https://doi.org/10.3311/PPso.21893

Periodica Polytechnica Social and Management Sciences

How Socioeconomic Status Differences Observable in Students' Delay of Gratification Evolved Over the Period of COVID-19-induced Online Education

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Received: 19 January 2023, Accepted: 17 January 2025, Published online: 21 February 2025

Abstract
We show the evolution of the delay of gratification (DG) in 950 students aged 10–14 during coronavirus-induced home-based online education, by analysing data from two waves of voluntary online surveys. Students in the highest SES category experienced an absolute increase in DG, whereas those in the lowest SES category suffered a decrease, resulting in a widening SES gap between the groups over a relatively short 30-day period.

Keywords
delay of gratification, socioeconomic status, COVID-19 pandemic, primary school students, online education

1 Introduction

Delay of gratification (DG), our capacity to resist the temptation of immediate pleasure instead of a larger reward to be received later (Mischel et al., 1989) enables us to pursue long-term goals such as obtaining a diploma or saving for retirement.[1] DG in childhood predicts numerous favourable outcomes later in life, including better school performance, higher lifetime income, better health, and greater social competence (Golsteyn et al., 2014; Mischel et al., 1988; 1989; Schlam et al., 2013).

Based on prior literature, we argue that the corona virus pandemic may have influenced students' DG. Furthermore, the pandemic has impacted people of various socio-economic statuses (SES) differently. Lastly, there is a potential association between SES and DG.

First, a growing body of literature documents that traumatic experiences, such as natural disasters or wars, can shape people's DG (Callen, 2015; Cassar et al., 2017). Nevertheless, a conflicting vein of literature reports contradictory results. For example, some studies indicate that negative economic shocks do not affect time preferences (Meier and Sprenger, 2015). In the context of the coronavirus pandemic, Bogliacino et al. (2021) found that shocks related to income, health, and mental problems due to economic vulnerability did not impact DG. Clearly, this contradictory evidence calls for further research. The coronavirus pandemic can be viewed both as an economic shock and a health disaster, making it unclear whether and how it is associated with DG.

Second, individuals with different levels of SES have been affected differently by the coronavirus pandemic. The pandemic has more severely impacted low-SES adults compared to their high-SES counterparts in terms of health and economic outcomes (Alstadsæter et al., 2020; Azar et al., 2020; Geranios et al., 2022; Strang et al., 2020; Wollenstein-Betech et al., 2020). A similar pattern is observed among students: adolescents from low-SES families have been more negatively affected in terms of mental health (Sama et al., 2021; Spinelli et al., 2020) and educational outcomes (Aucejo et al., 2020; Santibañez and Guarino, 2021).

Although the transition to online education was uniform across all SES levels, as all schools shifted to this format, parents' work conditions varied significantly by SES. A large proportion of high-SES parents transitioned to working from

1 Other disciplines like economics use different names for DG, as time preferences, patience, or self-control.

Cite this article as: Keller, T., Kiss, H. J. (2025) "How Socioeconomic Status Differences Observable in Students' Delay of Gratification Evolved Over the Period of COVID-19-induced Online Education", Periodica Polytechnica Social and Management Sciences. https://doi.org/10.3311/PPso.21893

home, whereas a considerable number of low-SES parents continued commuting to their workplaces as before the pandemic (von Gaudecker et al., 2020). Consequently, high-SES parents spent more time at home, potentially increasing interaction with their children compared to pre-pandemic times (von Gaudecker et al., 2020). This situation allowed high-SES parents greater control over their children's home-based learning activities. Thus, the coronavirus pandemic led to an exogenous increase in parental time investments in high-SES families relative to their low-SES counterparts.

Third, there is an established association between students' SES and their ability to delay gratification. Students from low-SES families are less likely to delay gratification compared to their higher-SES peers, which may contribute to disparities in outcomes such as academic achievement and health (Currie, 2009; Evans and Rosenbaum, 2008). Recent studies (Chowdhury et al., 2022; Falk et al., 2021) have confirmed that children from high-SES families exhibit better DG. However, the precise mechanisms through which SES influences students' DG are not fully understood. Parental investments, such as parenting style and time spent with children, appear to be significant determinants (Falk et al., 2021). Consequently, SES-related differences in parent-child interactions during the pandemic may have influenced DG.

Our paper is driven by two motivations. First, we aim to address a gap in the literature by investigating how the coronavirus pandemic affected students' DG – a topic not yet explored in previous studies. Second, we seek to determine whether the impact of the coronavirus pandemic on children's DG varies according to their SES.

2 Materials and methods

Due to a massive increase in COVID-19 cases, Hungarian schools officially transitioned to home-based online education on March 16, 2020. This mode of education lasted until the end of the 2019/2020 academic year, covering a period of 91 days. However, in practice, online learning did not begin until mid-April in many schools. This delay was due to initial challenges in implementing online education and was further extended by an eight-day spring break, which postponed the full adoption of online learning.

2.1 Initial sample

We use data from a project that began before the coronavirus-induced school closures, involving 4th-to-8th-grade students in rural Hungarian primary schools (Keller, 2020). Our initial sample consisted of 2,898 students across 148 classrooms and 29 schools. Of these, 53 students left the study, while 110 students joined. These changes resulted in a final sample size of 2,955 students.

Schools and students in our initial project were not representative of the corresponding Hungarian school population. The performance of students in these schools was approximately 0.2 standard deviations below the national average for math and reading comprehension tests.

2.2 Online surveys

After schools transitioned to home-based education, we reached out to students in our baseline sample through their schools, conducting two consecutive waves of an online survey. Participation in the surveys was voluntary. The study was reviewed and approved by the IRB office at the HUN-REN Center for Social Sciences in Budapest.

We obtained consent at multiple stages. Initially, school principals and teachers gave written consent to participate in the study. Subsequently, parents provided written active consent for the retrieval of administrative records through teachers and for their children's participation in the survey.

We began the first wave of data collection (W1) 32 days after schools switched to home-based digital education, reaching 1,872 students from 136 classrooms and 28 schools – a response rate of 63%. The median response in W1 occurred on the thirty-seventh day of digital education. Thus, in W1, most students' answers related to the first half of the online education period.

We began the second wave of data collection (W2) eight days after concluding W1. We reached 1,143 students from 126 classrooms and 28 schools – a response rate of 39%. The upper chart of Fig. 1 shows the number of responses per day in W1 and W2, respectively.

The number of days between W1 and W2 ranged between 12 and 48 days (see Fig. 1, lower chart). For the median student, the time elapsed between W1 and W2 was 32 days.

There is variation in the timing of our initial observation of students and the number of days between W1 and W2. The primary source of this variation is at the classroom level, as homeroom teachers were responsible for requesting that students complete the survey. For instance, 56% of the variance in the number of days between school closure and student participation in W1 occurs at the classroom level. Additionally, 72% of the variance in the number of days between W1 and W2 is also attributable to the classroom level.

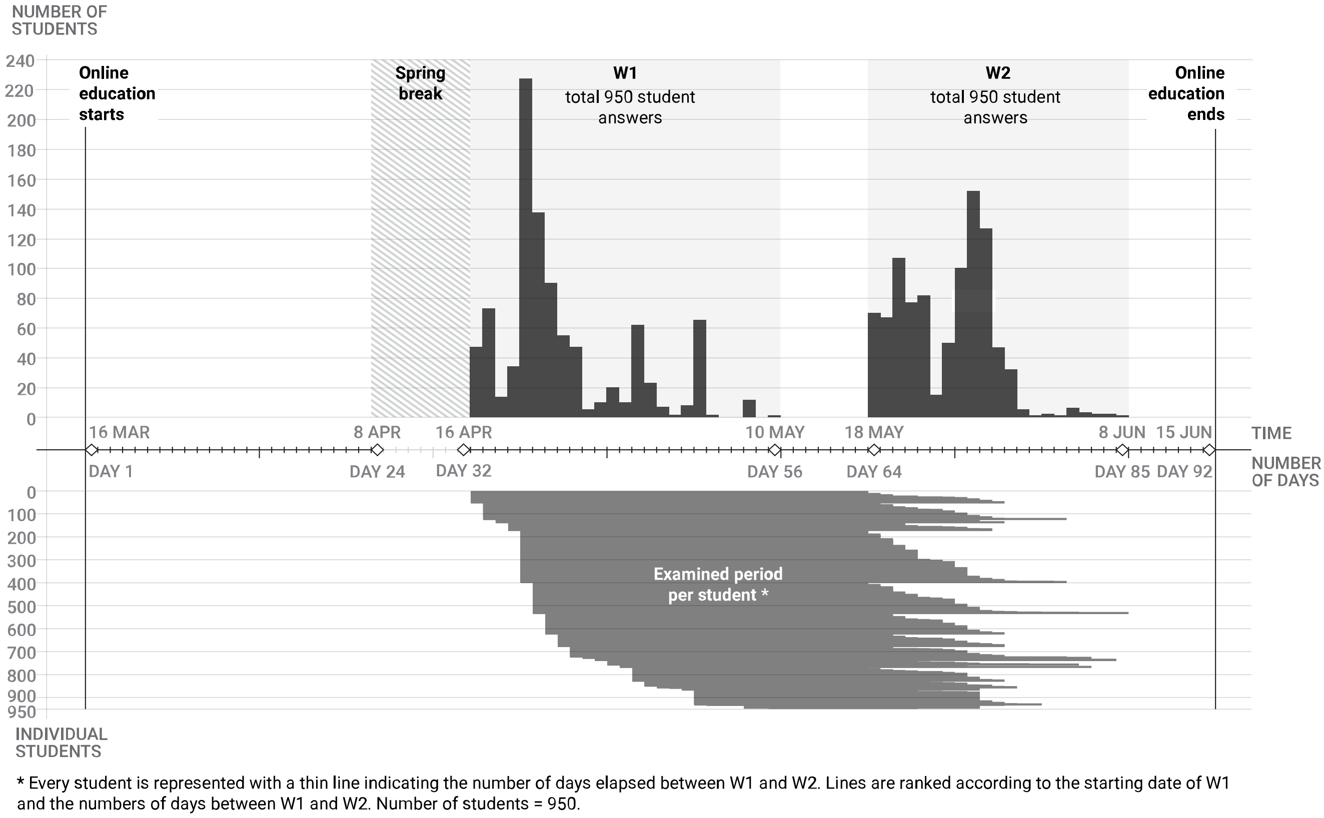

Fig. 1 Number of responses per day in W1 and W2 respectively (upper charts) and the period per student between W1 and W2 (lower chart)

2.3 Analytic sample

The number of students who participated in both waves was 983 (33% response rate). These students were nested in 122 classrooms and 28 schools. Our analytical sample consisted of students who participated in W1 and W2, have valid DG data in both waves and have non-missing SES data (N = 950).

The analytic sample comprises students from more favorable family backgrounds. As a result, the SES differences within this sample are less pronounced than those in our initial baseline data.

2.4 Measurements

In both W1 and W2, students completed a 25-min online questionnaire that, in addition to a question on DG, included items on academic self-concept (Keller, 2021), generosity (Kiss and Keller, 2022), and subject-liking. Additionally, students took a grade-specific math test during each wave. The W2 questionnaire also introduced a measure of students' honesty using an experimental approach (Keller and Kiss, 2021).

Our outcome variable was students' DG, measured in a hypothetical choice situation without incentives (Brañas-Garza et al., 2023).[2] We asked the following question "*You can see colorful wristbands in the picture below. Imagine you could choose from these wristbands. The number of wristbands you can choose depends on when you would like to receive them. If you would like to receive them today, then you can choose one wristband. If, however, you wait until tomorrow, you can choose two wristbands*."

Our DG measurement in experimental choice situations was introduced by Mischel (1974). Mischel proposed two different methods for assessing DG, both involving a choice between a less valuable immediate reward and a more valuable future reward. The first method entails making a choice under realistic conditions with varying reward values. The second method, later known as the 'marshmallow test', examines how young children resist the temptation of immediate gratification to achieve a greater reward later (Mischel et al., 1989).

We acknowledge that our DG measurement differs from Mischel's famous marshmallow test and adapts Mischel's first approach, which is widely used. For example, in a recent study based on the data of the German National

2 Brañas-Garza et al. (2023) show convincingly that incentivization does not matter when measuring time preferences.

Educational Panel Study (an ongoing large-scale survey among preschool children in Germany), children could choose between one sticker today or two stickers tomorrow (Lorenz et al., 2016). Another, more classical adaptation of the test is described in Mischel and Metzner (1962). Here children could choose between candy bars in a monetary value range of \$0.05–\$0.1.

Our DG measurement is adequate because it potentially mitigates social desirability bias, acquiescence bias, and reference bias (Duckworth et al., 2013:p.852). Wristbands are often used as incentives in this kind of research involving children (e.g., List and Samek, 2015; Paluck et al., 2016).

Students' SES was measured in the baseline questionnaire for our initial sample (before W1 and W2), which was a different survey than the one that asked students about their DG. We used the following question: "*How many books do you have? You should count the number of books that you and your parents own together. Please do not include your textbooks and newspapers*". Response categories: less than one shelf 0–50; one shelf ca. 50; 2–3 shelves (ca: 150); 4–6 shelves (ca: 300); 2 bookcases (ca: 300–600 books); 3 bookcases (ca: 600–1000 books); more than 1000 books. To have a comparable number of observations, we combined the last two categories and called them book > 1000. This question is a standard one in nationwide surveys.

Regarding the measurement of SES, parental education, household income, or home environment are the most commonly used measures. However, in our sample of rural students, we were concerned that students might not know their parents' education level or household income accurately. Nevertheless, we were fairly certain that students had more or less accurate knowledge about the number of books they had at home.

Books at home have been found in various studies to be a stronger predictor of student performance than parental education (Woessmann, 2004; Wößmann, 2003). Fuchs and Wößmann (2008) have convincingly shown that the number of books at home is a useful explanatory variable for academic achievement. The usefulness of the number of books at home as a measure of SES has also been reported in other studies (Hanushek and Woessmann, 2011; Wößmann, 2003; Schütz et al., 2008). The number of books at home is strongly correlated with parental education (e.g., Myrberg and Rosén, 2009), parental involvement (e.g., Bracken and Fischel, 2008), or household income (e.g., Schütz et al., 2008).

2.5 Analysis

Our analysis first observes the SES differences in DG in W1 and W2, respectively.

We used Eq. (1) (a fixed-effect linear probability model) to analyze the cross-sectional data of W1 and W2, respectively.

$$\mathrm{DG}_{i,c} = \beta_0 + \beta_1 \times \mathrm{SES}_{i,c} + \varphi_c + \varepsilon_{i,c} \tag{1}$$

In Eq. (1) $\mathrm{DG}_{i,c}$ represents student *i*'s DG in classroom *c*. The variable SES represents the number of books at home, introduced as separate dummy variables. The reference category is the lowest response category (books < 50). Classroom fixed-effects are denoted by φ_c. We eliminated most of the variance concerning the date when students participated in the surveys by controlling for classroom fixed-effects. The individual error term is $\varepsilon_{i,c}$. Standard errors are clustered at the school level.

In Eq. (1) β_0 represents the mean of DG in the reference SES category. In each subsequent SES category β_1 shows the mean difference in DG relative to the reference SES category.

We analyse the changes in DG between W1 and W2 by employing the following student fixed-effect linear probability model fitted to the pooled data of W1 and W2, where all students are observed twice, first in W1 and second in W2. Thus, Eq. (2) exploits the panel nature of our data.

$$\begin{aligned}\mathrm{DG}_{i,c,t} &= \gamma_0 + \gamma_1 \times T_{i,c,t} + \gamma_2 \times \mathrm{SES}_{i,c} \\ &+ \gamma_3 \times T_{i,c,t} \times \mathrm{SES}_{i,c} + \omega_{c,t} + \varepsilon_{i,c,t}\end{aligned} \tag{2}$$

In Eq. (2) $T_{i,c,t} = 1$ if the *i*-th students' DG in classroom *c* was measured in time *t* where *t* = W2. $T_{i,c,t}$ is 0 if students' DG was measured in time *t* where *t* = W1. The variable $\omega_{c,t}$ represents students' fixed-effects and eliminates every time-invariant factor that is associated with DG. Standard errors are clustered at the school level.

The parameter of interest is γ_3 which shows the change in DG in each SES category relative to the reference category, which is the lowest SES group. The coefficient γ_1 shows the changes in the reference category (books < 50) between W1 and W2. Note that γ_2 cannot be estimated since SES is time-invariant, and thus, its effect is captured in students' fixed-effects ($\omega_{c,t}$).

All statistical analyses were performed using Stata Statistical Software: Release 18. Data and analytical scripts are available on the project's OSF page (Keller and Kiss, 2024).

3 Results

Fig. 2 shows the share of students who opted for two wristbands (DG = 1) in each category of the variable *number of books at home*, our proxy for SES.

The first row in Panel A, Table 1, shows the mean in the lowest SES category (books < 50), which is 76% in W1 and 71% in W2. These mean values correspond to the share of students who opted for two wristbands. Relative to this lowest SES category, each subsequent row in Panel A, Table 1 shows the difference in the share of those who have chosen two wristbands.

For example, relative to the reference category, middle-SES students (books = 150 or books = 300) in W1 have a higher DG by 10 (p = 0.03) and 12 (p = 0.008) percentage points, respectively ($p < 0.05$), as shown in column (1) (Table 1). Nevertheless, there is no statistically significant difference between the two extremes of the SES-scale, i.e., between those who have books < 50 and those who have books > 1000 at home (the difference is 0.008, p = 0.888).

In W2, the difference between low (books < 50) and middle-SES students (books = 150 or books = 300) is 14 (p = 0.016) and 15 (p = 0.008) percentage points, respectively (column (2), Table 1). In contrast to W1, in W2, those who have books > 1000 instead of books < 50 at home have 13 percentage points higher DG (p = 0.035). Therefore, SES differences opened up in W2 between students in the lowest and highest SES categories.

Panel B in Table 1 shows the change in DG (ΔDG) between W1 and W2 relative to the change that occurred in the lowest SES category (books < 50). Calculations are made using the student fixed-effect linear probability model in Eq. (2). student fixed-effect linear probability model. Student fixed-effects eliminated all student-level, time-invariant confounding variables.

For example, as shown in column (3) (Table 1), DG has decreased by 6 percentage points between W1 and W2 in the lowest SES (reference) category. This change is marginally significant (p = 0.087). Relative to the changes at the bottom, DG changed by 13 percentage points (p = 0.016) in the highest SES category. Therefore, social differences in DG widened between students in the lowest and highest SES categories.

The relative changes translated into an increase in DG of 7 percentage points (−0.06 + 0.13 for students in the highest SES category (books > 1000) – a marginally significant change (p = 0.101).

We carried out the same analysis using logit regressions, yielding qualitatively similar results (see Appendix A).

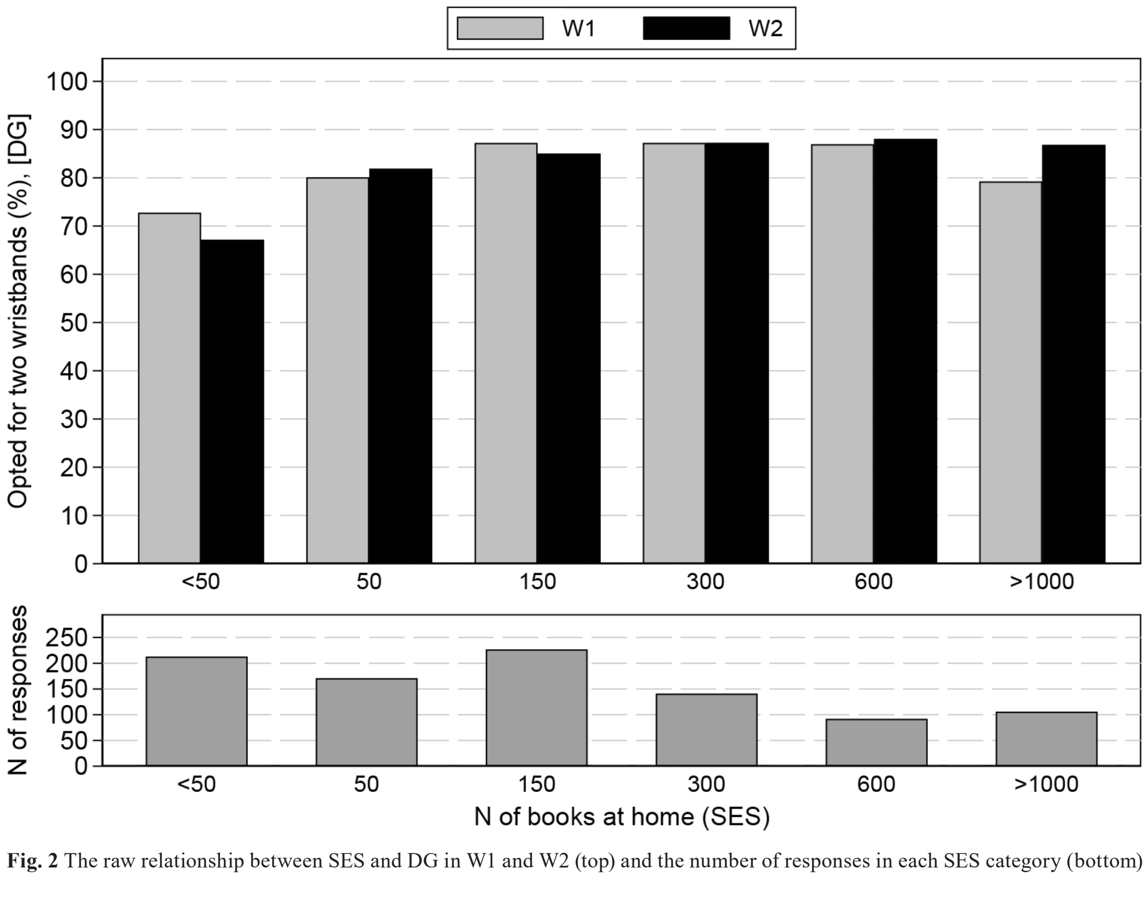

Fig. 2 The raw relationship between SES and DG in W1 and W2 (top) and the number of responses in each SES category (bottom)

Table 1 Relative SES-related-differences in the level (columns (1) and (2)) and change (column (3)) of DG – regression coefficients and robust standard errors

Panel A Classroom fixed-effects linear probability models	(1)[a] DG in W1	(2)[a] DG in W2	Panel B Student fixed-effects linear probability model	(3)[b] Change in DG: W1/W2
Mean DG in the ref.SES category, β_0			ΔDG in the ref.SES category, γ_1	
Book < 50	0.76^{**} (0.03)	0.71^{**} (0.03)	Book < 50	-0.06^{+} (0.03)
Difference in DG relative to ref.SES, β_1			ΔDG relative to ref.SES, γ_3	
Book = 50	0.04 (0.05)	0.11^{*} (0.04)	Book = 50	0.07 (0.06)
Book = 150	0.10^{*} (0.04)	0.14^{*} (0.05)	Book = 150	0.03 (0.05)
Book = 300	0.12^{**} (0.04)	0.15^{**} (0.05)	Book = 300	0.06 (0.06)
Book = 600	0.09^{+} (0.05)	0.15^{*} (0.06)	Book = 600	0.07 (0.05)
Book >1000	0.01 (0.06)	0.13^{*} (0.06)	Book > 1000	0.13^{*} (0.05)
Observations	950	950		1900

All models include constants.
Robust standard errors (clustered at school level) in parentheses, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$
[a] The coefficients in each category refer to the difference in the level of DG relative to the reference category (book < 50) and are obtained from a linear probability model. The models include classroom fixed effects. Standard errors are clustered at the school level.
[b] The coefficients in each category refer to the change in DG between W1 and W2 relative to the reference category (book < 50) and are obtained from a linear probability model fitted to the pooled data of W1 and W2. The model includes student-fixed-effect s. Standard errors are clustered at the classroom level.

4 Discussion and conclusions

We observed the evolution of primary school students' DG during the coronavirus-induced switch from classroom-based to home-based online education, focusing on socio-economic differences. We took advantage of having two observations of about 950 students in 122 classrooms from 28 rural Hungarian primary schools. We found that students in the highest SES category experienced a significant increase in DG, resulting in a widening of the SES gap by 7 percentage points between the lowest and highest SES categories. These changes are of substantial importance, considering the short period (30 days) between the two measurements.

Our results show that students' DG reacted to the exogenous shock of the coronavirus pandemic. We do not know whether the association we document is causal. Therefore, our contribution to the literature is exploratory.

Our results are conservative estimates for several reasons. First, even our first measurement of students' DG occurred during (not before) the transition to online education. Thus, we likely underestimated the total change in students' DG during the online education. Second, students may have attempted to be consistent in their responses – they might have remembered in W2 how they had answered the same DG question in W1 due to the short time between the two waves and anchored their later response to the earlier one. Accordingly, we may not have observed a change in DG in a group of students even though there was one. Third, the SES range of students in our volunteer sample is smaller than that of all students for whom we have baseline data. Thus, we might have seen larger SES differences if we had data on all students.

Our study has several limitations. Two of them are related to the fact that our subject pool consisted of primary school students who completed the online survey at home. In order to maximise the response rate, we attempted to keep the survey short, with questions that the subjects understood and could easily answer. This explains our choice of the DG and SES measures.

Another shortcoming of the study is that while it is plausible that the coronavirus pandemic influenced our results, we cannot make causal statements. Our speculative explanation is that during home-based online education, students needed the ability to delay gratification to overcome challenges such as logging in on time without external enforcement and staying focused on lectures instead of surfing the Internet. Since students lacked a controlled school-based learning environment, they needed parental involvement to manage their daily school responsibilites. For example, parents could control whether their children logged in to the online session or returned the daily homework to the teacher. Controlling students' daily school activities required additional parental effort. At the same time, the pandemic has induced a more intensive shift to home-working among high-SES families (von Gaudecker et al., 2020), increasing the amount of time parents could spend with their children. Thus, high-SES students may have benefited from parental involvement in their daily school lives, while low-SES students may have suffered from the lack of such involvement.

Our findings have two implications that warrant further investigation. First, our results show an increase in status differences in DG, which could exacerbate status differences in school performance. Thus, the change in DG represents a potential mechanism that could lead to even larger gaps in some educational outcomes. Further investigation is needed to determine if this mechanism is relevant and whether the coronavirus pandemic causally affects DG.

Second, DG seems to be amenable to change not only by purposefully planned interventions (Alan and Ertac, 2018), but also by the (random) shocks that change students' learning environment (Khanolainen et al., 2020; Lehrl et al., 2020), which should be taken into account in educational policy.

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Appendix A

Table A1 Relative SES-related-differences in the level (columns (1) and (2)) and change (column (3)) of DG–logit coefficients from conditional (fixed-effects) logistic regression and robust standard errors

	(1)[a] DG in W1	(2)[a] DG in W2	(3)[b] Change of DG: W1/W2
Book < 50	Ref.	Ref.	Ref.
Book = 50	0.22	0.61**	0.92+
	(0.31)	(0.23)	(0.54)
Book = 150	0.69*	0.76**	0.28
	(0.30)	(0.29)	(0.46)
Book = 300	0.75**	0.93**	0.65
	(0.29)	(0.33)	(0.77)
Book = 600	0.59+	0.91*	0.94
	(0.36)	(0.38)	(0.75)
Book > 1000	0.00	0.74*	2.26**
	(0.33)	(0.38)	(0.70)
Female	0.35*	0.33	
	(0.15)	(0.20)	
Observations	950	950	1900

All models include constants.
Robust standard errors (clustered at school level) in parentheses, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$
[a] The coefficients in each category refer to the difference in the level of DG relative to the reference category (book < 50) and are obtained from a linear probability model. The models include classroom effects. Standard errors are clustered at the school level.
[b] The coefficients in each category refer to the change in DG between W1 and W2 relative to the reference category (book < 50) and are obtained from a conditional (fixed-effects) logistic regression fitted to the pooled data of W1 and W2. The model includes student-fixed-effects. Standard errors are clustered at the classroom level.