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Post-COVID learning loss and the collapse of the education-economy link in Bulgaria

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ABSTRACT: This study examines how the COVID-19 pandemic affected the relationship between educational outcomes and regional economic indicators in Bulgaria and the Central and Eastern European (CEE) region. Using panel data from all 28 Bulgarian Nomenclature of Territorial Units of Statistics (NUTS) 3 regions between 2015 and 2024, we analyse weighted matriculation exam scores in conjunction with macroeconomic variables, including Gross Domestic Product per capita, internet access and share of educated population. The post-pandemic learning loss weakened the previously strong correlation between regional economic wealth and academic achievement, exposing structural inequalities. We find limited evidence that digital infrastructure improved outcomes, especially in marginalised regions. Furthermore, our findings indicate a persistent learning loss following the COVID-19 pandemic, with exam performance declining by up to 0.29 points (approximately 0.38 to 0.447 standard deviations) in 2021–2022, followed by a full recovery in 2024. We argue that learning losses were already happening before COVID-19, with an average magnitude of 0.01–0.03 standard deviations, with some years reaching as much as 0.1 standard deviations.

KEYWORDS: COVID-19, educational inequality, matriculation exams, statistical inference in education, panel regressions
JEL CODES: I21, I24, O15

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1. Introduction

COVID-19 has been one of the most disruptive shocks faced by the Bulgarian high school education system, triggering an abrupt and widespread shift toward online learning. During the school closures, distance learning became the norm, often delivered through a hybrid model combining asynchronous and synchronous formats (OECD 2021). Topalska (2021) reports that 48.59% of respondents rated this form of learning as largely effective ('close to yes'), with parental support reported at 46%. However, deeper structural issues continue to complicate this picture, especially when considering the digital exclusion of marginalised groups. Research indicates that, in the Central and Eastern European (CEE) region, inequities during the COVID crisis were exacerbated not through the strategic deployment of a crisis discourse but through governments' lack of recognition of the need to address inequity more explicitly in their first policy interventions (Mitescu-Manea et al. 2021).

The inequality argument is important because students' ability to engage in online learning depends heavily on how their economic, cultural, and social capital aligns or fails to align with the new, digitally mediated education field. What appear to be technical or logistical 'barriers' are objectified and technologised forms of structural exclusion (Zdravkov – Ilieva-Trichkova 2025). The pandemic did not merely expose these mismatches; they were amplified, particularly for marginalised groups such as the Roma population (Krumova – Kolev 2021), deepening the stratification of a system we argue has already been experiencing learning losses. In fact, we show that the relationship between exam results and internet access appears to be negative post-COVID.

Echoing recent research by Szécsi and Szunomár (2024), we demonstrate that learning outcomes – such as national matriculation exam results – are poor standalone predictors of economic development during a crisis. Szécsi and Szunomár (2024) find no consistent link between Program for International Student Assessment (PISA) score gains and GDP growth in their global panel study, even in East Asia, where test performance is among the highest. Similarly, in Bulgaria, we observe a post-pandemic decoupling between regional GDP per capita and state exam performance and show that educational resilience is shaped more by social capital, institutional context, and regional equity than by macroeconomic conditions or digital infrastructure alone.

As Bulgaria is the poorest Member State of the European Union (EU; Eurostat 2024) and one of the most vulnerable economies in Central and Eastern Europe, this manuscript:

1. Provides a learning-loss estimation in the CEE context by extending Cohen's d (Cohen 1988) and Glass' Δ-style metrics to national-level data, employing fixed-effects estimators rather than simple averages; and

2. Analyses the relationship between macroeconomic indicators and exam performance, revealing the deepening of educational inequalities following the COVID-19 crisis as well as the decoupling between GDP and exam performance.

Most importantly, this study extends Szécsi and Szunomár's (2024) findings by demonstrating that exam results, learning losses, and overall educational levels are closely linked to regional disparities and access to education, rather than to economic wealth itself. This addresses the question of whether macro or social policy is the more effective measure against learning loss.

2. Literature review

It is essential to acknowledge that the effects of COVID-19 can be understood in multiple ways. COVID-19 led to digital exclusion, created learning losses, altered the pedagogical dimensions of education, and was followed by a period of ongoing recovery. To justify the empirical strategy, we need to analyse the pandemic in full depth, especially in the underexplored context of CEE.

2.1. COVID-19, digital exclusion, and regional heterogeneity

The findings are consistent in showing that CEE countries (including Hungary) exhibit a general resemblance to one another and demonstrate comparatively lower levels of digital readiness than Northern and Western European countries (Dobos – Bánhidi 2025). Van Deursen and Helsper (2015) provide further empirical evidence supporting the notion that the internet is more beneficial to individuals with higher social status – not necessarily due to the frequency or extent of use, but rather in terms of what they can achieve with it. Similarly, Eynon and Geniets (2015) demonstrate that poor access to technology and limited support networks hinder young people from gaining the necessary skills to develop digital competencies. Zdravkov and Ilieva-Trichkova (2025) show that digital participation is shaped less by access or skills and more by how well an individual's social background and habitus fit the dominant logic of the digital education field. In Bourdieusian terms, merit reproduces privilege even online, and shocks such as COVID-19 deepen structural inequalities.

Imdorf et al. (2022) highlight that Bulgaria's (and, by extension, the regions immediately adjacent to it) educational and economic landscapes are marked by substantial regional disparities interlaced with ethnic inequalities in school-to-work transitions. Disparities in education, training, and digital access persist, notably due to the strong concentration of tertiary graduates in cities (where most possibilities to acquire tertiary education are concentrated), leading to imbalances that are sometimes further increased by the out-migration of tertiary-educated people from the regions where they graduated (European Commission 2024). These findings clearly demonstrate that learning inequality is evident at the regional level, particularly in the post-pandemic context, where digital exclusion has widened the educational divide and warrants further investigation.

2.2. Learning losses post-2020

Learning loss can be defined as any specific or general loss of knowledge and skills or reversals in academic progress, most commonly due to extended gaps or discontinuities in a student's education (Huong – Na-Jatturas 2020). Since the Bulgarian State Exam measures a specific complex of skills, it can be safely assumed that it can also measure learning losses (albeit imperfectly).

The root of learning loss, as Krumova and Kolev (2021) note, is that while participation in distance learning improved, systemic issues such as device shortages, digital illiteracy, and inadequate infrastructure persisted. The link between macroeconomic and microeconomic factors during crises and exam results (such as average state exam grades) has not been fully studied statistically in Bulgaria or the wider CEE region. Thus, questions remain regarding whether *the post-COVID learning losses stemmed from developmental inequalities* such as economic wealth or from structural barriers like weak school infrastructure and unequal regional development.

To provide further context, in 2020, 44% of countries and economies with available data reported assessing students in a standardised manner at the upper secondary general education level in response to the COVID-19 effects. The former included Austria, Chile, the Czech Republic, Denmark, the United Kingdom, Estonia, France, Italy, Korea, Latvia, Luxembourg, Mexico, Poland, and the Russian Federation. In 2021, a slightly smaller proportion of countries and economies (37%) implemented such assessments (OECD 2021). Bulgaria, however, continuously administered matriculation exams each year during the pandemic, ensuring one of the most consistent time series of standardised exam data globally. However, no comprehensive statistical analysis of learning losses has been undertaken – despite the availability of data extending back to the early 2008s.

From a comparative perspective, Lichand et al. (2021) conducted a difference-in-differences (DiD) study in São Paulo and observed that secondary school students scored 0.32 standard deviations lower on standardised tests during the pandemic – attaining only 27.5% of in-person learning – and experienced a 365% increase in dropout risk when comparing 2019 to 2020. This period is relatively short, as 2019–2020 is generally not considered long enough to assess the impact of an educational shock. Significant policy changes take longer to affect learning (Bolton 2013). Nevertheless, our finding of about 0.30 to 0.40 standard deviation in 2022 aligns broadly with the results reported by Lichand et al. (2021), despite differences in methodology and context.

Table A1 in the Appendix presents a comparative analysis of the impact of various national and international shocks on learning. It is evident that such disruptions typically result in changes ranging from 0.1 to 0.50 standard deviations in learning outcomes. However, few studies have explicitly considered whether macroeconomic or social conditions amplify learning losses.

2.3. Recovery and the new pedagogical realities

The educational and socioeconomic disruptions caused by the COVID-19 pandemic, as summarised by Zamfirov et al. (2020), also reveal a profound transformation in both pedagogical delivery and the structural conditions of learning. Overall, teachers reported heightened stress levels and increased workloads. Students simultaneously expressed frustration, disengagement, and perceived learning losses (Zamfirov et al. 2020). These effects have been echoed across the entire CEE region (Kovács et al. 2024; Dautbašić – Bećirović 2022). These changes were not merely qualitative; instead, they represent significant shocks to pedagogical realities with the potential to alter performance indicators, such as exam performance, by exacerbating learning losses in an already underperforming educational system.

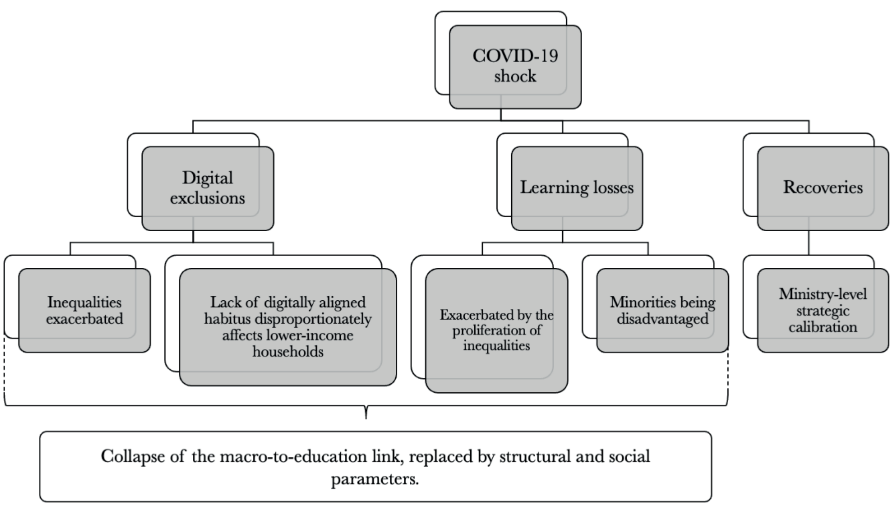
International evidence provides a valuable benchmark when triangulating the effects of COVID-19 on learning with those of educational programmes (not natural disasters per se). For instance, in India, a computer-assisted learning programme yielded an improvement of 0.47 standard deviations, while a remedial education programme yielded an improvement of 0.28 standard deviations. However, both effects faded to approximately 0.10 standard deviations one year after the programmes concluded (Banerjee et al. 2007; Bolton 2013). These effects are comparable in magnitude to the strong rebound observed in 2024 in Bulgaria, following targeted efforts by the Ministry of Education and Science to improve national learning quality through school-level interventions (Az-buki 2024).

To tie everything together, Figure 1 presents the hierarchy of concepts in the literature and their contributions to the collapse of the education-economy link. Digital exclusions and rising learning losses have widened the country's inequalities, disrupting macroeconomic conditions. Since the already fragile system was at high risk of socioeconomic collapse, especially in the education sector, COVID reinforced the previously hidden link between forces beyond measurable macroeconomic indicators. It is reasonable to assume that this conceptual hierarchy also manifests spatially, as shown in Figure 2, where regional disparities mirror the regional inequalities presented as some of the results in later sections. An EU document classifies most of the Bulgarian NUTS 2 regions as 'talent development traps' (Figure 2), meaning they exhibit the following characteristics (European Commission 2024):

- a shrinking working-age population,
- below-average and stagnant level of tertiary education and/or
- net out-migration of people aged 15–39.

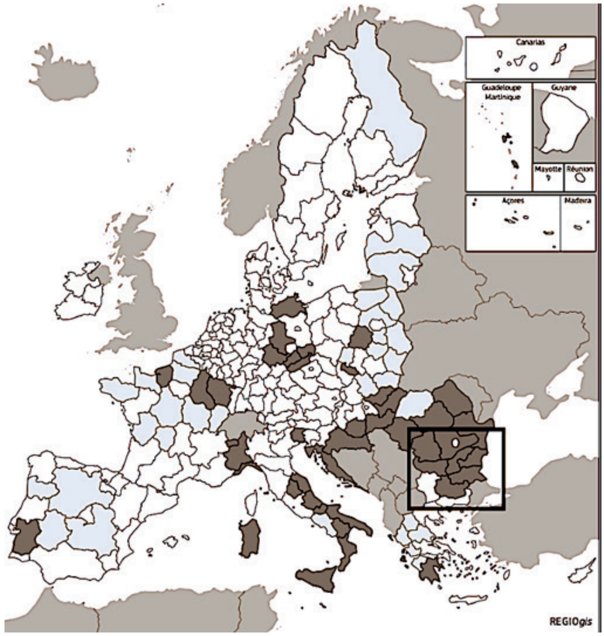
This makes the country an important example of how vulnerable systems react to stress. Interestingly, according to Eurostat (2021), after North-West Bulgaria (32% of the EU average GDP per capita), the lowest-performing NUTS 2 regions in the entire EU were Bulgaria's North-Central (35%), South-Central (37%), South-East (40%), and North-East (41%) regions, highlighting the country's persistent regional divide. Hence, we treat Bulgaria not as an isolated case study but rather as a *socioeconomic laboratory*, illustrating how inequality, education, and digital exclusion interact on a global scale.

Figure 1. Hierarchy of concepts from the literature and thematic synthesis



Source: authors.

Figure 2. Regions classified as being in a talent development trap at the NUTS 2 level, with Bulgaria marked in a black square



Note: Regions identified as experiencing a talent development trap are highlighted in the darkest shade of grey. All Bulgarian NUTS 2 regions, except Yugozapaden, are categorised as talent development traps. Yugozapaden concentrates the majority of Bulgaria's wealth, demonstrating significant regional disparities in economic development.
Source: European Commission (2024).

3. Data

Time-series data on high school–level state exam results in Bulgarian Language and Literature were obtained from the Bulgarian Ministry of Education and Science in response to an individual request. This indicator was selected because of its universal applicability. Despite the constraints imposed by the COVID-19 pandemic, the Ministry of Education repeatedly required Bulgarian students to sit for the exam annually between 2020 and 2024, which provided an indicator more time-consistent than the PISA 3-year cycles.[3] One limitation is that the state exam is not psychometrically equated across years and may be influenced by

3 The exam was selected because it is the only compulsory graduation exam in Bulgaria; all other state exams are optional. Its universal administration eliminates self-selection bias and ensures full population coverage.

factors such as private tutoring, topic choice, or school-level preparation. This limits its use for measuring absolute proficiency. However, because learning loss is defined as a disruption in expected performance trajectories rather than as a fixed ability score (Huong – Na-Jatturas 2020), the exam remains suitable for detecting relative declines over time, especially given its uninterrupted, nationwide annual coverage.

The grades are aggregated at the NUTS 3 regional level (as detailed in the subsequent section), enabling integration with corresponding macroeconomic indicators at the exact spatial resolution. We divide the panel into two distinct four-year periods – 2015–2018 (pre-treatment) and 2020–2023 (post-treatment) – to enable a comparative analysis of how educational outcomes relate to macro-level indicators before and after the COVID-19 shock. Macroeconomic indicator data were obtained from the National Statistics Institute's 'INFOSTAT' web portal. All variables that were used are outlined in Table 1.

Table 1. Description and sources of all indicators used in the panel models.

Indicator	Description	Source
GDP_PER_CAPITA	Regional macroeconomics indicator that shows the average wealth per person	National Statistical Institute
share_higher_education_25_64	Number of individuals who received higher education among all individuals in that age bracket (in %)	
enrolled_students_total	Number of students enrolled in school	
households_with_internet	Households with a stable internet connection (in %)	
matriculation_score	Average matriculation exam scores at the school level	Ministry of Education and Science
students_per_school	Total number of students who took the exam per school	

Source: authors.

It is important to note that, since the National Statistical Institute does not deflate GDP at the regional level, a particularly striking shift is observed in the context of *elevated* post-2020 inflation, which followed the sudden increase in energy prices in the second quarter of 2022. This was largely triggered by the Russia–Ukraine war, in which inelastic demand led to significant changes in the share of household expenditure on energy (Chowdhury – Dixon 2025). These disruptions likely absorbed and blurred income-based heterogeneity, undermining the reliability of basic correlation coefficients. Hence, the correlation between regional GDP and exam outcomes declined sharply – from 0.63 to 0.17 – reflecting a 74% relative decrease and suggesting a breakdown in macro-educational coherence under stress. Similarly, digital access variables, such as the share of regular internet users (aged 16–74 years) and the percentage of households with internet access, also showed inverse relationships with the exam results. While these indicators increased (due to emergency-driven digitalisation), exam scores decreased, resulting in counterintuitive negative correlations: from 0.38 to –0.12 and from 0.32 to –0.18, respectively.

4. Methodology

We compute a weighted average matriculation exam score for each NUTS 3 district in Bulgaria, using school-level data from the Ministry of Education and Science. The score reflects the average performance of all students in a region, with weights proportional to school enrolment to avoid bias from small institutions. Formally, for region r and year t, the score is calculated as:

$$\overline{\mu_{rt}} = \frac{\sum_{j=1}^{J_{rt}} w_{jrt} X_{jrt}}{\sum_{j=1}^{J_{rt}} w_{jrt}} \tag{1}$$

where w_{jrt} is the number of students in school j, and x_{jrt} is the average grade in that school. This aggregation produces a consistent panel dataset at the regional level, which serves as the dependent variable in the subsequent analysis. Hence, the model is expressed as follows:

$$\log(\overline{\mu_{it}}) = \beta_0 + \beta_1 \cdot \log(GDP\ per\ capita_{it}) + \boldsymbol{\rho}'\boldsymbol{x}_{it} + \lambda_i + \tau_t + \varepsilon_{it} \tag{2}$$

Where:

- $\log(\overline{\mu_{it}})$ is the weighted average matriculation score in region i and year
- x_{it} is a vector of time-varying covariates, including the number of university graduates aged 25–64 years – treated as a form of cultural capital (Huang 2019), thereby serving as a direct macroeconomic proxy – as well as the ratio of households with an internet connection to the number of enrolled students, which acts as a proxy for digital access.
- λ_i and τ_t denote region and year fixed effects, respectively.
- ε_{it} is the idiosyncratic error term.

This two-way fixed effects model is estimated using the within transformation. To assess the changes before and after the pandemic, we ran separate regressions for 2014–2018 and 2020–2023, excluding 2019 as a transitional year.

We also estimated year-specific effects to capture annual fluctuations and investigate whether regional effects on student performance remain stable over time.

Additionally, we estimated an alternative specification with time fixed effects only, omitting group fixed effects. This specification prevents post-2020 inflation shocks from biasing the GDP coefficient and producing sign reversals. We used group-clustered, HC1-consistent standard errors with Arellano's (1987) correction to ensure robust inference. This adjustment accounts for potential heteroskedasticity and serial correlation within panel units.

To verify the assumption of independence across cross-sectional units, we conducted tests for cross-sectional dependence using the Pesaran CD test (Pesaran 2004), due to the presence of N significantly greater than T. We show that across all specifications, the null hypothesis of cross-sectional independence cannot be rejected (p-values consistently exceed 0.10), indicating the absence of significant spatial or interregional correlation in the residuals. These results validate the use of standard two-way fixed effects models without spatial corrections.

Finally, to enrich the post-2020 analysis and explore ethnic-level heterogeneity within regions, we incorporated an additional control derived from the 2021 Population Census. The ratio $RtB = \frac{\text{Roma population}}{\text{Bulgarian population}}$ serves as a proxy for concentrated poverty, school segregation, and linguistic barriers, since the Roma population usually adopts Bulgarian (the main language of instruction) as a second language. This part of the population is generally poorer and sometimes isolated in specific regions. Hence, the extended specification is as follows:

$$\log(\overline{\mu_{it}}) = \beta_0 + \beta_1 \cdot \log(GDP\ per\ capita_{it}) + \beta_2 \cdot RtB_i + \boldsymbol{\rho}'\boldsymbol{x}_{it} + \tau_t + \varepsilon_{it} \qquad (3)$$

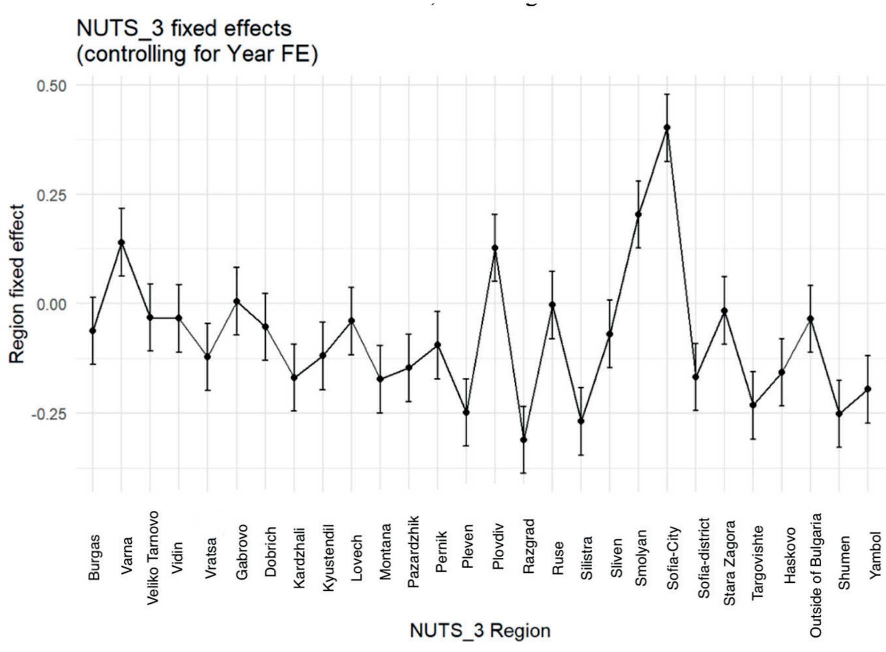
Because both RtB_i and the fixed effects are time-invariant, the variation in RtB_i would be entirely absorbed by the fixed effects, implying that the identification of the effect of RtB_i on the weighted exam averages is only possible under time-fixed effects.

5. Regional heterogeneity and time-fixed effects: Effects of COVID-19 on exam performance

Figure 3 shows that only four regions – Sofia City, Smolyan, Plovdiv, and Varna – exhibit positive effects on the regional weighted average exam score. These effects are estimated using a fixed-effects regression model with separate dummy variables for each year (β_t) and each region, without a global intercept. In this setup, the estimated coefficients measure deviations from the overall annual mean, allowing for a direct comparison of regional performance after accounting for year-specific shocks. The results in Figure 1 demonstrate persistent regional heterogeneity across Bulgaria's NUTS 3 regions.

Figure 3 also shows that schools located in Sofia City exhibit an effect of 0.40 grade points when compared to the baseline average. Other positive contributors include Smolyan, Plovdiv, and Varna. At the other end of the spectrum, Razgrad shows the weakest performance, with a –0.30 point effect on the annual average grade. Interestingly, Bulgarian students studying abroad perform no better than those in regions such as Stara Zagora, Ruse, and Vratsa and perform worse than those in Sofia City. These findings suggest that while regional differences in educational performance are not extreme, they are still significant enough to warrant closer investigation. The effects are not uniform across regions, supporting the value of a disaggregated regional analysis.

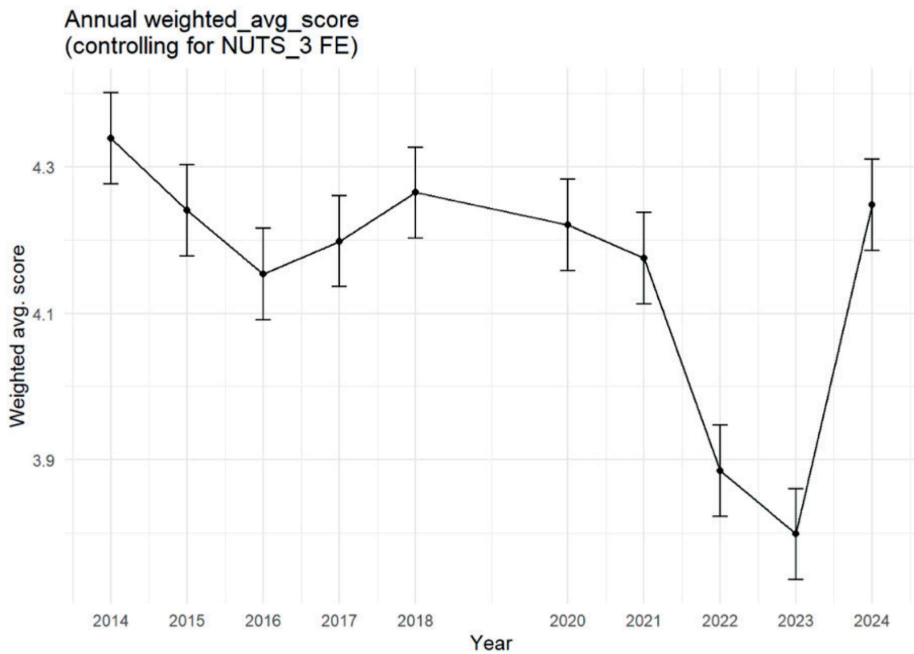
Figure 3. Regional heterogeneity of Bulgarian NUTS 3 effects on weighted average grades from 2015 to 2024, excluding 2019



Source: authors, based on data from the Ministry of Education and Science.

Figure 4 presents the estimated annual effects on the average matriculation exam score. Using approximately 230 degrees of freedom, the results indicate a total post-2020 decline of approximately 0.40 grade points, with the sharpest drop occurring in 2021–2022 (reflecting the cohort directly affected by the 2020 school disruptions). A smaller dip is also observed in 2014–2016, followed by a relatively rapid recovery. These early declines are most plausibly linked to an ageing teaching workforce, chronically low salaries, and weak incentives within a system already on the verge of structural instability.

Figure 4. Annual effects on the average matriculation score, controlling for NUTS 3 FE



Source: authors, based on data from the Ministry of Education and Science.

Table 2 provides a more robust quantification of the effects of COVID-19 on matriculation exam performance. The left panel presents a student-weighted regression with annual fixed effects, while the right panel adds region-level estimation for triangulation. To aid interpretation, we express year-on-year changes in the fixed effects relative to the pre-COVID standard deviation in school-average scores:

$$Standardized\ Change_{t,t+1} = \frac{\beta_{t+1} - \beta_t}{\sigma_{pre-COVID}} \tag{4}$$

where the outcome remains in raw grade points. This allows us to approximate the magnitude of shifts in national performance in terms of typical school-level variation – analogous to standardised effect sizes such as Cohen's d (Cohen

1988),[4] though here we use a single baseline standard deviation of school-average grades (Glass's Δ–style). For a broader discussion on standardised interpretability in regression, see Gelman (2008).

Table 2 shows that Bulgaria experienced modest but persistent learning losses averaging approximately 0.01–0.03 standard deviations per year in the pre-COVID period, with some years reaching 0.129–0.133 standard deviations. As mentioned earlier, these trends reflect the structural deterioration in learning conditions, demographic decline, and an ageing teacher workforce. Against this backdrop, the estimated 0.38 standard deviation drop between 2021 and 2022 likely reflects both the exacerbating effects of the pandemic and the ongoing downward trajectory in educational performance. The learning loss was slightly mitigated in the next period, declining by 0.203 to 0.103 standard deviations (stronger across schools and weaker across regions). However, the overall decline in grades was so severe that the Ministry implemented a series of interventions in 2023–2024, leading to a complete rebound to pre-COVID levels, followed by the normalisation of the grade distribution and a 0.70 standard deviation gain in 2024.

The Minister of Education publicly stated that the 2024 result was a 'historic achievement', explicitly attributing it to a series of direct, targeted interventions (holding mock exams in schools, as well as additional preparatory classes in Bulgarian Language and Literature) implemented by the Ministry in coordination with regional education authorities (Az-buki 2024). The Ministry of Education's systemic intervention demonstrates that exam performance responds strongly to external educational efforts and private tutoring. This suggests that wealth and socio-economic status influence exam results, rather than the other way around (because wealthier parents can afford private tutoring and additional preparation for their children).

Our findings generally align with the broader literature, but they lie at the higher end of the estimated learning losses. For instance, Di Pietro (2023) reports a 0.19 standard deviation learning deficit attributable to COVID-19, while a meta-analysis of 30 studies by Storey and Zhang (2024) estimates an average loss of 0.21 standard deviations. Similarly, Betthäuser et al. (2023) document a persistent deficit (Cohen's $d = -0.14$, 95% CI [−0.17, −0.10]) that emerged early in the pandemic. Across these studies, learning losses are consistently found to be larger for students from low socioeconomic backgrounds. However, most studies do not explicitly consider the possibility that learning conditions were already deteriorating prior to the pandemic. If educational systems were already in decline because of structural weaknesses, the negative impact of COVID-19 may have been more severe, compounding pre-existing trends.

4 The main difference is that our indicator is based on year-on-year fixed effects from a regression model, rather than a simple mean comparison.

Additionally, pandemic-related measures were not implemented uniformly but were staggered across regions and countries (hence, the difference in the estimated school level and NUTS 3 level losses). These issues are particularly salient in Central and Eastern Europe, where long-term structural decline, demographic collapse, and deepening inequalities may violate the parallel trends assumption that underpins most (DiD) designs. In cases such as Bulgaria, assuming trend stability may obscure the long-run educational decay that predates COVID-19. Our findings suggest that part of the observed post-pandemic learning loss (at least 0.01 standard deviations) reflects not only the shock itself but also the continuation of pre-existing negative trajectories.

Table 2. Summary of the derived standardised changes in exam performance.

School-level annual fixed effects weighted regression (N = 9714)			Region-level annual fixed effects (N ~ 240) (controlling for region-specific heterogeneity)	
Year	$\frac{\Delta\beta_t}{1}$	$\frac{\Delta\beta_t}{\sigma_{preCovid}}$	$\frac{\Delta\beta_t}{1}$	$\frac{\Delta\beta_t}{\sigma_{preCovid}}$
2014–2015	-0.058	-0.089	-0.099	-0.152
2015–2016	-0.084	-0.129	-0.086	-0.133
2016–2017	0.05	0.077	0.045	0.069
2017–2018	0.057	0.088	0.066	0.102
2018–2020	-0.023	-0.036	-0.044	-0.068
2020–2021	-0.043	-0.066	-0.045	-0.069
2021–2022	-0.246	-0.38	-0.29	-0.447
2022–2023	-0.131	-0.203	-0.086	-0.133
2023–2024	0.463	0.714	0.449	0.692

Note: In the first panel, a weighted OLS-type regression is used to control for heterogeneity at the individual school level. In the second panel, region-level panels with annual and entity effects were utilised. For triangulation, we provide both the absolute change in the time intercepts $\left({}^{\Delta\beta_t}/_{1}\right)$ and the change relative to the pre-COVID school level standard deviations $\left({}^{\Delta\beta_t}/_{\sigma_{preCovid}}\right)$.
Source: authors.

6. Macroeconomic predictors of average matriculation exam scores pre- and post-COVID

Table 3 presents the results from multiple fixed-effects regressions estimating the relationship between macroeconomic indicators and regional average matriculation exam performance from 2015 to 2018. Across most specifications, the log of GDP per capita remains a consistent positive predictor of exam scores (β=0.06 to β=0.08). However, its significance weakens in models that account for both regional and year fixed effects. This suggests that underlying wealth inequalities explain part of the variance in regional-level exam scores.

When we relax region-fixed effects and rely solely on time fixed effects, proxies for cultural capital – such as Roma share and adult education – capture a substantial share of the between-region variation in exam outcomes (~40–50%). This suggests that higher Roma shares or lower levels of adult education are associated with poorer exam outcomes in regions. The statistical significance of these cultural capital proxies reflects their strong correlation with underlying unobserved cross-sectional heterogeneity. The panel regression demonstrates that regional differences in exam performance are not solely due to wealth; entrenched socioeconomic gaps, as reflected in these proxies, play a critical role in shaping educational outcomes nationwide, which is why coefficients in two-way models lose significance. Overall, the pattern of coefficient insignificance provides evidence that Bulgaria's educational inequality persists due to long-standing regional disparities, which are strongly correlated with proxies of cultural capital. Consequently, short-run changes do not substantially affect outcomes.

Table 3. Summary of NUTS 3 weighted average scores and macroeconomic indicators: fixed effects regression

Variable	log(NUTS 3 weighted average score)			
	(I)	(II)	(III)	(IV)
log(GDP PER CAPITA)	0.06**	0.062**	0.08***	0.037*
	(0.029)	(0.030)	(0.014)	(0.022)
share_higher_education_25_64		0.0002		0.003***
		(0.001)		(0.001)
log(households_with_internet/ enrolled_students_total)		0.003		-0.003
		(0.01)		(0.012)
Entity	Yes	Yes	No	No
Time	Yes	Yes	Yes	Yes
Observations	112	112	112	112
R^2	0.04	0.05	0.41	0.50
Pesaran CD test	p > 0.10			

Note: All models use group-clustered robust standard errors. The period is 2015–2018, and the panel is balanced. The significance levels are *p < 0.1; **p < 0.05; ***p < 0.01.
Source: authors.

The post-COVID regressions (Table 4) show structural decoupling between regional economic performance and educational outcomes. Specifically, after COVID, the influence of GDP per capita on educational outcomes decreases markedly when cultural and structural inequality measures are added. With only time-fixed effects, GDP is initially significant (coefficient = 0.083) but becomes statistically insignificant after controlling for education, internet access, and ethnic composition. The pivotal finding is that the R-squared value for model (IV) in Table 3 is nearly identical to that of model (III) in Table 4 (which adds only the Roma-to-Bulgaria population). Notably, the post-COVID model (II) explains 41% of the variance (with time-fixed effects only), whereas the pre-COVID model (IV) explains 50% (Model IV). This change shows that, post-COVID, the Roma population now accounts for approximately 10% of the variance formerly attributed to other factors, underscoring a shift in the explanatory structure. It also exerts a significant adverse effect, underscoring the persistent role of ethnic stratification in shaping educational outcomes (similar to results previously observed in Imdorf et al. 2022). Thus, the main conclusion is that deep-seated structural factors, rather than economic conditions alone, have become the strongest predictors of educational outcomes.

A striking post-COVID development is the role of the internet access ratio. Before the pandemic, the share of households with internet access relative to enrolled students was statistically insignificant, suggesting that basic infrastructure availability did not translate into measurable educational benefits. After COVID, however, the coefficient becomes negative and strongly significant, implying that regions with greater nominal connectivity experienced relatively worse exam outcomes. This shift likely reflects a mismatch between mere access and the absence of a digitally aligned habitus: without the cultural capital and institutional capacity to integrate digital learning effectively, connectivity alone became insufficient – and may even have amplified existing inequalities. This result is further reinforced by the data presented in Table A3, in which the interaction *Internet access* × *Post-2020* is negative and marginally statistically significant.

Further support for the regression estimation is provided by the Hausman tests. These tests compare fixed- and random-effects specifications and confirm the structural break observed after the pandemic (Table A2). Pre-COVID models demonstrated that random effects could be rejected after including key covariates ($p = 1.069e-13$). Post-COVID estimations also decisively rejected the random effects assumption ($p < 0.001$), even with identical controls.

We also implemented an extended interaction model that further reinforces the central claim of this study: the pandemic did not intensify the traditional GDP–learning gradient but dissolved it (Table A3). While GDP per capita remains a strong and statistically significant predictor of exam performance in the pre-COVID period ($\beta = 0.06$, $p < 0.001$), its post-2020 interaction term not only loses significance (β = –0.010, p = 0.53) but reverses sign. In other words, regional wealth ceased to function as an explanatory mechanism once the system entered crisis: richer regions *did not maintain an advantage*, and poorer regions did not fall further behind. Instead, inequality reorganised along different axes – accumulated human capital (β = 0.0016, p < 0.001) and post-pandemic digital access (β = –0.012, p = 0.06) – confirming that the education–economy link did not deepen but structurally collapsed.

Table 4. Summary of NUTS 3 weighted average scores and macroeconomic indicators: fixed effects regression.

Variable	log(NUTS 3 weighted average score)				
	(I)	(II)	(III)	(IV)	(V)
log(GDP PER CAPITA)	0.083***	0.051***	0.031	0.027	0.031
	(0.017)	(0.02)	(0.02)	(0.032)	(0.031)
share of higher education from 25 to 64		0.001**	0.001**		0.0003*
		(0.001)	(0.0004)		(0.0002)
log(households_with_internet/ enrolled_students_total)		-0.013	-0.015		-0.04***
		(0.014)	(0.011)		(0.014)
Roma to Bulgaria			-0.324*		
			(0.175)		
Entity	No	No	No	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Observations	112				
R^2	0.36	0.41	0.51	0.01	0.07
Pesaran CD test	p > 0.10				

Note: All models use clustered robust standard errors. The period is 2020–2023, and the panel is balanced. The significance levels are *p < 0.1; **p < 0.05; ***p < 0.01.
Source: authors.

7. Conclusions and policy implications

This study provides robust panel-based evidence on the long-term educational impact of COVID-19 in Bulgaria; one of the most important lessons is that growth in economic wealth in socially fragile societies is insufficient to maintain human capital accumulation. Countries similar to Bulgaria should be aware that access to digital technologies and macroeconomic policies alone are insufficient for improving student performance. More robust and inclusive interventions, as well as open dialogue on stratification and ethnic marginalisation, are required.

Between 2021 and 2023, national exam performance declined by 0.38–0.447 standard deviations, with a strong recovery observed in 2024. These losses align with those of other crisis-affected CEE countries (Blaskó et al. 2022) and rival the magnitude of major natural disasters (Table A1). This educational collapse is a direct consequence of inequalities within Bulgarian society hidden deeply in the social fabric of the country.

Finally, based on our findings, we propose the following targeted policy implications with a specific focus on the CEE region:

- **Institutionalise crisis resilience:** Most CEE educational systems, including Bulgaria's, lacked adaptive protocols during the COVID-19 pandemic (Blaskó et al. 2022). To build resilience, permanent monitoring mechanisms – both quantitative and qualitative – must be institutionalised to detect disruption, flag at-risk groups, and trigger early intervention. Strikingly, countries such as Bulgaria lack the research infrastructure and literacy to maintain long-term panel databases that track student outcomes over time. Moreover, there are no dedicated journals on the economics of education tailored to the data-scarce CEE context, which makes it difficult to engage publicly in academic discussions on region-specific structural problems.
- **Confront ethnic stratification and pre-existing learning losses:** The persistent adverse effect of the Roma population share on performance echoes findings observed across the region (Krumova – Kolev 2021; Dautbašić – Bećirović 2022) and the learning losses prior to COVID further reinforce the need to focus on future reforms to institutionalise desegregation and promote community-level engagement, ethnicity-sensitive pedagogy, and both students' and teachers' welfare.

Most importantly, success should be understood as a function not merely of effort but of socio-economic conditions. It is crucial to mention that the state exam is an integral aspect of the Bulgarian higher education admission process. The persistent inequality hidden in the variance associated with state exam results will inversely affect future generations entering higher education; hence, the structural differences will be transmitted to the labour force and manifest themselves in the later distribution of economic outcomes.

In conclusion, the pandemic not only delayed learning but also exposed the deep fragility of Bulgaria's educational system and its dependence on pre-existing social capital. However, Bulgaria has also created one of the most powerful long-run panel databases that has helped uncover the systemic learning losses exacerbated by the COVID-19 crisis. Any serious post-pandemic recovery plan should address these structural dimensions. The Glass panel fixed effect models proposed here can be used to measure all types of learning losses in other countries that administer state exams in the CEE region.

Appendix

Table A1. Summary of average learning loss per natural disaster across the world

Event / Country	Type of Shock	Learning Loss	Source
COVID-19 (global average)	Pandemic school closures	−0.16 to ~−0.50 standard deviations	Betthäuser et al. (2023); Storey and Zhang (2024)
Pakistan Earthquake (2005)	Earthquake (Kashmir)	0.27 standard deviations over a 30 km range	Andrabi et al. (2020)
Hurricane Katrina (USA, 2005)	Hurricane/ displacement	In the first year following the hurricanes, evacuee math scores dropped between 0.10 and 0.25 standard deviations relative to other Louisiana students.	Sacerdote (2012)
Rwanda genocide (1994)	Conflict/school collapse	The findings show a strong negative impact of the genocide on schooling, with exposed children completing one-half year less education, representing an 18.3 per cent decline.	Akresh and de Walque (2008)

Source: authors.

Table A2. Hausman tests comparing fixed effects and random effects specifications.

Model		p-value	Interpretation
		Pre-COVID	
(I)	GDP only	0.92	fail to reject H_0 → Random effects acceptable
(II)	+ controls	1.069e-13	reject H_0 → Fixed effects strongly preferred
		Post-Covid	
(IV)	GDP only	2.98E-15	reject H_0 → Fixed effects strongly preferred
(V)	+ controls	<2.2e-16	reject H_0 → Fixed effects strongly preferred

Source: authors.

Table A3. Interaction model with post-2020 COVID dummy (1(*Year*≥2020)).

	Coefficient	Std. Error	t-stat
log(GDP per capita)	0.06***	0.01	4.964
log(GDP per capita)×Post-2020 dummy	-0.01	0.02	-0.633
Share of higher-educated (25–64)	0.002***	0.001	4.129
Internet access × Post-2020	-0.0119†	0.006	-1.888
Observations	224 (balanced panel)		
Regions (NUTS 3)	28		
Years	8		
Model	FE (time, within)		
Adj. R squared	0.414		
F-Statistic	42.1 (p < 0.001)		

Note: The reference period is 2015 to 2023, with 2019 excluded. Significance levels are indicated with ***p < 0.001, **p < 0.01, *p < 0.05, † p < 0.10.
Source: authors.

Data availability statement

The data and code presented in this paper are available upon request from the corresponding author.

Conflict of interest

The authors declare no conflict of interest.

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