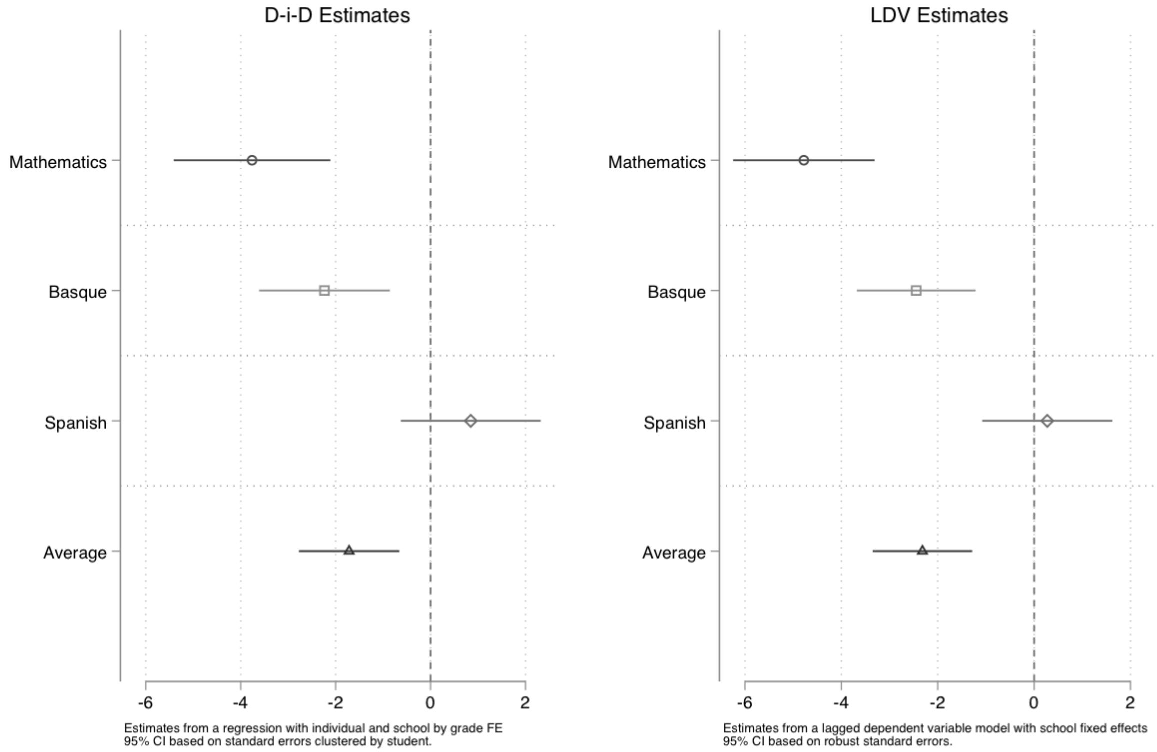
The pattern in the results of figure 2 across subjects is not surprising. Mathematics and Basque are complex subjects, which may have made the periods of online teaching especially challenging. On the other hand, students are more exposed to Spanish in their daily life (i.e., in the media). Moreover, it is interesting to note that the magnitude of these learning loss estimates is smaller compared to that documented by the literature in the early months of the pandemic (Engzell *et al.*, 2021; Maldonado and De Witte, 2021). This could be explained by two reasons: (i) a measurement effect, due to measuring learning immediately after a break (as in the summer learning loss, (von Hippel and Hamrock, 2019; Von Hippel, 2019)); (ii) an actual catch up following an efficient school reopening. Regarding the latter, it is interesting to recall that the reopening campaign in the Basque Country and in Spain was one the most successful among OECD countries, as explained in section 2.2.

We also estimate lagged-dependent-variable specifications, in which we regress the grade in secondary school of student i on the student's grades in the three subjects in primary school, school fixed effects $\alpha_{s(i)}$, and a Covid Cohort indicator.

$$y_{i,Secondary} = \alpha_{s(i)} + \beta \text{Covid Cohort}_i + \delta y_{i,Primary} + \epsilon_i$$

The right panel of figure 2 shows the learning loss estimates from lagged dependent variable models, which are very similar. One concern about these results is whether they come from a population with particularly low learning losses due to the pandemic. For instance, this could be the case if schools' selection into exam taking is based on their perceived learning losses (Werner and Woessmann, 2021). As a robustness check, we estimate the learning

Figure 2: Learning Loss. Main Effects



loss by differences-in-differences as in the baseline specification, but reweighting the covid cohort sample such that the distribution of schools' and students' characteristics matches that of the control cohort (i.e., that of a full regular cohort), using entropy balancing (Hainmueller, 2012). Entropy balancing relies on a maximum entropy reweighting scheme that calibrates unit weights so that the reweighted treatment and control group satisfy a potentially large set of prespecified balance conditions which incorporate information about known sample moments. In this case, we reweight the covid cohort so that the reweighted sample features the same fraction of public schools, high performing schools, high SES schools, high performing students, high SES students, females, migrants, Basque-speakers at home, and linguistic model types. The results in the bottom panel of table A2 in the Appendix show estimates that are slightly larger but very similar. This suggests that heterogeneous attrition across groups is not significantly related to treatment effect heterogeneity.

3.1 Heterogeneous effects

The concern about the long-lasting effects of the pandemic on learning goes beyond its average effects on the student population. We next study heterogeneous effects across students and schools and its implications for inequality. We estimate the heterogeneous effect of a pre-determined covariate Z_i (which may vary at student or at the school level) with the following specification:

$$y_{ig} = \alpha_i + \delta_g + \lambda \left(\text{Covid Cohort}_i \times Z_i\right) + \rho \left(\text{Covid Cohort}_i \times \text{Secondary School}_g\right)$$

$$+\mu \left(\text{Secondary School}_g \times Z_i\right) + \beta \left(\text{Covid Cohort}_i \times \text{Secondary School}_g \times Z_i\right) + \gamma X_{ig} + \epsilon_{ig}$$

We follow a triple difference estimator, in which we compare the learning loss (a difference-in-difference) across groups (Z). Table 1 reports the learning loss estimates across students' and schools' demographic and academic characteristics: results are presented for the average of the three subjects' test scores as dependent variable.

Column (1) shows that females and migrants have slightly larger learning losses, although these differences are not significant. It also shows that we do not find differences by language spoken at home. Column (2) shows that on average, there's no learning loss difference between students of low and high socio-economic status (SES).

Column (3), however, shows that students with high learning outcomes back in primary school tend to have higher learning losses (we classify students as high or low performers depending on whether they scored above or below average). This means that the pandemic led to a regression to the mean in learning outcomes. Column (4) considers all individual covariates together in the same model, with similar findings.

Columns (5) to (7) focus on heterogeneous effects across schools. Column (5) shows that the learning loss was significantly larger for public schools, compared to private schools, which on average feature a learning loss close to zero. Column (6) shows that there are no significant learning loss differences between schools mostly enrolling students of high or low SES. Column (7), instead, shows that learning losses are significantly larger for schools which enrol pupils which on average had lower grades in elementary school, compared to those schools enrolling pupils with above-average grades in elementary school (High Perf. Schools). These results are interesting because they show that there is an important divergence in learning outcomes between schools due to the pandemic, mainly depending on school ownership and on average past academic performance. Importantly, column (9) shows that these differences are not driven by differences in SES across public and private schools or across high performing vs. low performing schools. Column (9) summarizes the main result of this section, which is that the pandemic leads to unequal learning losses between schools, while at the same time, it leads to regression to the mean (with respect to past academic performance) within schools. The within-school regression into the mean is emphasized in column (10), which reports a very similar coefficient after accounting for school-by-cohort-by-grade fixed effects.

In columns (11) to (14), we examine whether these heterogeneity patterns are driven by specific subsets of schools. Columns (11) and (12) split the sample by school ownership. The results show that the unequal learning loss between schools takes place mostly within private schools, and not at all in public schools. This means that the learning loss was rather evenly distributed across public schools, but very unequally distributed across private schools: private schools with high performing pupils display no learning loss, or even learning gains, whereas private schools with previously low performing pupils display significant learning losses. On the other hand, we observe regression to the mean within both groups.

Table 1: Heterogeneous learning effects

	Average (Math, Basque, Spanish)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Covid Cohort× Secondary School	-0.826	-1.721**	-3.371***	-2.388***	-0.242	-0.690	-0.724	0.637	-0.473		0.294	-11.03***	-5.178***	1.702	-2.646***
	(0.743)	(0.670)	(0.713)	(0.916)	(0.620)	(0.725)	(0.902)	(0.937)	(0.998)		(1.085)	(2.132)	(1.472)	(1.235)	(0.682)
CC× SS × Female	-1.094			-0.599											
	(0.888)			(0.864)											
CC× SS × Migrant	-1.109			-1.583											
	(1.830)			(1.830)											
CC× SS × Basque-speaking	-0.353			-0.535											
	(1.119)			(1.094)											
CC× SS × Low SES Student		0.417		0.0974					0.306	-0.213					
		(0.921)		(0.935)					(0.958)	(0.981)					
CC× SS × Low Perf. Student			2.445***	2.288**					2.647***	2.519***	2.022*	3.929**	4.418***	0.279	
			(0.885)	(0.898)					(0.913)	(0.926)	(1.081)	(1.730)	(1.246)	(1.338)	
CC× SS × Public School					-5.882***			-7.458***	-7.202***				-1.418	-9.273***	
					(1.258)			(1.613)	(1.568)				(1.965)	(2.414)	
CC× SS × Low SES School						-0.666		5.312***	4.060**						
						(1.239)		(1.722)	(1.723)						
CC× SS × Low Perf. School							-3.052**	-4.477***	-4.309***		-5.069***	3.836			
							(1.390)	(1.569)	(1.544)		(1.669)	(2.641)			
CC× SS × Ling. Model A (Spanish)															0.681
															(2.029)
CC× SS × Ling. Model B (Mixed)															2.811**
															(1.200)
N	41476	41476	41476	41476	41476	41476	41476	41476	41476	41316	24956	16290	20322	20924	41476
School × Covid Cohort × Sec. School FE										✓					
Schools Sample	All	All	All	All	All	All	All	All	All	All	Semi-private	Public	Low perf.	High perf.	All
Mean Dep. Var	253.0	253.0	253.0	253.0	253.0	253.0	253.0	253.0	253.0	253.0	254.4	250.9	244.4	261.4	253.0
SD Dep. Var	39.84	39.84	39.84	39.84	39.84	39.84	39.84	39.84	39.84	39.82	39.36	40.41	38.59	39.22	39.84

Standard errors clustered by student. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions include student FE, grade FE, school FE, and school by grade FE.

All regressions control for interactions of cohort and grade FE with the interacted variables.

Columns (13) and (14) split the sample by the average students' academic performance in primary education (i.e., above and below average). We observe that regression to the mean happens mostly within schools which tend to enrol students with lower scores in primary education. In those schools, we also observe very small differences between private and public schools. On the other hand, this pattern reverses for schools with high-performing students. In those schools, we see no regression to the mean, but large differences between public and private schools in learning outcomes due to the pandemic. This reinforces the idea that schools were a crucial moderator of the effect of the pandemic on learning. Finally, in column (15), we show heterogeneous effects by linguistic model, showing that the effects were concentrated in the Basque (model D, enrolling 65% of students) and Spanish (model A, enrolling 7.5% of students) lines, but that there were little effects in the mixed model (model B, enrolling 27.5% of students).

We also report estimates of heterogeneous learning effects on each of the subjects (Mathematics, Basque, Spanish) in tables A3, A4 and A5 in the Appendix. The main message is rather similar, especially for Basque and Spanish. We observe more negative effects in Basque and Spanish for those who speak it respectively at home, which is consistent with regression to the mean (they tend to have higher scores as well in those subjects). For Mathematics, the heterogeneity patterns are slightly different. We still find very large learning losses for public schools, and very small effects for private schools. However, we find that it is high SES schools rather than high performing schools which exhibit smaller learning losses. On the other hand, we still find regression to the mean within schools, and again, that this is especially high within low-performing schools.

Overall, these heterogeneous effects across schools, especially regarding public vs. private schools, are consistent with existing survey evidence for Spain. Bonal and González (2020) fielded an online survey in March 2020 to examine variation in learning opportunities in Spain. They show that students enrolled in private schools, both independent and private subsidised ones, had significantly higher opportunities to learn scores than those in public schools. The authors argue that this could be because public schools did not develop school tasks at the very beginning of the lockdown, while waiting for new instructions from the Government. However, private subsidised and independent schools did not stop their teaching activity. One of the plausible explanations for this difference lies in the economic dependency of private schools on fees, which means that hey need to keep providing a service to users despite the exceptional circumstances.

Finally, we quantify the explanatory power of schools vs. individual characteristics. To this aim, we construct an individual-level measure of learning loss due to the pandemic. In a first step, we regress $\Delta^{Secondary-Primary}_{Test\ Scores}$ on a vector of school fixed effects and individual characteristics (female, migrant, language at home, SES, and performance in primary school), for the control cohort. Then, we study, for the Covid cohort, how much of the deviation from the prediction of the regression of the first step $\left(\Delta^{Secondary-Primary}_{Test\ Scores} - \hat{\Delta}^{Secondary-Primary}_{Test\ Scores}\right)$ is explained by school fixed effects, compared to individual characteristics. The results in table 2 show that indeed, school effects explain a much larger percentage of the sample variation in learning loss than individual characteristics. This exercise is done on an estimate of the individual learning loss due to the pandemic (which we cannot perfectly observe, by construction, but simply approximate by comparison with the control cohort), which implies that these results are noisy. Nevertheless, the difference between the variation explained by school characteristics vis-à-vis individual characteristics is clear and favours the school effect hypothesis.

Table 2: Importance of school vs. individual characteristics for learning losses

	School FE	Individual characteristics	School FE& Individual characteristics
R^2	0.1190	0.0056	0.1239
Adjusted R^2	0.0985	0.0043	0.1026

3.2 Socio-emotional well-being and its link to learning loss

A unique feature of our dataset is that it combines cognitive outcomes with survey responses about students' deterioration of socio-emotional well-being and attitudes towards school due to the pandemic: such survey was conducted during the external assessments. The survey questions answered by students are the following. On emotional well-being, (1) I have more anxiety and stress, (2) I want the pandemic to be over and live like before, (3) I rely on food to feel better, (4) Lately, I feel more attacked on social media. On social and familiar well-being, (5) I get along worse with my classmates, (6) I get along worse with my family. On attitudes towards school, (7) I behave worse in the classroom, (8) I'm not motivated to study.

Students reply on a scale from 1 to 4 their degree of agreement with the given statements, with the answer taking a value of 1 if they fully disagree and a value of four if they fully agree with those statements. We measure socio-emotional well-being problems by constructing an average of the survey responses to all these questions. The average response is around 1.9, indicating that students rather disagree with those statements (i.e., students fully agreeing to 50% but fully disagreeing to 50% of the questions would score 2.5), with a standard deviation of 0.5.

Panel A of table 3 presents a descriptive analysis of the prevalence of well-being deterioration due to the pandemic across students and schools. It shows that the groups doing worse due to the pandemic are male students, students enrolled in public schools and schools with lower SES, and schools with prior lower performance in primary school. Overall, the results show a substantial heterogeneity in well-being deterioration across groups, consistent with previous findings (Werner and Woessmann, 2021).

In panel B of table 3, we study the relationship between self-reported well-being deterioration and the test score difference between secondary and primary school. In column (1), we regress within-student changes in academic performance on our measure of well-being. The results show that students self-reporting more deterioration due to the pandemic are those performing worse in secondary school (compared to primary school). Nevertheless, this result could be simply capturing that students that typically perform worse in secondary school (compared to primary school) are those with more socio-emotional well-being issues.

In column (2), we relate socio-emotional well-being challenges to the learning losses which arise due to the pandemic. The dependent variable is now the difference between the student's learning loss and her predicted learning change between secondary and primary education. This predicted change is estimated with the control cohort, with a regression of learning differences between secondary and primary education on school FE and individual characteristics (gender, migrant status, language at home, SES, elementary school performance). Hence, this outcome variable excludes variation coming from students who typically perform worse in secondary school than in primary school in any case. The results show that socio-emotional well-being issues are indeed significantly associated with learning losses that arise due to the COVID-19 and the school closures.

Finally, in column (3), we study whether the relationship between well-being challenges and learning losses due to the pandemic is driven by cross-group variation in learning losses, or instead it also takes place within groups (i.e., after controlling for school and individual characteristics). The results show that this is indeed the case: the association between learning losses and well-being challenges is very similar when focusing on within-group variation. In table A6 in the Appendix, we show that this pattern is very similar across each of the subjects.

To sum up, these results show that students' socio-emotional well-being challenges due to the pandemic largely overlap with learning losses, which suggests a role for more targeted and holistic policy responses. Moreover, the results also indicate that students' are aware of these challenges, which could facilitate policy responses.

Table 3: Socio-emotional well-being

Panel A: Student socio-emotional well-being deterioration across groups

	Dependent Variable: Socio-emotional Well-being Deterioration								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-0.145***								-0.147***
	(0.0129)								(0.0129)
Migrant	0.0494*								0.00883
	(0.0279)								(0.0284)
Basque at home	-0.00810								-0.00276
	(0.0154)								(0.0157)
Public School		0.0365**			0.0305				0.0315
		(0.0152)			(0.0197)				(0.0196)
Low SES School			0.0286**		0.00466				-0.0199
			(0.0132)		(0.0184)				(0.0187)
Low Perf. School				0.0256*	0.0209				0.0106
				(0.0131)	(0.0145)				(0.0146)
Low SES student						0.0738***		0.0631***	0.0687***
						(0.0131)		(0.0135)	(0.0143)
Low Perf. Student							0.0614***	0.0472***	0.0413***
							(0.0130)	(0.0133)	(0.0134)
N	5621	5621	5621	5621	5621	5621	5621	5621	5621
Mean Dep. Var	1.918	1.918	1.918	1.918	1.918	1.918	1.918	1.918	1.918
SD Dep. Var	0.489	0.489	0.489	0.489	0.489	0.489	0.489	0.489	0.489

Panel B: Learning loss and student socio-emotional well-being deterioration

	ΔMean Math-Basque-Spanish	ΔAvg. Math-Basque-Spanish $-\Delta$Avg. $\widehat{\text{Math-Basque}}$-Spanish	
	(1)	(2)	(3)
Socio-emotional Well-being Deterioration	-5.069***	-6.062***	-6.497***
	(0.830)	(0.815)	(0.808)
N	5621	5621	5621
Controls			✓
Mean Dep. Var	-6.520	-1.783	-1.783
SD Dep. Var	29.29	29.34	29.34

Sample: covid cohort, secondary school.

Socio-emotional Well-being Deterioration measured with the mean of survey responses.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Controls: school FE, female, migrant, Basque at home, low SES student, low Perf. Student.

Predicted outcomes based on a regression of $\Delta on the set of controls$,

for the control cohort sample.

4 Conclusion and Policy Discussion

The findings of the study are policy relevant for various reasons. First, we present evidence of learning loss one year after the start of the COVID-19 pandemic in March 2020, hence measuring the composite effect of three months of school closures and remote learning (March to June 2020), the summer break 2020, and six months (September 2020 to March 2021). Our case study has been one of the most successful school reopening campaigns (in terms of school closure days) among OECD countries. The fact that the learning loss found is lower compared to other countries' experiences is consistent with what is found by Lichand *et al.* (2021) or by the UK Department of Education Reports regarding the effect of school reopening on learning loss alleviation.

Regarding heterogeneous effects, we find no major learning loss gaps between students by socioeconomic status. This suggests that the reopening campaign was successful in mitigating inequality, and that there is no trade-off between a safe reopening and catching up interventions. A safe reopening which focuses on all students could be, in the short-term, the most efficient catching up strategy for the pandemic's learning loss.

However, we find that factors linked to schools are crucial mediators driving learning loss differences. The results show that the learning effects of the pandemic are mostly explained by between-school differences: we observe a large decline in learning for public schools, as well as a learning loss in private schools with prior low performance. One possible explanation for these differences are differences in school autonomy between public and private schools, which are notable in Spain, especially when it comes to human and financial resource management (OECD, 2016): this would entail an important advantage at the time of managing remote teaching (while schools are closed) as well as school reopening campaigns.

While the pandemic increases differences between schools, we also find a regression to the mean within schools. We observe that students with higher scores in primary school are those with the largest learning losses, which could reflect a compressed curriculum following the COVID-19 outbreak.

We also find heterogeneous effects across subjects, with a higher learning loss in mathematics and in Basque language. One possible explanation for this is that these are complex subjects, which may have made the periods of online teaching especially challenging. On the other hand, students are more exposed to Spanish in their daily life (i.e., in the media). Mathematics and Basque are both taught in Basque language for the vast majority of students, including many of which do not speak it as primary language at home. However, if anything and contrarily to what is expected, those who speak Basque at home are those who feature larger learning losses in those subjects: this would be consistent with the regression to the mean, as Basque-speakers at home tend to have higher scores in both subjects.

Moreover, to the best of our knowledge, this is the first paper showing a link between learning losses and socio-emotional well-being deterioration during the pandemic, suggesting strong complementarities. This is relevant regarding early detection and assessment, as socio-emotional well-being surveys (easier to implement than external assessment) can serve as optimal instruments to simultaneously detect student socio-emotional and academic challenges. But also regarding policy: policy responses that address students learning loss should incorporate socio-emotional and psycho-social support strategies to address both challenges.

Finally, our results lead to a number of interesting questions, which we hope will be addressed by future research. First, we would like to keep monitoring the learning loss over time. We believe studying the persistence of this shock can be broadly informative about the dynamics of human capital accumulation and learning. Second, following the results on the overlap between learning losses and socio-emotional well-being, it will be interesting to study how other measures of cognitive and non-cognitive skills, beyond test scores, are affected by the pandemic. Finally, it will be crucial to evaluate the effectiveness of the upcoming policy interventions aimed at mitigating the learning loss due to the pandemic.

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Learning loss One Year After School Closures: Evidence from the Basque Country

Online Supporting Information

Data access: all data have been accessed in collaboration with ISEI-IVEI.

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Table A1: Descriptive statistics

Variable Name	Control Cohort	Covid Cohort	Total
Female	0.498	0.518	0.503
	(0.500)	(0.500)	(0.500)
Migrant	0.0610	0.0686	0.0631
	(0.239)	(0.253)	(0.243)
Speaks Basque at home	0.306	0.215	0.281
	(0.461)	(0.411)	(0.449)
Low SES student	0.443	0.445	0.444
	(0.497)	(0.497)	(0.497)
Avg. (Math-Basque-Spanish), Secondary School	251.5	247.1	250.3
	(41.93)	(40.94)	(41.70)
Avg. (Math-Basque-Spanish), Primary School	256.4	253.7	255.7
	(37.86)	(37.18)	(37.69)
Mathematics Test Score, Secondary School	252.7	247.7	251.3
	(51.32)	(51.38)	(51.38)
Mathematics Test Score, Primary School	254.6	251.5	253.8
	(47.60)	(47.96)	(47.72)
Basque Test Score, Secondary School	246.3	238.7	244.2
	(49.43)	(44.77)	(48.32)
Basque Test Score, Primary School	254.3	249.6	253.0
	(45.16)	(45.42)	(45.28)
Spanish Test Score, Secondary School	255.4	255.0	255.3
	(45.94)	(48.64)	(46.70)
Spanish Test Score, Primary School	260.3	260.2	260.3
	(40.96)	(39.84)	(40.65)
Public School (Secondary School)	0.449	0.255	0.396
	(0.497)	(0.436)	(0.489)
Low SES School (Secondary School)	0.416	0.450	0.425
	(0.493)	(0.498)	(0.494)
Low Perf. School (Average, Secondary School)	0.458	0.583	0.492
	(0.498)	(0.493)	(0.500)
N	15076	5672	20748

Standard deviations in parentheses.

Table A2: Learning Loss, Main Effects

Differences-in-differences estimates

	Mathematics	Basque	Spanish	Avg., 3 subjects
	(1)	(2)	(3)	(4)
Covid Cohort× Secondary School	-3.761***	-2.235***	0.847	-1.716***
	(0.842)	(0.703)	(0.752)	(0.540)
Student FE	✓	✓	✓	✓
School-by-grade FE	✓	✓	✓	✓
Mean Dep. Var	252.6	248.6	257.8	253.0
SD Dep. Var	49.60	47.02	43.84	39.84
N	41476	41476	41476	41476

Standard errors clustered by student in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Lagged Dependent Variable estimates

Dep. Var: Test Scores in Secondary School

	Mathematics	Basque	Spanish	Avg., 3 subjects
	(1)	(2)	(3)	(4)
Covid Cohort	-4.777***	-2.446***	0.273	-2.317***
	(0.749)	(0.628)	(0.689)	(0.526)
Elementary School Learning Outcomes	✓	✓	✓	✓
School FE	✓	✓	✓	✓
Mean Dep. Var	251.4	244.2	255.3	250.3
SD Dep. Var	51.38	48.32	46.70	41.70
N	20738	20738	20738	20738

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions control for elementary school test scores of the three subjects separately.

School FE include FE for elementary and secondary schools.

Differences-in-differences entropy balancing estimates

	Mathematics	Basque	Spanish	Avg., 3 subjects
	(1)	(2)	(3)	(4)
Covid Cohort× Secondary School	-4.547***	-2.710***	1.164	-2.031***
	(0.895)	(0.744)	(0.797)	(0.575)
Student FE	✓	✓	✓	✓
School-by-grade FE	✓	✓	✓	✓
Mean Dep. Var	252.6	249.9	257.8	253.4
SD Dep. Var	49.88	46.49	43.91	39.72
N	41476	41476	41476	41476

Standard errors clustered by student in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Heterogeneous learning effects, Mathematics

	Mathematics														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Covid Cohort× Secondary School	-2.967**	-3.713***	-6.927***	-6.136***	-1.386	-1.733	-2.633*	-1.427	-3.469**		-3.344**	-14.66***	-9.539***	-3.031*	-7.130***
	(1.180)	(1.051)	(1.088)	(1.438)	(0.971)	(1.144)	(1.345)	(1.393)	(1.467)		(1.561)	(3.462)	(2.146)	(1.743)	(1.058)
CC× SS × Female	-0.702			0.552											
	(1.401)			(1.325)											
CC× SS × Migrant	1.577			1.775											
	(2.900)			(2.793)											
CC× SS × Basque-speaking	-2.220			-2.343											
	(1.780)			(1.683)											
CC× SS × Low SES Student		0.182		-0.505					1.156	0.720					
		(1.437)		(1.408)					(1.436)	(1.468)					
CC× SS × Low Perf. Student			4.562***	4.397***					4.781***	4.751***	4.376***	4.039	8.043***	1.352	
			(1.338)	(1.360)					(1.368)	(1.392)	(1.640)	(2.578)	(1.877)	(2.021)	
CC× SS × Public School					-9.475***			-9.944***	-9.807***				-6.251**	-8.481**	
					(1.939)			(2.507)	(2.361)				(2.734)	(3.882)	
CC× SS × Low SES School						-3.796**		2.918	1.668						
						(1.927)		(2.761)	(2.653)						
CC× SS × Low Perf. School							-2.913	-1.481	-2.755		-2.889	1.400			
							(2.021)	(2.373)	(2.281)		(2.343)	(4.055)			
CC× SS × Ling. Model A (Spanish)															15.25***
															(3.362)
CC× SS × Ling. Model B (Mixed)															7.202***
															(1.844)
N	41476	41476	41476	41476	41476	41476	41476	41476	41476	41316	24956	16290	20548	20742	41476
School × Covid Cohort × Sec. School FE										✓					
Schools Sample	All	All	All	All	All	All	All	All	All	All	Semi-private	Public	Low perf.	High perf.	All
Mean Dep. Var	252.6	252.6	252.6	252.6	252.6	252.6	252.6	252.6	252.6	252.6	256.2	247.1	241.9	263.3	252.6
SD Dep. Var	49.60	49.60	49.60	49.60	49.60	49.60	49.60	49.60	49.60	49.59	49.44	49.31	47.52	49.30	49.60

Standard errors clustered by student. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions include student FE, grade FE, school FE, and school by grade FE.

All regressions control for interactions of cohort and grade FE with the interacted variables.

Table A4: Heterogeneous learning effects, Spanish

	Spanish														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Covid Cohort× Secondary School	4.507***	1.088	-3.002***	1.275	1.847**	1.899*	0.294	1.300	-1.022		-1.870	-10.55***	0.0879	-0.654	1.516
	(1.050)	(0.934)	(0.949)	(1.228)	(0.867)	(1.010)	(1.075)	(1.134)	(1.227)		(1.254)	(3.450)	(2.163)	(1.336)	(0.944)
CC× SS × Female	-8.022***			-7.796***											
	(1.262)			(1.214)											
CC× SS × Migrant	-3.073			-4.416*											
	(2.488)			(2.460)											
CC× SS × Basque-speaking	4.248***			3.214**											
	(1.582)			(1.530)											
CC× SS × Low SES Student		0.0407		-0.233					-0.915	-1.426					
		(1.311)		(1.303)					(1.332)	(1.364)					
CC× SS × Low Perf. Student			6.934***	6.878***					7.337***	7.444***	7.206***	7.665***	6.803***	7.830***	
			(1.241)	(1.241)					(1.270)	(1.293)	(1.512)	(2.439)	(1.830)	(1.765)	
CC× SS × Public School					-3.993**			-4.638**	-4.220**				-5.178*	-9.748**	
					(1.744)			(2.225)	(2.133)				(2.845)	(4.016)	
CC× SS × Low SES School						-0.318		1.180	0.371						
						(1.727)		(2.339)	(2.314)						
CC× SS × Low Perf. School							0.00438	1.339	-0.0127		-1.068	4.933			
							(1.812)	(2.075)	(2.021)		(2.135)	(4.233)			
CC× SS × Ling. Model A (Spanish)															-7.970**
															(3.136)
CC× SS × Ling. Model B (Mixed)															-0.157
															(1.665)
N	41476	41476	41476	41476	41476	41476	41476	41476	41476	41316	24956	16290	19214	22064	41476
School × Covid Cohort × Sec. School FE										✓					
Schools Sample	All	All	All	All	All	All	All	All	All	All	Semi-private	Public	Low perf.	High perf.	All
Mean Dep. Var	257.8	257.8	257.8	257.8	257.8	257.8	257.8	257.8	257.8	257.8	260.4	253.8	248.9	265.6	257.8
SD Dep. Var	43.84	43.84	43.84	43.84	43.84	43.84	43.84	43.84	43.84	43.84	43.66	43.77	43.37	42.76	43.84

Standard errors clustered by student. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All regressions include student FE, grade FE, school FE, and school by grade FE.
All regressions control for interactions of cohort and grade FE with the interacted variables.

Table A5: Heterogeneous learning effects, Basque

	Basque														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Covid Cohort× Secondary School	-4.016***	-2.537***	-5.410***	-6.546***	-1.188	-2.236**	-3.361***	-1.822	-3.261**		-3.860***	-8.109***	-4.014**	-4.265***	-2.326***
	(0.966)	(0.871)	(0.916)	(1.178)	(0.816)	(0.960)	(1.098)	(1.264)	(1.293)		(1.351)	(2.133)	(1.761)	(1.448)	(0.895)
CC× SS × Female	5.441***			5.088***											
	(1.134)			(1.072)											
CC× SS × Migrant	-1.829			-3.341											
	(2.438)			(2.357)											
CC× SS × Basque-speaking	-3.086**			-2.990**											
	(1.462)			(1.394)											
CC× SS × Low SES Student		1.029		0.550					0.177	-0.287					
		(1.177)		(1.138)					(1.185)	(1.211)					
CC× SS × Low Perf. Student			5.028***	4.510***					5.101***	5.382***	5.877***	2.844	3.286*	7.147***	
			(1.116)	(1.133)					(1.166)	(1.189)	(1.430)	(2.099)	(1.742)	(1.579)	
CC× SS × Public School					-4.177***			-7.082***	-7.541***				-1.233	-4.626*	
					(1.607)			(2.208)	(2.104)				(3.235)	(2.435)	
CC× SS × Low SES School						2.117		5.780***	5.334**						
						(1.599)		(2.187)	(2.150)						
CC× SS × Low Perf. School							1.673	-0.878	-3.007*		-2.084	0.946			
							(1.633)	(1.802)	(1.775)		(1.886)	(3.533)			
CC× SS × Ling. Model A (Spanish)															-5.243**
															(2.661)
CC× SS × Ling. Model B (Mixed)															1.390
															(1.555)
N	41476	41476	41476	41476	41476	41476	41476	41476	41476	41316	24956	16290	17924	23344	41476
School × Covid Cohort × Sec. School FE										✓					
Schools Sample	All	All	All	All	All	All	All	All	All	All	Semi-private	Public	Low perf.	High perf.	All
Mean Dep. Var	248.6	248.6	248.6	248.6	248.6	248.6	248.6	248.6	248.6	248.7	246.6	251.8	232.4	261.2	248.6
SD Dep. Var	47.02	47.02	47.02	47.02	47.02	47.02	47.02	47.02	47.02	47.01	46.94	46.93	43.85	45.52	47.02

Standard errors clustered by student. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All regressions include student FE, grade FE, school FE, and school by grade FE.
All regressions control for interactions of cohort and grade FE with the interacted variables.

Table A6: Socio-emotional well-being and learning loss across subjects

	Δ Mathematics	Δ Mathematics $-\Delta \widehat{\text{Mathematics}}$	
	(1)	(2)	(3)
Socio-emotional Well-being Deterioration	-6.380***	-6.484***	-6.027***
	(1.273)	(1.303)	(1.305)
N	5621	5621	5621
Controls			✓
Mean Dep. Var	-3.704	-4.902	-4.902
SD Dep. Var	45.78	47.06	47.06

Sample: covid cohort, secondary school.
Socio-emotional Well-being Deterioration measured with the mean of survey responses.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Controls: school FE, female, migrant, Basque at home, low SES student, low Perf. Student.
Predicted outcomes based on a regression of $\Delta on the set of controls$,
for the control cohort sample.

	ΔSpanish	ΔSpanish $-\Delta \widehat{\text{Spanish}}$	
	(1)	(2)	(3)
Socio-emotional Well-being Deterioration	-5.211***	-6.201***	-8.497***
	(1.229)	(1.232)	(1.243)
N	5621	5621	5621
Controls			✓
Mean Dep. Var	-5.119	0.784	0.784
SD Dep. Var	42.96	43.37	43.37

Sample: covid cohort, secondary school.
Socio-emotional Well-being Deterioration measured with the mean of survey responses.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Controls: school FE, female, migrant, Basque at home, low SES student, low Perf. Student.
Predicted outcomes based on a regression of $\Delta on the set of controls$,
for the control cohort sample.

	ΔBasque	ΔBasque $-\Delta \widehat{\text{Basque}}$	
	(1)	(2)	(3)
Socio-emotional Well-being Deterioration	-3.615***	-5.500***	-4.966***
	(0.999)	(1.053)	(1.021)
N	5621	5621	5621
Controls			✓
Mean Dep. Var	-10.74	-1.231	-1.231
SD Dep. Var	35.93	38.06	38.06

Sample: covid cohort, secondary school.
Socio-emotional Well-being Deterioration measured with the mean of survey responses.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Controls: school FE, female, migrant, Basque at home, low SES student, low Perf. Student.
Predicted outcomes based on a regression of $\Delta on the set of controls$,
for the control cohort sample.

2018

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2019

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2020

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2021

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2022

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ieb@ub.edu
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