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School Closures and Implications for Student Outcomes: Evidence from Lithuania [*]

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ABSTRACT

This paper studies the effect of school closure on student outcomes in the Lithuanian context. Using administrative student-level data over 2013–2017 and propensity score matching, we create a balanced sample of control and treatment groups. In contrast to other studies, we focus on students in the final years of high school, possibly eliciting the upper bar of the disruption effect. Also, we follow students after high school graduation, providing evidence on labor market outcomes. We find that the school closure effect depends on the main teaching language. If we match students on a large set of student and school characteristics but the main teaching language, school closings have a lasting negative effect on exam performance and enrolling in higher education. Matching students on the main teaching language significantly reduces the negative school closure effect, suggesting that the disruption effect is considerably smaller and also has limited outcomes after high school if we take the main teaching language into account.

Keywords: School closure, education finance, student outcomes.

JEL Classification: H52, I22, I24.

Introduction

In many advanced economies school closures have become a norm (Kirshner et al., 2016). Often school closures are used as a strategy to improve student outcomes (Sunderman et al., 2017) or increase the efficiency of the school network. By closing low performing schools, government can transfer students to better schools as well as incentivize other schools. However, the transfer creates a trade-off: although displaced students might benefit from exposure to better schools, the disruption in existing peer and teacher networks may affect displaced students negatively. Hence, the impact of school closures on student performance is an empirical question.

In this paper we contribute to the literature in two ways. First, we study the school closure effect on students who are in the final years of high school. Final-year students should be the most affected by school closings: they have limited time to adjust to the disruption before taking final exams, so the negative effect on their educational attainment can be larger. Thus, by focusing on final-year students, we possibly obtain the upper bar of the school closure effect on high school educational attainment. Second, we provide evidence that school closings affect student outcomes after high school graduation. Students who experience school closings in their final years of high school education are less likely to enroll in higher education and graduate. The results on their labor market outcomes are inconclusive possibly due to a small sample.

We assess the impact of school closure on student outcomes in the Lithuanian context. Lithuania provides an excellent setting to analyze school closures for three reasons. First, over the period 2008–2018, about 24 percent of high schools in Lithuania were closed. Second, administrative data on the Lithuanian education system allows us to track student achievements in high school and later in higher education. Finally, we merge this dataset with labor income data, obtaining measures of parent and student labor income and qualification. Detailed information on student ability, social-economic factors and school characteristics allows us to control for differences between displaced students and students who did not experience a school closing, obtaining causal estimates of the school closure effect.

In our empirical analysis we focus on displaced students who experience a school closure after the 10^{th} grade. Besides the lack of evidence on the school closure effect on final-year students, this choice is driven by the timing of national exams in Lithuania and the need to measure pre-closure ability. National exams provide an objective measure of student ability, because their content and assessment criteria are uniform across the country, however, in Lithuania national exams occur at the 10^{th} grade and the 12^{th} grade only. Due to this, we proxy student ability before a school closure with the 10^{th} grade exam score and use the 12^{th} grade exam score to proxy for the post-closure educational attainment. As a result, displaced students (treatment group) in our analysis are students who experience a school closure after the 10^{th} grade and take their 12^{th} grade exams in receiving schools. Over the period 2013–2017, we identify 1,048 displaced students and 42 closed high schools.

To estimate the school closure effect, we have to take into account that schools are not closed randomly and thus displaced students differ from non-displaced students in several ways. The data shows that displaced students on average perform worse in the 10^{th} grade exams (i.e. even before a school closure), study in smaller rural schools and come for poorer social-economic background. To control for these differences, we match displaced students to non-displaced students on observable measures of pre-closure student ability, social-economic factors and school characteristics. We estimate the school closure effect in the matched sample as the difference between the outcomes of displaced students and non-displaced students.

The estimation results show that the school closure effect depends on teaching language. After matching and controlling for a large set of student and school characteristics but the main teaching language, we find that students who experience a school closing two years before high school graduation perform worse in high school exams at the 12^{th} grade and are less likely to attain higher education. Displaced students are 5.3 percentage points less likely to attempt the Mathematics exam and 9.3 percentage points less likely to attempt the Lithuanian state exam, but 8.1 percentage points more likely to take Lithuanian school exam, which is less challenging, compared to non-displaced students. The school closing effect also manifests in on average 8 percent lower Mathematics exam score, 10.1 percent lower Lithuanian state exam score and 4.8 percent lower Lithuanian school exam score for displaced students. Lower educational attainment in high school possibly spills over to lower attainment of higher education as displaced students are 6.2 percentage points less likely to enroll at any higher education institution and 7.2 percentage points less likely to enroll at a university. The results suggest that displaced students experience persistent negative outcomes after high school.

As the treatment group has a substantially higher share of students who study in other native languages than Lithuanian, we extend the baseline set of confounding variables by accounting for non-Lithuanian teaching language. The findings suggest that non-Lithuanian teaching language also has a bearing on educational attainment and its response to the school closure. We find that the school closing effect becomes smaller or even insignificant for some outcomes. The school closing effect on attempting different exams at 12^{th} grade becomes insignificant in most cases, except for the Lithuanian state exam (5.1 percentage points lower probability of attempting). Displaced students still receive significantly lower exam scores from the Mathematics exam (on average 8.7 percent lower). The probability of enrolling at a university is lower for displaced students by 3.2 percentage points and the probability of graduating conditional on enrolling is 5.7 percentage points lower, when compared to non-displaced students with similar student and school characteristics. So matching students on the main teaching language significantly reduces the negative school closure effect, suggesting that the disruption effect is considerably smaller and also has limited outcomes after high school.

Related literature: To the best of our knowledge, this is the first study that addresses the school closure effect on after-school outcomes. Our findings on educational attainment in high school relate to a broad literature on school closings and consolidation in general. Further, we discuss the relevant studies in more detail.

The effect on high school education outcomes has been mostly analyzed using data on elementary and middle school students in selected cities or states in the US. Several studies find that school closings do not reduce the achievement of displaced students (De la Torre and Gwynne, 2009; Steinberg and MacDonald, 2019; Bifulco and Schwegman, 2020). Others indicate a transitory negative effect that vanishes after one year Engberg et al. (2012); Brummet (2014). The exception to the literature is documented in Beuchert et al. (2018) that employ a difference-in-difference method in evaluating school consolidation effects on the 2-4th grade students in Denmark and are able to eliminate student time-invariant factors. They find that the effect vanishes after four years after the closure only for some schools. Differently from these studies, we focus on the final grades of high school rather than middle schools or elementary schools.

Although Kemple (2015); Kirshner et al. (2016) analyze the effect on educational attainment in the final years of high school too, there are several key differences between them and this study. Kemple (2015) focuses on the 9th grade students in 29 low-performing high schools in New York City that were designated for closure. These students had an opportunity to remain in the same high school until graduation, thus, in contrast to our study, the transition costs would not be automatically imposed on them. Unsurprisingly, Kemple (2015) do not find systematic differences in academic outcomes and attendance of students in closing schools compared to students in similar low-performing schools. The graduation rate for students who remained in closing schools might have even increased. Kirshner et al. (2016) focuses on experiences of Latino and African American high school students, more than 90% of whom were eligible for free or reduced-price lunch, in one although large school and find that students who were at the 9-10th grade during the closure announcement performed worse in standardized tests compared to unaffected but otherwise similar students. The study does not evaluate the effects on the 12th grade exam scores, but document a 40%

lower student's graduation odds ratio in post-closure years.

The discussion on mechanisms often lists the receiving school quality, the disruption in schooling and increased commuting time as determining factors. These factors have received some support in empirical studies, however, existing studies typically focus on one of the factors rather than try disentangling them. De la Torre and Gwynne (2009); Engberg et al. (2012); Brummet (2014); Carlson and Lavertu (2016); Steinberg and MacDonald (2019) show that the transitory negative effect could be offset or even become become positive, if displaced students transfer to better schools. Similarly, we provide suggestive evidence in favor of transferring to better quality schools as a way to compensate for the negative disruption effect.

The disruption in schooling is likely to be the main channel of reduced achievement and there is suggestive evidence in favor of this channel. Bifulco and Schwegman (2020); Taghizadeh (2020) attempt to eliminate the disruption effect from the total effect. These studies focus on students who would have attended closed schools if they had not closed rather than students who actually had to transfer. Using New York City data on 47 closed middle schools, Bifulco and Schwegman (2020) find that school closings do not affect educational achievement. Taghizadeh (2020) uses all public middle school closures in Sweden from 2000 to 2012 and also tracks younger siblings of displaced students. The study shows that on average educational achievement of displaced students was not affected, moreover, educational achievement of displaced students was not different from their non-displaced siblings.

Beuchert et al. (2018) provide evidence that the disruption in schooling cannot explain the whole effect. They show that closing small and rural schools has significant effects on student educational achievement even four years after the closure, thus school inputs or increased commuting time must also play a role. Hanushek et al. (2004) attempt to disentangle the role of receiving school quality from the disruption effect using the availability of multiple test score observations per student in the Texas Schools Project micro-data for elementary and middle schools. Analyzing voluntary school changes, they find that only moves across school districts yield a small improvement in average school quality. The costs of moving materialize in the year of the move only but the benefits from a better school do not vanish after one year.

Our study also comes close to the literature on school consolidation. Beuchert et al. (2018) show that school closings is the only type of school consolidation that diminishes educational attainment. Using the 1980 census in the US, Berry and West (2010) relate the state-wide increase in school size to fewer years of schooling and lower returns to education. The study, however, uses state-wide measures of consolidation and cannot distinguish the effect of mergers from the effect of closings. The positive consolidation effect have been documented by De Haan et al. (2016) that exploits the increase in the minimum school size for primary schools in the Netherlands in 1994. They find an increase in student achievement in standardized tests of 0.72% of a standard deviation, suggesting that the benefits of a larger school size offset the decline in school competition. They also show that benefits of attending a larger school are primarily driven by returns to scale rather than the closure of small under-performing schools.

1. Background

This section is divided into two parts. In the first part we outline the broad picture of the Lithuanian education system. The second part describes the school network reform which led to the closure of some schools.

1.1 Lithuanian education system

In Lithuania the general education system consists of twelve years which is divided into three stages: (i) primary education (1-4th grades), (ii) lower secondary education (5-10th grades), and (iii) upper secondary education (11-12th grades). In our analysis we focus only on those schools which provide education for 9-12th grades.[1]

National exams: The national level exams take place at the 10th grade and the 12th grade. For each national level exam, exam tasks, instructions for organization and assessment criteria are developed and approved at the national level.

At the 10th grade exam, which occurs at the end of the 10th grade, the majority of students are tested on Lithuanian language and literature (henceforth, Lithuanian) and Mathematics.[2]. Although, the participation in these exams is required since 2013, obtained grades do not limit further educational options – students can continue to upper secondary education regardless of their grades. Grades are allocated on a ten point scale (1-10), where 4 is the passing grade. Exams are evaluated based on pre-defined evaluation criteria, which are prepared along with exams. Examinations and assessment take place at schools. Exam results are evaluated by a commission appointed by the head of the school. The commission usually consists of teachers from the school. However, if there are too few teachers in a particular school, additional teachers from other schools would be included too. To ensure the objectivity of the assessment, some results might be taken for re-examination by the National Agency for Education.

The national exams at the end of the 12th grade are called Matura exams. The maximum number of Matura examinations a student can take is six. To receive Matura certificates students must pass at least two Matura examinations. The Lithuanian Matura exam is compulsory for all students.

There are two types of Matura exams: school level exams and state level exams. These two exams differ in content and assessment. In comparison to the state Matura exam, the school Matura exam is prepared based on fewer topics and is less demanding. The evaluation

[1]In Lithuania there are two types of schools which provide education for 9-12th grade: secondary schools and gymnasiums. Secondary schools provide all levels of education or at least both lower secondary education and upper secondary education, whereas gymnasiums (with some minor exceptions) have only 9-12th grades. Although secondary schools were phased out until 2017 by transforming them into pre-gymnasiums or gymnasiums, during the period 2013–2017, our sample period, secondary schools still existed.

[2]Students for whom Lithuanian is not a native language can also take exams on their native languages (Belorussian, Polish, Russian, German).

systems for the two types of Matura exams have some differences too. Although both state and school level Matura exams are evaluated using pre-defined evaluation criteria, school Matura exams are conducted and evaluated in schools and assessed on a ten-point scale (1-10), whereas state Matura exams are conducted and evaluated at examination centers and assigned scores from 0 to 100. For school level Matura exams, 4 is the passing grade. For state level Matura exams, a score below 16 points means failure, a score between 16 and 35 points is considered as a satisfactory level of attainment, whereas scores between 36 and 85 points reflect a basic level of educational attainment and scores between 86 and 100 points – a higher level of attainment.

Non-Lithuanian native languages (Belorussian, Polish, Russian, German), Arts and technologies have only school Matura exams. All other Matura exams than these and the Lithuanian Matura exam are available as state Matura exams only.

Higher education: Matura exams play a large role in admission to universities or universities of applied sciences. Applications are assessed based on admission scores computed using Matura exam scores.[3] So lower Matura exam scores can reduce chances of enrolling in a preferred program. As state level Matura exams are more demanding than school level exams, this is reflected in both university admission score as well as possible funding opportunities for students. For instance, since 2015 students applying for the majority of higher education programs are eligible for state funding only if they passed the Lithuanian state Matura exam and at least one foreign language Matura exam. Since 2016, passing the Mathematics state Matura exam is required too.

1.2 School network reform

The decision to close a school is primarily within the rights of the school owner. The ownership of most high schools belongs to one of the 60 counties in Lithuania. In 2013, 90% of high schools belonged to counties, 5% belonged to the state and the remaining 5% were

[3] Different higher education programs can apply different weights to Matura exams and might also add additional points for participation in national competitions, etc.

privately owned. However, when making the decisions regarding the school network, owners are obliged to consult with the interested parties, i.e. parents and teachers. State institutions also exert considerable influence on school closure decisions by providing recommendations and financial incentives.

The influence of state institutions on the school network is reflected in several documents. However, the key document that provides the guidelines for the transformation of the school network was released in 2011 in the resolution of the Government of the Republic of Lithuania (Government of the Republic of Lithuania, 2011). The guidelines announce that the reform should be aimed at creating conditions for the development of high-quality general education and increasing its accessibility at a reasonable price that is acceptable to the state and counties. The guidelines also state that the average number of pupils in a public school class may be lower than specified in the legislation if and only if the school owner provides the school with additional funds, so that the overall funding per class would equal the funding level of the medium-sized class. Thus, counties have to substitute state financing with their own funds for schools where the average number of pupils is below the number specified in the legislation.

Why a school is closed? The minimum number of pupils described in the legislation depends on school location and type. In particular, the guidelines define the minimum number of 11^{th} grade classes (and students). The guidelines state that city schools or schools in counties that represent regional centers have to form at least three classes of the 11^{th} grade, with 75 students in total. Schools in less urbanized counties are expected to form at least two classes of the 11^{th} grade. If high schools meet these criteria, they can provide upper secondary education (11-12^{th} grades). If schools do not meet these criteria, they should be transformed to lower-secondary schools or pre-gymnasiums, thus losing the right to provide upper secondary education.

How a school is closed? Information about the upcoming school closure is not regulated at the state level and its dissemination is left to the discretion of school owners. Typically, the decision to close a school would be made public about two years before the closure so that the school community would have time to prepare for the upcoming change. In the case that is the most relevant for the paper, when high schools lose the right to provide upper secondary education, the first generation of students who are not going to be able to finish secondary education in the same school would learn this information in the 9^{th} grade. Students in more senior grades would still be able to finish secondary education at the same school, although they might decide to leave as well.

2. Data and Empirical Framework

This section unfolds in three steps. First, we provide a description of administrative datasets employed in this paper. Second, we describe the sample and summary statistics associated with the selected sample. Third, we provide the details of our empirical strategy.

2.1 Data

We use three datasets: (1) the Education Management Information System (Svietimo valdymo informacine sistema, henceforth SVIS), which provides administrative information on educational attainment; (2) the report on school restructuring from the Ministry of Education, Science and Sports, and (3) the labor market information data from the State Social Insurance Fund Board (henceforth, SODRA).

The SVIS database is an education information system run by the National Agency of Education. The database combines the results of the 10^{th} grade exams for Mathematics and Lithuanian and Matura exams for several subjects, including Mathematics and Lithuanian. As these two subjects – Mathematics and Lithuanian – are common between the 10^{th} grade and the 12^{th} grade exams, we only focus on them throughout our analysis.

The database also records student transition from high school to higher education: has s/he enrolled to any higher education institution, the type of the higher education institution (university or university of applied sciences), and the year of graduation. In addition to education outcomes, the database provides information whether a student receives free lunch and a few other demographic characteristics: gender, age, primary teaching language (Lithuanian, non-Lithuanian).

Although the SVIS database identifies schools and provides school addresses, this information is insufficient to determine the year of school closure. In some cases, schools are not closed but restructured: they cease to exist in their old name but become a branch of another school without any significant changes to the number of classes, students, personnel, etc. Hence, to identify occurrence and timing of school closures, we use the report on school restructuring prepared by the Ministry of Education, Science and Sport (Ministry of Education, Science and Sport, 2017). From this report we manually identify schools which were closed and when they were closed.

We merge the SVIS database with the labor market information provided by the State Social Insurance Fund Board (SODRA). The benefits of merging with the SODRA data are two-fold. First, the SODRA data provides information on parents' labor income and the level of job qualification. Student-parent relationships are identified using a separate dataset provided by the State Enterprise Centre of Registers. Job qualification is determined based on the profession code provided by employers. In line with the International Standard Classification of Occupations (ISCO), job qualification is classified as high if the profession belongs to one of the following professional groups: managers, professionals, technicians and associate professionals. Thus, the job qualification measure provides us with a proxy for parents' education. Second, the SODRA data also provides student's labor market outcomes over the period 2018–2020. Hence, we also provide evidence on whether school closings affect student labor market outcomes.

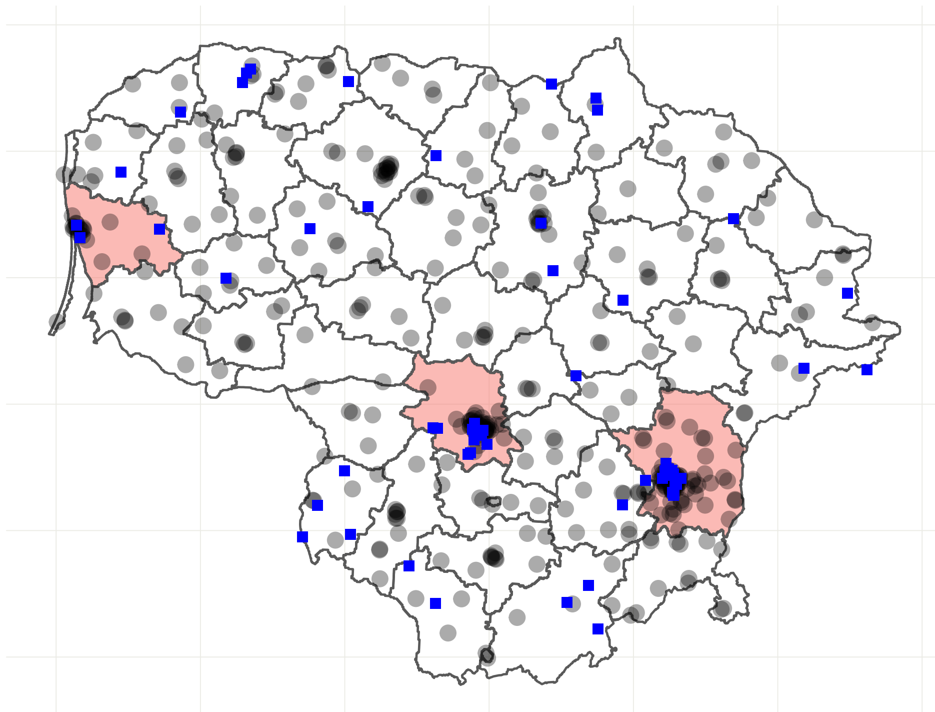
2.2 Sample selection

Our constructed data includes 473 high schools out of which 42 (8.9 percent) were closed over the period 2013–2015. We define a high school closing as the end to providing upper secondary education (11-12^{th} grades). So the closed school by our definition may still provide lower secondary education. The beginning of the sample is chosen as year 2013 because in this year the 10^{th} grade exams became compulsory. We consider school closings up to year 2015, because students who took the 10^{th} grade exam in 2016 or later would not have finished higher education by 2020.

Figure 1 plots the geographic location of closed and non-closed high schools across Lithuania. Closed schools, represented by blue squares, are spread throughout the country. However, the majority of school closures happened around three major urban locations, Kaunas, Klaipėda, and Vilnius, shown by three shaded regions.

For closed schools we define displaced students as students who because of school closings have to change the school after the 10^{th} grade exams. As closed schools differ from non-closed schools, displaced students differ from non-displaced students. For comparison, we provide summary statistics in Table 1. The first part of the table refers to summary statistics at the student level and the second part reports school-level statistics. The table indicates differences in education attainment at the 10^{th} grade: displaced students have on average 5.7 percent lower grade from the Mathematics exam and 3.3 percent lower grade from the Lithuanian exam. Significant differences in education attainment occur at the 12^{th} grade as well: displaced students are less likely to reach the 12^{th} grade, take final exams and perform worse conditional on taking the exams. While 98 percent of non-displaced students progress to the 12^{th} grade, 61 percent of them take the Mathematics Matura exam and 57 percent pass it, the respective rates for displaced students are 95 percent, 46 percent and 41 percent. The difference in attempting the Lithuanian state Matura exam is even larger: 67 percent of non-displaced students take this exam, whereas only 42 percent of displaced students do. Displaced students get on average 6.2 percent lower scores from the Mathematics Matura

Figure 1: Geographic variation of high schools over 2013–2015



Source: the list of closed schools in Ministry of Education, Science and Sport (2017).
Notes: This figure provides a spatial map of non-closed and closed schools in Lithuania. Non-closed schools are represented by grey circles, and closed schools by blue squares. The three shaded regions refer to Kaunas, Klaipėda and Vilnius, home to three most populated cities in Lithuania.

exam, 13.8 percent lower scores from the Lithuanian state Matura exam and 5.2 percent lower grade from the Lithuanian school Matura exam compared to non-displaced students. We also observe differences in the primary study language: 33 percent of displaced students and only 6 percent of non-displaced students study not in Lithuanian. This finding suggests that over this period a large number of closed high schools were minority schools or schools with a large population of minority students.

Differences among students persist after high school graduation as well. The most stark difference is visible for higher education (universities and universities of applied sciences combined) and university enrollment. Focusing on higher education, 71 percent of non-displaced students enroll in higher education, compared to 50 percent of displaced students. Similarly, only 24 percent of displaced students enroll at a university, whereas 44 percent of non-displaced students do. Table 1 also compares average labor income in November 2020

Table 1: Summary statistics

Statistics of:	non-displaced students (1)	displaced students (2)
# students	76,508	1,048
average grade/score at		
the 10^{th} grade Mathematics exam	5.98	5.64
the 10^{th} grade Lithuanian exam	6.73	6.51
the Mathematics Matura exam	47.57	44.63
the Lithuanian state Matura exam	46.79	40.34
the Lithuanian school Matura exam	5.19	4.92
share of students who		
reached the 12^{th} grade	0.98	0.95
took the Mathematics Matura exam	0.61	0.46
passed the Mathematics Matura exam	0.57	0.41
took the Lithuanian state Matura exam	0.67	0.42
passed the Lithuanian state Matura exam	0.66	0.41
took the Lithuanian school Matura exam	0.31	0.56
passed the Lithuanian school Matura exam	0.27	0.45
study not in Lithuanian	0.06	0.33
changed teaching language (10^{th}-11^{th} grades)	0.01	0.08
share of 12^{th} grade students who		
enrolled in higher education	0.71	0.50
enrolled at a university	0.44	0.24
average income in Eur (Nov, 2020) of students who		
reached the 12^{th} grade	964.89	880.64
enrolled in higher education	997.76	914.77
Statistics of:	**non-closed schools**	**closed schools**
# schools	431	42
share of schools located in		
an urban area	0.65	0.48
top 3 cities	0.27	0.33
share of schools that teach in non-Lithuanian	0.12	0.19
average number of the 10^{th} grade students	63	30
average grade of the 10^{th} grade Mathematics exam	6.06	5.78

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.

between two groups of students. Among the students who reach the 12^{th} grade, displaced students have 8.7 percent lower average labor income in November 2020 compared to non-displaced students. Among students who enrolled in higher education, displaced students receive 8.3 percent lower average labor income in November 2020.

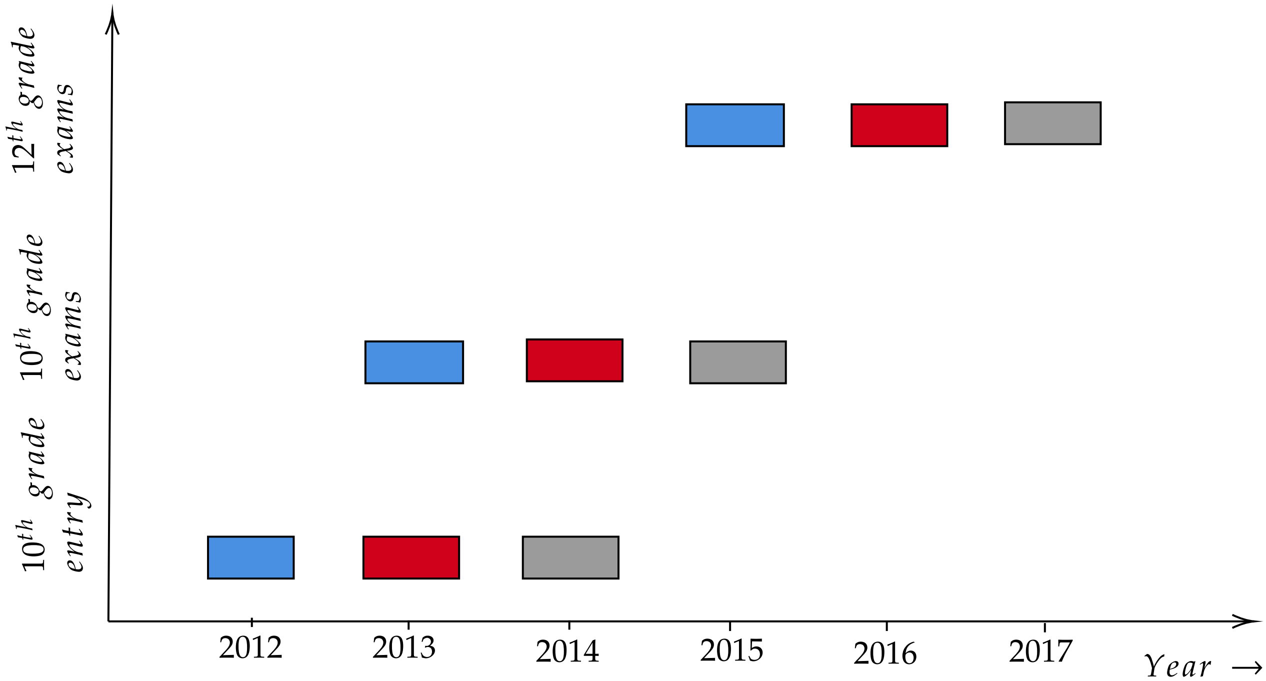
Comparing school level outcomes shows that closed schools perform worse on average compared to non-closed schools and are smaller. We find that the average grade of the 10^{th} grade Mathematics exam is 4.6 percent lower for closed schools. The size differential is linked to the primary rationale for closing schools – lack of efficiency. Closed schools in our sample have on average 30 students attending the 10^{th} grade and non-closed schools have 63 students on average.

The table also provides the distribution of schools in urban and rural areas, where urban areas are defined as cities and towns using the location qualification in the SVIS dataset. In contrast to the view that closed schools are primarily village schools, we find that closed schools are often located in urban areas as well. 48 percent of closed schools are in cities or towns rather than villages. In addition to this, closed schools are more likely to be in the three largest cities than non-closed schools: 33 percent of closed schools and 27 percent of non-closed schools are located in Vilnius, Kaunas or Klaipėda. The closing rate of schools in urban areas is smaller than in other areas: we compute that closed schools constitute 6.7 percent of all schools in urban area, whereas 12.7 percent of all rural schools got closed. However, the closing rate of schools in the three largest cities in this period is 10.8 percent and the closing rate in the rest of the country is 8.2 percent.

2.3 Empirical strategy

Our empirical strategy is to compare outcomes between displaced students and non-displaced students. To this end, we follow three cohorts of students who took the 10^{th} grade exams during the period 2013–2015. The cohort means the year when the student takes the 10^{th} grade exams (2013, 2014 or 2015). Figure 2 depicts the progression of these three cohorts over time. The 10^{th} grade cohort of 2012 (depicted by blue rectangle) participates in the 10^{th} grade exams in 2013 and the 12^{th} grade exams in 2015. Within this cohort, some students become displaced: they experience school closings in 2013 and thus they have to change schools after the 10^{th} grade exams. We assign them to the treatment group. Within this

Figure 2: Study sample illustration



Notes: The present figure provides a schematic representation of the progression of student cohorts in our sample. Year 2012 cohort is represented by blue, 2013 cohort by red and 2014 cohort by grey.

cohort, the control group is comprised of those students whose schools do not close in 2013[4]. Similarly, we assign students to the treatment group and the control group from cohorts that took the 10^{th} grade exams in 2014 and 2015. To identify the school closure effect on student outcomes, we compare Matura exam outcomes and other outcomes for displaced students (treatment group) and non-displaced students (control group).

Summary statistics in Table 1 show that students in the treatment group and the control group are different along several dimensions. For instance, students in closed schools perform worse in the 10^{th} grade exams and thus they could be more likely to underperform in Matura exams even without the school closure disruption. A higher chance of living in a rural area can be related to on average lower socioeconomic status. As we will show later, a few several stylized facts confirm that displaced students are more likely to be from economically challenged families. So if a lower socioeconomic status correlates with a less stable family environment and lower parent support for obtaining education, this could be

[4]Even if their school closes in 2014, they are allowed to graduate in the same school.

yet another reason for lower educational attainment. Another type of the potential bias is related to school characteristics. Closed schools are less likely to be located in an urban area and have fewer students, so these schools might struggle to attract teachers both due to more shallow labor markets and lower available workload (fewer classes to teach). To that end, simply comparing the control sample to the treatment sample could result in biased results. To correct for this, we implement propensity score matching, which is described next.

Matching: We use a logistic regression model to construct propensity scores. Specifically, we estimate the following regression model

$$\text{treat}_{ick} = \gamma_0 + \gamma_x X_{ick} + \varepsilon_{ick} \tag{2.1}$$

where $\text{treat}_{ick} = 1$ if student i from cohort c and school k experiences a school closure in the year of finishing her 10^{th} grade. The cohort means the year when the student takes the 10^{th} grade exams (2013, 2014 or 2015). For each student i, the vector X_{ick} includes a logarithm of Mathematics exam results and a logarithm of Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade Mathematics and Lithuanian exam results, the number of the 10^{th} grade students from cohort c and school k (henceforth, cohort size), a school-level indicator for urban location, a logarithm of parents' income, a gender indicator, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. Logarithms of the Mathematics exam score and the Lithuanian exam score at the 10^{th} grade control for student pre-closure ability. We control for school pre-closure quality by including the school average of the 10^{th} grade Mathematics exam score. We use parents' income, qualification and information on receiving free lunch to describe potential differences in home environment that can lead to differences in parents' support for studies and student motivation to study. The squares of continuous control variables should capture non-linear relationships between the probability of treatment and student or school characteristics.

The predicted probability from (2.1) is our measure of the propensity score. In the second step, we implement nearest neighbor matching to construct a balanced sample. We test the balance of the constructed sample in two ways. First, Table 2 provides the covariate balance summary before and after matching on the propensity score. Second, we plot the propensity score distribution, conditional on students belonging to treatment or control group, for the full sample and the matched sample.

Table 2 shows that in the full sample the control group is different from the treatment group along multiple dimensions. Further, these differences, illustrated through absolute values of standardized mean differences, are large. While students in the treatment group are concentrated in the cohort of year 2015, control group students are evenly distributed over the period 2013–2015. Control group students have better Mathematics and Lithuanian grades, they belong to on average better performing schools, have a larger class size, have parents with higher income or a high qualification job, and are less likely to receive free lunch. However, as columns (4) and (5) of Table 2 show, the differences between control and treatment group students become small in the matched sample. For all covariates, the absolute value of the standardized mean difference is less than 0.1, implying negligible differences.

Figure 3 presents the distribution of propensity scores in the full sample (panel a) and the matched sample (panel b) for both the control group and the treatment group. In the full sample, observations from the control group have a higher mass on the left compared to the treatment group. After matching, the distributions of propensity scores almost completely overlap for both the treatment group and the control group.

We test the robustness of our results along three dimensions. First, instead of the baseline specification of nearest neighbor matching, we implement nearest neighbor matching with replacement and also increase the number of control units to be matched to each treated unit from one to two. Second, instead of using a logistic regression, we use probit. Third, instead of matching we use inverse probability weights. Our results are mostly robust to these modifications. The robustness checks are described in more detail after presenting the

Table 2: Covariate balance summary

	Treatment group (1)	Full sample: Control group (2)	Full sample: Std. mean difference (3)	Matched sample: Control group (4)	Matched sample: Std. mean difference (5)
attended the 10^{th} grade in 2013	0.121	0.361	-0.736	0.133	-0.035
attended the 10^{th} grade in 2014	0.309	0.330	-0.045	0.335	0.008
attended the 10^{th} grade in 2015	0.570	0.309	0.527	0.562	0.015
log Mathematics grade	1.617	1.685	-0.132	1.605	0.023
log Lithuanian grade	1.830	1.872	-0.138	1.832	-0.006
school average grade	6.046	6.484	-0.563	6.038	0.010
cohort size	41.859	113.745	-2.912	41.063	0.032
log parents' income	8.786	9.012	-0.206	8.702	0.076
male	0.536	0.481	0.111	0.537	-0.002
city school	0.775	0.865	-0.216	0.758	0.041
receives free lunch	0.240	0.160	0.189	0.246	-0.013
parent with a high qualification job	0.351	0.525	-0.364	0.341	0.022
# students	1,048	76,508	-	1,048	-

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table provides the co-variate balance summary for the matched sample and the unmatched sample. The treatment group refers to students whose high school closed after they graduated from the 10^{th} grade. The control group includes all other students. The matched sample is obtained using propensity score matching with the nearest neighbor method. Logs of Mathematics and Lithuanian grades refer to grades received from the 10^{th} grade exams. School average grade refers to the average grade in school from the 10^{th} grade Mathematics and Lithuanian exams. Cohort size is computed as the number of students who attended the 10^{th} grade in a given school at the time when the student was at the 10^{th} grade.

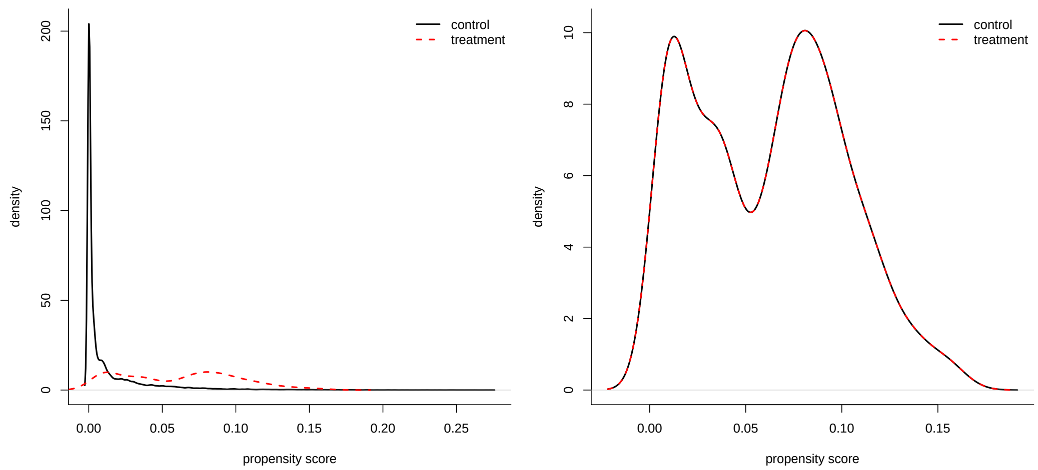
main results.

Empirical specification: After matching, we estimate an OLS model to determine the school closing effect on student outcomes as the average effect on the treated (ATT):

$$y_{ick} = \beta_0 + \beta_1 \times \text{treat}_{ick} + \beta_x X_{ick} + \epsilon_{ik} \tag{2.2}$$

y_{ick} denotes the outcome for student i from cohort c and school k. y_{ick} includes several outcomes of educational achievement: attempting different Matura exams (Mathematics and Lithuanian), scores from different Matura exams (Mathematics and Lithuanian), enrolling in higher education, enrolling at a university, receiving higher education. We also test the school closing effect on having a high qualification job and labor income. X_{ick} includes student and school characteristics used to obtain the propensity score. The school closing

Figure 3: Distribution of propensity scores



(a) full sample   (b) matched sample

Source: SVIS database 2013–2017

effect is captured by coefficient β_1.

3. School closure effect

This section documents the effect of school closings on displaced students. The section unfolds in two steps. First, we document the effect on Matura exam outcomes. Second, we document the effect on higher education enrollment and labor market outcomes.

3.1 Effects on educational attainment in high school

After a school closure, students study in another school and take their final exams in the receiving school. We focus on two performance measures: the probability of taking the 12^{th} grade exams and average scores conditional on taking and passing exams.

Table 3 reports the regression results from estimating model 2.2 when the dependent variable is a binary indicator for attempting an exam. All model specifications estimate the treatment effect by controlling for student and school characteristics: logarithms of the

Mathematics exam score and the Lithuanian exam score at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, a gender indicator, an indicator for urban location, a logarithm of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. Even columns report the results obtained using the matched sample and odd columns report the results from the OLS estimation with the full sample.

We contrast the estimates obtained using the matched sample with the full-sample estimates to demonstrate the presence of the negative bias in displaced students' results and the role of matching to remove the negative bias. For instance, column (2) reports that the probability of attempting the Mathematics Matura exam is lower by 5.3 percentage points for displaced students relative to non-displaced students. The estimate in the full sample (column (1)) is 8 percentage points. The estimated reduction in the matched sample bears economic significance, because 5.3 percentage points amount to 11 percent of the average rate of taking the Mathematics exam in the matched sample (48 percent of all students in the matched sample) and thus displaced students are 11 percent less likely to attempt the Mathematics exam compared to the average rate in the matched sample.

Measuring educational achievement with the Mathematics exam score rather than scores from other subjects is a ubiquitous choice in similar studies (e.g. Brummet (2014)). We measure the outcomes of the Lithuanian exam too for two reasons. First, the Lithuanian exam is required to receive a graduation diploma, so the majority of students take the Lithuanian exam. Second, the Lithuanian exam provides additional evidence in favor of under-performance by showing that displaced students consistently opt out of higher-level (state Matura exam) exams. Although students need the Lithuanian exam to get a graduation diploma (Matura certificate), they can choose between two types: a higher-level (Lithuanian state Matura exam) and lower-level (Lithuanian school Matura exam). Columns (3)-(6) report the estimated effect on attempting the Lithuanian state exam and the Lithuanian school exam.

Table 3: School closure effect on the probability of attempting an exam

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.080***	−0.053**	−0.102***	−0.093***	0.098***	0.081**
	(0.024)	(0.024)	(0.024)	(0.026)	(0.035)	(0.036)
Mean dep. var.	0.61	0.48	0.66	0.46	0.31	0.51
Clusters	529	382	529	382	529	382
Observations	77,556	2,096	77,556	2,096	77,556	2,096
R^2	0.399	0.447	0.434	0.483	0.287	0.217

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

The results show two opposite effects: displaced students are 9.3 percentage points less likely to attempt the Lithuanian state exam, but 8.1 percentage points more likely to take Lithuanian school exam compared to non-displaced students. 9.3 percentage points lower probability to take the Lithuanian state exam is economically significant, since it corresponds to 20.2 percent of the average rate of taking the Lithuanian state exam in the matched sample.

The difference between the full-sample estimates and the matched-sample estimates (columns (3)-(4)) is smaller than in the case of the Mathematics Matura exam. The potential explanation for this difference across subjects could be related to the size of the selection bias. Students need to take the Lithuanian Matura exam in order to graduate, but they can graduate without taking the Mathematics Matura exam. If displaced students are discouraged or less prepared to take the Mathematics Matura exam, the selection bias in taking the Mathematics exam might be stronger than for the Lithuanian Matura exams.

Displaced students are not only less likely to attempt Matura exams (except for the

Table 4: School closure effect on exam scores

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.077*	−0.083**	−0.136**	−0.106**	−0.031*	−0.049***
	(0.043)	(0.038)	(0.054)	(0.050)	(0.017)	(0.018)
Mean dep. var.	3.72	3.64	3.7	3.56	1.62	1.58
Clusters	471	244	477	254	512	245
Observations	44,046	915	51,232	962	21,225	856
R^2	0.625	0.610	0.420	0.362	0.217	0.195

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Lithuanian school Matura exam), but they also perform worse in all Matura exams. Table 4 provides the results of model (2.2) when the dependent variable is the log score of a given exam conditional on passing the exam (failed outcomes are codified as non-available for all Matura exams). We find that displaced students get on average 8 percent lower Mathematics Matura exam score, 10.1 percent lower Lithuanian state Matura exam score and 4.8 percent lower Lithuanian school Matura exam score (columns (2), (4) and (6)). The presence of the negative bias is not as clear as in the case with attempting exams. This suggests that students self-select themselves into taking exams and if they pass these exams, they should be rather similar across the treatment and control groups. However, the Lithuanian exam (of any type) is necessary to get the diploma, so more and more diverse students might still opt to take it and so in the case of the Lithuanian state Matura exam the difference between the full-sample estimates and the matched sample estimates is still negative.

3.2 Role of school quality

The school effect on student achievements is well documented in the literature (e.g. Deming et al. (2014)). Transferring to a good quality school might create positive externalities, potentially offsetting the negative effect of the transition itself. We analyze how the treatment effect varies by the quality of receiving schools, shedding some light on the variation of the effect across the sample. However, we cannot assign causal interpretation to this set of results.

We extend model (2.2) with a term where the treatment indicator is interacted with the school quality indicator. We proxy for school quality based on average results of the 10^{th} grade Mathematics exams: first, we assign each (including closed) school a quantile (1-100) based on the 10^{th} grade exam results, second, we assign the school quality indicator value one, if the displaced student transfers to the school in the top third of the school distribution. In the alternative definition, we assign the school quality indicator value one, if the displaced student transfers to the school in the top half of the school distribution. Students who transfer to vocational schools after closings are automatically assigned zeros due to the significantly lower academic focus of vocational schools. The specification with the interaction term has two main shortcomings. First, we do not match observations on the receiving school quality indicator[5], only on pre-closure school quality and student pre-closure ability, so the sample is not balanced with the respect to receiving school quality and thus students who transfer to higher quality schools are not necessarily comparable to students who do not. Second, the school quality indicator is not predetermined from the treatment perspective. Due to this, the results should be interpreted with caution. We report the results in Tables 5 and A1 as suggestive evidence of the role of school quality.

Table 5 suggests that in the case of some exams displaced students who transfer to a school in the top third (half) of the school distribution experience less negative outcomes

[5]Matching on the receiving school quality indicator would violate the assumption that all confounding variables should be measured before the treatment, i.e. the closure.

on attempting exams compared to other displaced students. In the case of the Mathematics exam, the receiving school quality significantly differentiates student outcomes only if we look at the top half of schools rather than the top third. The probability of attempting the Mathematics Matura exam is 1.2 percentage points lower for displaced students who transfer to a high quality school (column (2)) when the high quality school is a school in the top half distribution of schools based on the 10^{th} grade Mathematics exams. The results are more robust across different school quality definitions in the case of the Lithuanian state Matura exam. The probability for attempting the Lithuanian state Matura exam is 3.6 percentage points lower (column (3)) or 5.2 percentage points lower (column (4)) for students who transfer to high quality schools depending on the higher quality definition. These estimates are equal to approximately one half of the estimate without conditioning on the receiving school quality as reported in Table 3 and thus suggests that the school closure effect varies across the distribution of receiving school quality. The probability of attempting the Lithuanian school Matura exam, however, does not differ significantly between displaced students who transfer to high quality schools and displaced students who do not (columns (5)-(6)).

The finding that the receiving school quality has a significant effect only for some exam outcomes can be driven by the fact that students spend only two years in the receiving school and it takes time to accrue the benefits of the receiving school quality (e.g. Hanushek et al. (2004)). Also, as we mentioned before, even the significant results should be interpreted with caution: the quality of receiving schools correlates with student grades at the 10^{th} grade or parent income, however, we cannot balance observations based on the quality of receiving schools exactly. So we cannot attribute better performance to the school quality entirely – it might be driven by other confounding variables such as motivation if it is not captured by included variables.

For other dependent variables, we mostly do not find significant variation across the quality of receiving schools. Exam scores, especially for the Mathematics Matura exam, have

Table 5: School closure effect on the probability of attempting an exam

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	NN	NN	NN	NN	NN	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.078***	−0.113***	−0.144***	−0.153***	0.093***	0.059*
	(0.030)	(0.035)	(0.024)	(0.030)	(0.032)	(0.033)
treat × school quality (top third)	0.052		0.108**		−0.026	
	(0.043)		(0.044)		(0.062)	
treat × school quality (top half)		0.101**		0.101**		0.036
		(0.045)		(0.042)		(0.050)
Mean dep. var.	0.48	0.48	0.46	0.46	0.51	0.51
Clusters	382	382	382	382	382	382
Students to high quality schools	499	623	499	623	499	623
High quality schools	41	50	41	50	41	50
Observations	2,096	2,096	2,096	2,096	2,096	2,096
R^2	0.448	0.451	0.488	0.487	0.218	0.218

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

significantly fewer observations than attempting an exam, so a small sample can affect the precision of the interaction estimate. We report the interaction term results for exam scores in the appendix in Table A1.

3.3 Effects after high school

Matura exam scores directly affect access to higher education: universities admit students based on Matura exam scores. In the remaining of the section we confirm that school closures reduce student entry to higher education, suggesting long-lasting implications for lifetime income (Nybom, 2017). The results on labor market outcomes after graduation are, however, inconclusive.

We analyze the school closure effect on higher education attainment by computing the probability of enrollment at a higher education institution (either university or university of applied sciences), the probability of enrolling at a university and the probability of graduating conditional on enrollment. Table 6 reports the results. Columns (2) and (4) show that displaced students are 6.2 percentage points less likely to enroll at any higher education institution and 7.2 percentage points less likely to enroll at a university, when compared to non-displaced students with similar student and school characteristics. The estimated effects are economically significant, since the average rate of enrollment in the matched sample is 52 percent and 26 percent for a higher education institution and a university respectively. The probability of graduation conditional on enrollment differs for displaced students relative to non-displaced students too (column (6)). This finding suggests that worse results of Matura exams is not the only barrier to acquiring a higher education degree for displaced students as displaced students are more likely to drop out too when enrolled in higher education. However, the school closure effect on the graduation probability is not robust across different specifications as discussed in section 3.6, so it should be interpreted with caution.

Since our sample begins in 2013, only the first two cohorts of students (graduated from high school in 2015 and 2016) could have graduated from a university before autumn 2020 and got the first job after graduation. This restricts the set of observed labor market outcomes considerably. Nevertheless, we consider two definitions of jobs: 1) the job held in November 2020; and 2) the first job held after graduation from a higher education institution. In the first case, the sample includes both students who work while studying for their undergraduate degree and students who work after completing their undergraduate degree. The matching model accounts for the cohort year, so in all cases we still compare within the cohort rather than across different cohorts of students. In the second case, the comparison is even less contaminated as we do not include jobs held while studying. With both definitions we

Table 6: School closure effect on after-school outcomes

Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.090***	−0.062**	−0.077***	−0.072***	−0.009	−0.097***
	(0.023)	(0.025)	(0.026)	(0.025)	(0.024)	(0.032)
Mean dep. var.	0.69	0.52	0.43	0.26	0.58	0.56
Clusters	529	382	529	382	491	272
Observations	77,556	2,096	77,556	2,096	53,850	1,081
R^2	0.254	0.305	0.297	0.298	0.068	0.094

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

include students who do not pursue a higher education degree over the observed period: with the first definition we include data on the job they had in November 2020 and with the second definition we focus on their first job after graduating from high school. We analyze two aspects of the job – income and the job qualification level (high or low).

Table 7 reports the treatment effect on the job qualification variable in columns (1)-(4) and the effect on the logarithm of labor income in columns (5)-(8). The estimates for the job qualification variable from the matched sample (columns (2) and (4)) are not robust across different job definitions. Columns (6) and (8) suggest insignificant effects on student labor income regardless of the job definition. The results thus suggest that at the early start of their career displaced students are not significantly more likely to earn less or less likely to obtain a high qualification job relative to non-displaced students. However, this finding does not rule out the spillovers from higher education to future job prospects, since a lower probability of acquiring a higher education degree possibly translates into a lower probability of having a high qualification job in later stages of career.

Table 7: School closure effect on labor market outcomes

Dep. var.:	have a high qualification job				log income			
	in 2020		after graduation		in 2020		after graduation	
Method:	OLS	NN	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treat	−0.039***	−0.051***	−0.021	−0.013	−0.205	−0.172	−0.097	−0.245
	(0.014)	(0.019)	(0.015)	(0.018)	(0.137)	(0.167)	(0.154)	(0.195)
Mean dep. var.	0.35	0.21	0.28	0.13	4.99	4.44	4.16	3.63
Clusters	529	365	528	336	529	366	528	336
Observations	55,513	1,648	39,745	1,269	55,666	1,653	39,784	1,269
R^2	0.161	0.149	0.197	0.138	0.081	0.073	0.091	0.079

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results for two outcome variables: having a high qualification job (columns (1)-(4)) and a log of labor income (columns (5)-(8)). Columns (1)-(2) and columns (5)-(6) define the job as the job held in November 2020 and in the remaining columns the job is defined as the first job after graduating from a higher education institution (or high school if a higher education degree is not pursued). Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

3.4 Role of main teaching language

Stylized facts in Table 1 suggest that a substantial share of treatment group students study in non-Lithuanian. Since the main teaching language might affect educational attainment in addition to what can be captured with pre-closure student ability or school pre-closure quality, we extend the propensity score model to account for studying in non-Lithuanian in addition to the baseline set of confounding variables.

Using updated propensity scores, we can still balance covariates (Table A11) and continue estimating model 2.2. In contrast to its previous version, model 2.2 now includes the dummy for the non-Lithuanian teaching language as well. Tables 8-10 show that the difference in student outcomes becomes less pronounced in some cases. We still identify a significant negative effect on attempting the Lithuanian state Matura exam. Displaced students are 5.1 percentage points less likely to take the Lithuanian Matura exam. Exam scores from

Table 8: School closure effect on the probability of attempting an exam when matching on teaching language

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.054***	−0.017	−0.060***	−0.051***	0.008	0.028
	(0.020)	(0.021)	(0.019)	(0.019)	(0.029)	(0.030)
Mean dep. var.	0.61	0.46	0.66	0.44	0.31	0.54
Clusters	529	367	529	367	529	367
Observations	77,556	2,096	77,556	2,096	77,556	2,096
R^2	0.404	0.461	0.448	0.502	0.356	0.280

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, an indicator for non-Lithuanian study language, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

the Mathematics exam for displaced students are lower by 8.7 percent. The probability of enrolling at a university is lower for displaced students by 3.2 percentage points, whereas chances of enrolling in higher education are not statistically different from those of non-displaced students. This suggests that a substantial share of the previously estimated school closing effect might be driven by minority or mixed schools as students who study in non-Lithuanian seem to struggle more with Matura exams, even after accounting for student and school characteristics.

3.5 Anticipation effect

The school closing announcement may precede the school closing by more than a year, so our empirical strategy is prone to the bias arising from the anticipation effect. The closing announcement might potentially create student and teacher outflows before the

Table 9: School closure effect on exam scores without students when matching on teaching language

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.056	−0.091**	−0.051	−0.060	−0.021	−0.015
	(0.044)	(0.041)	(0.036)	(0.039)	(0.015)	(0.016)
Mean dep. var.	3.72	3.64	3.7	3.55	1.62	1.57
Clusters	471	237	477	247	512	244
Observations	44,046	860	51,232	917	21,225	845
R^2	0.626	0.575	0.441	0.379	0.225	0.209

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, an indicator for non-Lithuanian study language, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

school closing and affect the remaining students' motivation and training negatively. If students who remain in the school until the time of the actual closure are significantly different from the pre-announcement student sample, the estimated school closing effect could not be generalized to the pre-announcement cohort of students. More importantly, the 10^{th} grade exam performance could be potentially affected by the announcement. Further, we discuss these two potential problems.

Selection. Figure 4 shows that the number of students starts decreasing two years before the school closure and the decrease reaches on average 5 percent one year before the school closure compared to schools that do not close during the sample period 2013–2015. Thus, student outflows before the school closure exist and they may bias our estimates. However, the result would suggest that student outflows mostly begin two years before the school closure, which narrows down the scope of the analysis.

Table 10: School closure effect on after-school outcomes when matching on teaching language

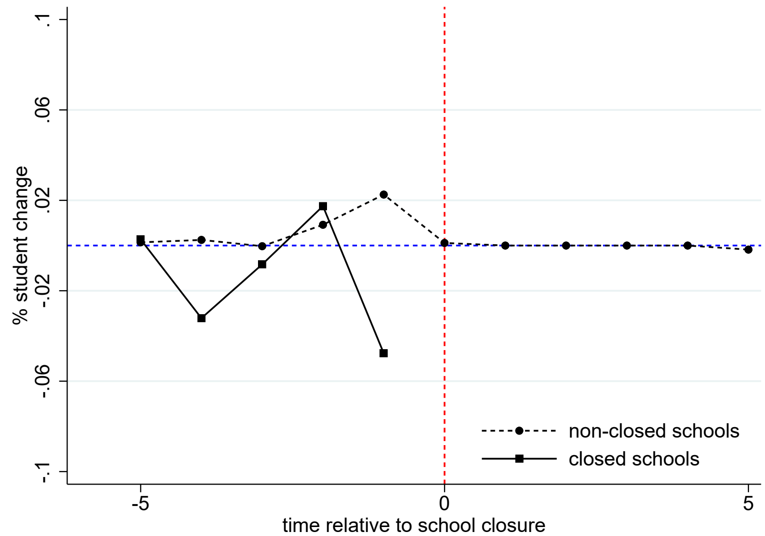
Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.071***	−0.029	−0.052***	−0.032*	0.009	−0.057*
	(0.021)	(0.023)	(0.018)	(0.019)	(0.027)	(0.032)
Mean dep. var.	0.69	0.5	0.43	0.24	0.58	0.53
Clusters	529	367	529	367	491	261
Observations	77,556	2,096	77,556	2,096	53,850	1,044
R^2	0.258	0.301	0.301	0.299	0.070	0.079

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, an indicator for non-Lithuanian study language, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

We identify early leavers in our sample – students who switch schools after the 10^{th} grade but 1–2 years before the school closure takes place. These students should be allowed to finish the school but choose to leave possibly due to the anticipation effect, although personal idiosyncratic reasons are possible too. In Table 11 we compare them to displaced students – students who have to change the school after the 10^{th} grade because the school closed. We identify 445 early leavers in our sample. The summary statistics suggest that early leavers are not systematically higher-ability students. On the contrary, early leavers on average score less in the 10^{th} grade exams and the Mathematics Matura exam compared to displaced students. They are also less likely to take the Mathematics Matura exam and the Lithuanian state Matura exams.

We also compare early leavers to displaced students after controlling for demographic and socioeconomic characteristics. Table 12 shows the results of regressing the 10^{th} grade exam results on the early leaver status indicator after controlling for school and student characteristics. The results indicate that students who change schools voluntarily after the 10^{th} grade are not better performing students. Thus, the anticipation effect arising from early

Figure 4: Student outflows before the school closure



Source: SVIS database 2013–2017

leavers should not bias our main sample and the main results considerably.

Post-announcement covariates. The 10^{th} grade exam performance can be affected by the announcement of school closings since school closings are typically announced in advance. Due to the timing of national exams in Lithuania, we cannot fully address the announcement effect: we cannot measure pre-announcement ability and still be able to measure post-closure educational attainment. For instance, if the school is closed in 2015 and the closing is announced two years before the closure, we would be able to measure pre-announcement ability (the 10^{th} grade exam performance in 2013), but students who took the 10^{th} grade exams in 2013 would be able to graduate in the same school in 2015, i.e. before the closure. This shortcoming might lead to the potential bias in our results. If the announcement affects the 10^{th} grade exam results negatively, this is likely to spill over to the 12^{th} exam results and have a negative effect on them even without the school closure because the preparation for Matura exams would be disrupted already. So by not capturing the announcement effect, we might overestimate the school closure effect on educational attainment and mis-assign the whole decrease in educational attainment to the closure. We acknowledge that a share of the potential decline in educational attainment might be driven by the announcement too and not

Table 11: Summary statistics for early leavers and displaced students

Statistics of:	early leavers	displaced students	p value
	(1)	(2)	(3)
# schools	57	42	
# students	445	1,048	
average grade/score at			
the 10^{th} grade Mathematics exam	4.36	5.64	0.00
the 10^{th} grade Lithuanian exam	5.52	6.51	0.00
the Mathematics Matura exam	39.88	44.63	0.07
the Lithuanian state Matura exam	48.37	40.34	0.00
the Lithuanian school Matura exam	4.75	4.92	0.05
share of students who			
reached the 12^{th} grade	0.96	0.95	0.24
took the Mathematics Matura exam	0.26	0.46	0.00
passed the Mathematics Matura exam	0.21	0.41	0.00
took the Lithuanian state Matura exam	0.25	0.42	0.00
passed the Lithuanian state Matura exam	0.24	0.41	0.00
took the Lithuanian school Matura exam	0.60	0.56	0.23
passed the Lithuanian school Matura exam	0.54	0.45	0.00
study not in Lithuanian	0.21	0.33	0.00
share of 12^{th} grade students who			
enrolled in higher education	0.33	0.50	0.00
enrolled at a university	0.21	0.24	0.29
average income in Eur (Nov, 2020) of students who			
reached the 12^{th} grade	423	425	0.97
enrolled in higher education	992	915	0.32

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.

only by actual displacement. However, the anticipation effect is likely to be less disruptive than the actual closure, so it is unlikely that our estimates capture only the anticipation effect. Also by matching we compare displaced students to students with similarly low exam results, so if we still identify a difference in the 12^{th} grade exam results for these two groups, the difference is most likely to occur due to either the closing effect or the combination of closing and announcement.

Table 12: Difference in the 10^{th} grade exam scores for early leavers and displaced students

Dep. var.:	Logarithm of scores			
Subject:	Mathematics		Lithuanian	
	(1)	(2)	(3)	(4)
early leave	−0.116	−0.187*	−0.067	−0.007
	(0.093)	(0.112)	(0.050)	(0.075)
School FE	No	Yes	No	Yes
Mean dep. var.	1.53	1.53	1.78	1.78
Clusters	164	164	164	164
Observations	1,493	1,493	1,493	1,493
R^2	0.255	0.397	0.335	0.435

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the OLS regression results. The regression model controls for student and school characteristics: the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, an indicator for city location, gender, studying in non-Lithuanian, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

3.6 Robustness checks

We conduct a battery of robustness checks to validate our results. First, we implement different estimation methods. Performed variations of the nearest neighbor method include matching with replacement and increasing the number of control units to be matched to each treated unit from one to two. Tables A2-A4 show the results. We also perform the same variations of the nearest neighbor method as before, but estimate propensity scores with a probit model (Tables A5-A7). Inverse probability weighting exploits the full sample for estimation rather than only a set of observations but also addresses confounding, so we also compare the main results to the estimates obtained using inverse probability weighting. The weights are normalized to avoid cases when very low propensity scores produce extreme weights. Tables A8-A10 show that with inverse probability weighting the school closing effect on attempting exams is similar to the baseline set of results, but the difference in log exam scores for displaced and non-displaced students becomes insignificant. Also, both with inverse probability weighting and matching when the probit model is used, the school closure effect on the graduation probability become insignificant.

Second, we re-estimate the baseline propensity score model (without matching on non-Lithuanian teaching language) using different samples. Before running estimations, we check the covariate balance in each adjusted sample. If we exclude students who changed their main teaching language from non-Lithuanian to Lithuanian after the 10^{th} grade, the covariate balance becomes worse for a logarithm of the Lithuanian 10^{th} grade exam score, but all other standardized mean differences remain below 0.1 (Table A12). Tables A13-A15 show results that are qualitatively similar to the baseline set. If instead of dropping students who switch teaching languages, we drop all students that study in non-Lithuanian at the 10^{th} grade, standardized mean differences are 0.102 and 0.1 for the logarithm of the Mathematics 10^{th} grade exam score and the Lithuanian 10^{th} grade exam score respectively, but in other cases the control group and the treatment group are balanced (Table A20). The sample without students who study in minority or mixed schools at the 10^{th} grade allows to obtain covariate balance for all confounding variables (Table A16). In general, the results with these subsamples are closer to the ones obtained with matching on the teaching language rather than the baseline results. Tables A21-A23 show that the probability of attempting the Mathematics exam, all exam scores and the probability of enrolling at a university are not significantly different for displaced compared to non-displaced students. Tables A17-A19 also do not report significant differences in attempting the Mathematics exam, some exam scores or enrolling at a university. Although excluding students with non-Lithuanian teaching language or minority schools does not deteriorate the covariate balance significantly, in these two cases, the matched sample becomes considerably smaller. For instance, the matched sample for exam scores decreases by approximately 40 percent and insignificant estimates on exam scores could be caused by the considerably smaller sample.

Dropping students from the three largest cities violates the covariate balance, so we do not use this sample for re-estimation.

Our sample is insufficient to use school fixed effects in matching next to the set of other control variables, however, we run the OLS regression including receiving school fixed effects. Tables A24-A26 compare the results to our baseline results, i.e. the matching results. We find that including school fixed effects in the OLS model specification yields similar estimates of the school closing effect as our baseline model (matching). There are only two cases when the OLS specification with receiving school fixed effects yields insignificant estimates: the regression for the Lithuanian school Matura exam score and the regression for the graduation probability.

4. Conclusion

A growing literature shows that the negative effect of school closings on student educational attainment is small and transitory (Engberg et al., 2012; Brummet, 2014) or even zero. However, the majority of studies analyze elementary and middle school closings. This paper contributes to the discussion by analyzing the effects on students in the final years of high school and thus shedding light on the upper bound of the disruption effect as students in the final years of high school have limited time to adjust and accrue the potential benefits of receiving schools. The analysis shows that the school closing effect is limited and manifests only for some exams, e.g. the average score of the Mathematics exam. This suggests that even the upper bound of the disruption effect is smaller than could be expected.

Can it be the case that the negative effect of school closings manifests only after graduating from high school? Another novelty of this study is that the data allows us to study whether displaced students only lose points in Matura exams or also experience negative effects after high school in attainment of higher education or performance in the labor market. The evidence on labor market outcomes is inconclusive and the most conservative matching strategy delivers only three percentage point difference in the probability of enrolling in higher education between displaced and non-displaced students. The findings suggest that the negative effect on displaced students is limited after graduating from high school even if they get displaced in the final years of high school.

Our findings offer insights for future policy on school closings. First, our findings can be generalized to inform about the closings of both minority and non-minority schools. The optimization of the school network in Lithuania primarily aimed to address the inefficiency of small schools, so a significant fraction of closed schools happened to serve students who study in other native languages than Lithuanian. To that end, we extend the baseline set of confounding variables by accounting for non-Lithuanian teaching language. So although the network of minority schools became concentrated over time and is less likely to be reformed again, due to the chosen methodology our results speak to the closure of non-minority schools too. Second, in line with the broad literature on the role of school quality (e.g. Engberg et al. (2012)), we provide suggestive evidence that the quality of receiving schools partially compensate for the negative disruption effect even when time for accruing benefits from studying in a higher quality school is limited. Creating incentives for students to allocate to higher quality schools thus might be key in managing the negative outcomes of school closings.

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Table A1: School closure effect on exam scores

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	NN	NN	NN	NN	NN	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.135***	−0.087**	−0.098	0.022	−0.053***	−0.047**
	(0.038)	(0.037)	(0.085)	(0.094)	(0.020)	(0.021)
treat × school quality (top third)	0.082		−0.012		0.012	
	(0.059)		(0.101)		(0.025)	
treat × school quality (top half)		0.005		−0.157		−0.004
		(0.052)		(0.102)		(0.024)
Mean dep. var.	3.64	3.64	3.56	3.56	1.58	1.58
Clusters	244	244	254	254	245	245
Students to high quality schools	289	351	302	362	151	199
High quality schools	32	40	35	43	25	33
Observations	915	915	962	962	856	856
R^2	0.613	0.610	0.362	0.367	0.196	0.195

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A2: School closure effect on the probability of attempting an exam with alternative specifications

Dep. var.:	*Attempting an exam indicator (1=Yes, 0=No)*								
Subject:	Mathematics			Lithuanian					
Level:	state exam			state exam			school exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treat	−0.053**	−0.037	−0.061**	−0.093***	−0.092***	−0.096***	0.081**	0.079**	0.096***
	(0.024)	(0.025)	(0.024)	(0.026)	(0.027)	(0.026)	(0.036)	(0.036)	(0.036)
Method:	NN	NN	NN	NN	NN	NN	NN	NN	NN
Matching ratio:	1	1	2	1	1	2	1	1	2
With replacement:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean dep. var.	0.48	0.47	0.49	0.46	0.45	0.47	0.51	0.52	0.5
Clusters	382	370	411	382	370	411	382	370	411
Observations	2,096	1,922	2,734	2,096	1,922	2,734	2,096	1,922	2,734
R^2	0.447	0.458	0.444	0.483	0.493	0.469	0.217	0.214	0.197

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results using the nearest neighbor (NN) method to match student-level observations. The propensity score is estimated with a logit model. Matching ratio refers to how many control units should be matched to each treated unit. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A3: School closure effect on exam scores with alternative specifications

Dep. var.:	*Logarithm of scores*								
Subject:	Mathematics			Lithuanian					
Level:	state exam			state exam			school exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treat	−0.083**	−0.073*	−0.070*	−0.106**	−0.110**	−0.110**	−0.049***	−0.054***	−0.050***
	(0.038)	(0.038)	(0.038)	(0.050)	(0.052)	(0.049)	(0.018)	(0.020)	(0.016)
Method:	NN	NN	NN	NN	NN	NN	NN	NN	NN
Matching ratio:	1	1	2	1	1	2	1	1	2
With replacement:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean dep. var.	3.64	3.65	3.63	3.56	3.56	3.57	1.58	1.58	1.59
Clusters	244	231	283	254	245	285	245	229	293
Observations	915	826	1,222	962	873	1,289	856	792	1,075
R^2	0.610	0.612	0.621	0.362	0.367	0.350	0.195	0.186	0.187

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results using the nearest neighbor (NN) method to match student-level observations. The propensity score is estimated with a logit model. Matching ratio refers to how many control units should be matched to each treated unit. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A4: School closure effect on after-school outcomes with alternative specifications

Dep. var.:	enrolled in higher education			enrolled at a university			graduated		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treat	−0.062**	−0.057**	−0.074***	−0.072***	−0.074***	−0.081***	−0.097***	−0.102***	−0.086***
	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)	(0.026)	(0.032)	(0.031)	(0.029)
Method:	NN	NN	NN	NN	NN	NN	NN	NN	NN
Matching ratio:	1	1	2	1	1	2	1	1	2
With replacement:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean dep. var.	0.52	0.51	0.53	0.26	0.26	0.28	0.56	0.55	0.56
Clusters	382	370	411	382	370	411	272	261	299
Observations	2,096	1,922	2,734	2,096	1,922	2,734	1,081	990	1,460
R^2	0.305	0.318	0.309	0.298	0.313	0.299	0.094	0.099	0.079

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results using the nearest neighbor (NN) method to match student-level observations. The propensity score is estimated with a logit model. Matching ratio refers to how many control units should be matched to each treated unit. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A5: School closure effect on the probability of attempting an exam with alternative specifications and the probit model

Dep. var.:	*Attempting an exam indicator (1=Yes, 0=No)*								
Subject:	Mathematics			Lithuanian					
Level:	state exam			state exam			school exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treat	−0.066**	−0.071***	−0.058**	−0.093***	−0.089***	−0.086***	0.105***	0.101***	0.088**
	(0.027)	(0.027)	(0.025)	(0.026)	(0.026)	(0.025)	(0.035)	(0.036)	(0.036)
Method:	NN	NN	NN	NN	NN	NN	NN	NN	NN
Matching ratio:	1	1	2	1	1	2	1	1	2
With replacement:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean dep. var.	0.49	0.49	0.49	0.46	0.45	0.47	0.51	0.51	0.5
Clusters	373	358	420	373	358	420	373	358	420
Observations	2,096	1,926	2,749	2,096	1,926	2,749	2,096	1,926	2,749
R^2	0.452	0.468	0.428	0.472	0.480	0.465	0.208	0.213	0.214

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results using the nearest neighbor (NN) method to match student-level observations. The propensity score is estimated with a probit model. Matching ratio refers to how many control units should be matched to each treated unit. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A6: School closure effect on exam scores with alternative specifications and the probit model

Dep. var.:	*Logarithm of scores*								
Subject:	Mathematics			Lithuanian					
Level:	state exam			state exam			school exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treat	−0.078*	−0.085**	−0.072*	−0.103**	−0.090*	−0.110**	−0.042***	−0.029	−0.033**
	(0.041)	(0.041)	(0.042)	(0.049)	(0.049)	(0.050)	(0.016)	(0.018)	(0.016)
Method:	NN	NN	NN	NN	NN	NN	NN	NN	NN
Matching ratio:	1	1	2	1	1	2	1	1	2
With replacement:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean dep. var.	3.64	3.65	3.65	3.56	3.55	3.57	1.58	1.58	1.58
Clusters	228	217	273	245	234	285	248	228	297
Observations	910	833	1,205	956	878	1,301	863	787	1,095
R^2	0.602	0.595	0.609	0.354	0.357	0.335	0.177	0.174	0.149

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results using the nearest neighbor (NN) method to match student-level observations. The propensity score is estimated with a probit model. Matching ratio refers to how many control units should be matched to each treated unit. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A7: School closure effect on after-school outcomes with alternative specifications and the probit model

Dep. var.:	enrolled in higher education			enrolled at a university			graduated		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treat	−0.052*	−0.054**	−0.076***	−0.083***	−0.084***	−0.088***	−0.063**	−0.066*	−0.035
	(0.027)	(0.027)	(0.026)	(0.023)	(0.024)	(0.023)	(0.032)	(0.034)	(0.031)
Method:	NN	NN	NN	NN	NN	NN	NN	NN	NN
Matching ratio:	1	1	2	1	1	2	1	1	2
With replacement:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean dep. var.	0.51	0.51	0.53	0.27	0.26	0.28	0.53	0.53	0.52
Clusters	373	358	420	373	358	420	250	237	304
Observations	2,096	1,926	2,749	2,096	1,926	2,749	1,067	973	1,462
R^2	0.305	0.312	0.298	0.298	0.302	0.305	0.083	0.084	0.065

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results using the nearest neighbor (NN) method to match student-level observations. The propensity score is estimated with a probit model. Matching ratio refers to how many control units should be matched to each treated unit. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exam results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A8: School closure effect on the probability of attempting an exam using inverse probability weighting

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	NN	IPW	NN	IPW	NN	IPW
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.053**	−0.081***	−0.093***	−0.112***	0.081**	0.101***
	(0.024)	(0.024)	(0.026)	(0.024)	(0.036)	(0.031)
Mean dep. var.	0.48	0.5	0.46	0.51	0.51	0.44
Clusters	382	529	382	529	382	529
Observations	2,096	77,556	2,096	77,556	2,096	77,556
R^2	0.447	0.486	0.483	0.528	0.217	0.325

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Odd columns report the results obtained using the nearest neighbor method to match student-level observations. Even columns report the results obtained using inverse probability weighting. The propensity score model controls for student and school characteristics: logs of mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A9: School closure effect on exam scores using inverse probability weighting

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	NN	IPW	NN	IPW	NN	IPW
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.083**	−0.038	−0.106**	−0.050	−0.049***	0.021
	(0.038)	(0.028)	(0.050)	(0.041)	(0.018)	(0.015)
Mean dep. var.	3.64	3.67	3.56	3.67	1.58	1.61
Clusters	244	471	254	477	245	512
Observations	915	44,046	962	51,232	856	21,225
R^2	0.610	0.620	0.362	0.407	0.195	0.227

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results. Odd columns report the results obtained using the nearest neighbor method to match student-level observations. Even columns report the results obtained using inverse probability weighting. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A10: School closure effect on after-school outcomes using inverse probability weighting

Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	NN	IPW	NN	IPW	NN	IPW
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.062**	−0.104***	−0.072***	−0.046***	−0.097***	−0.006
	(0.025)	(0.030)	(0.025)	(0.017)	(0.032)	(0.046)
Mean dep. var.	0.52	0.57	0.26	0.33	0.56	0.57
Clusters	382	529	382	529	272	491
Observations	2,096	77,556	2,096	77,556	1,081	53,850
R^2	0.305	0.348	0.298	0.349	0.094	0.108

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results. Odd columns report the results obtained using the nearest neighbor method to match student-level observations. Even columns report the results obtained using inverse probability weighting. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A11: Covariate balance summary when matching on teaching language

	Treatment group (1)	Full sample: Control group (2)	Full sample: Std. mean difference (3)	Matched sample: Control group (4)	Matched sample: Std. mean difference (5)
attended the 10^{th} grade in 2013	0.121	0.361	-0.736	0.141	-0.061
attended the 10^{th} grade in 2014	0.309	0.330	-0.045	0.296	0.029
attended the 10^{th} grade in 2015	0.570	0.309	0.527	0.563	0.013
log Mathematics grade	1.617	1.685	-0.132	1.593	0.046
log Lithuanian grade	1.830	1.872	-0.138	1.829	0.002
school average grade	6.046	6.484	-0.563	6.008	0.048
cohort size	41.859	113.745	-2.912	40.126	0.070
log parents' income	8.786	9.012	-0.206	8.738	0.044
male	0.536	0.481	0.111	0.512	0.048
city school	0.775	0.865	-0.216	0.754	0.050
receives free lunch	0.240	0.160	0.189	0.246	-0.013
parent with a high qualification job	0.351	0.525	-0.364	0.339	0.026
non-Lithuanian teaching language	0.333	0.062	0.576	0.329	0.008

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table provides the co-variate balance summary for the matched sample and the unmatched sample. The treatment group refers to students whose high school closed after they graduated from the 10^{th} grade. The control group includes all other students. The matched sample is obtained using propensity score matching with the nearest neighbor method. Logs of Mathematics and Lithuanian grades refer to grades received from the 10^{th} grade exams. School average grade refers to the average grade in school from the 10^{th} grade Mathematics and Lithuanian exams. Cohort size is computed as the number of students who attended the 10^{th} grade in a given school at the time when the student was at the 10^{th} grade.

Table A12: Covariate balance summary without students switching teaching language

	Treatment group (1)	Full sample: Control group (2)	Full sample: Std. mean difference (3)	Matched sample: Control group (4)	Matched sample: Std. mean difference (5)
attended the 10^{th} grade in 2013	0.124	0.361	-0.720	0.140	-0.050
attended the 10^{th} grade in 2014	0.305	0.330	-0.054	0.297	0.019
attended the 10^{th} grade in 2015	0.571	0.309	0.529	0.563	0.016
log Mathematics grade	1.611	1.684	-0.140	1.588	0.045
log Lithuanian grade	1.826	1.871	-0.148	1.795	0.100
school average grade	6.031	6.479	-0.576	6.048	-0.022
cohort size	42.252	113.738	-2.899	41.701	0.022
log parents' income	8.792	9.010	-0.200	8.800	-0.007
male	0.535	0.482	0.106	0.542	-0.016
city school	0.771	0.865	-0.223	0.770	0.002
receives free lunch	0.237	0.160	0.181	0.245	-0.018
parent with a high qualification job	0.347	0.524	-0.371	0.350	-0.006

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table provides the co-variate balance summary for the matched sample and the unmatched sample. The treatment group refers to students whose high school closed after they graduated from the 10^{th} grade. The control group includes all other students. The matched sample is obtained using propensity score matching with the nearest neighbor method. Logs of Mathematics and Lithuanian grades refer to grades received from the 10^{th} grade exams. School average grade refers to the average grade in school from the 10^{th} grade Mathematics and Lithuanian exams. Cohort size is computed as the number of students who attended the 10^{th} grade in a given school at the time when the student was at the 10^{th} grade.

Table A13: School closure effect on the probability of attempting an exam without students switching teaching language

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.032	−0.040*	−0.082**	−0.096***	0.089**	0.088**
	(0.045)	(0.023)	(0.041)	(0.026)	(0.040)	(0.039)
Mean dep. var.	0.48	0.48	0.45	0.45	0.52	0.52
Clusters	371	371	371	371	371	371
Observations	2,050	2,050	2,050	2,050	2,050	2,050
R^2	0.001	0.480	0.007	0.473	0.008	0.216

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results after dropping students who switch teaching language from non-Lithuanian to Lithuanian after the 10^{th} grade. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A14: School closure effect on exam scores without students switching teaching language

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.027	−0.092**	−0.056	−0.138***	−0.007	−0.029
	(0.077)	(0.040)	(0.047)	(0.046)	(0.016)	(0.017)
Mean dep. var.	3.66	3.66	3.57	3.57	1.57	1.57
Clusters	237	237	249	249	248	248
Observations	884	884	921	921	855	855
R^2	0.001	0.588	0.003	0.362	0.0003	0.181

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results after dropping students who switch teaching language from non-Lithuanian to Lithuanian after the 10^{th} grade. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A15: School closure effect on after-school outcomes without students switching teaching language

Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.060	−0.075***	−0.070**	−0.074***	−0.063*	−0.070**
	(0.039)	(0.025)	(0.028)	(0.024)	(0.034)	(0.033)
Mean dep. var.	0.52	0.52	0.26	0.26	0.53	0.53
Clusters	371	371	371	371	265	265
Observations	2,050	2,050	2,050	2,050	1,065	1,065
R^2	0.004	0.313	0.006	0.308	0.004	0.084

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results after dropping students who switch teaching language from non-Lithuanian to Lithuanian after the 10^{th} grade. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A16: Covariate balance summary without minority or mixed schools

	Treatment group	Full sample		Matched sample	
		Control group	Std. mean difference	Control group	Std. mean difference
	(1)	(2)	(3)	(4)	(5)
attended the 10^{th} grade in 2013	0.171	0.360	-0.500	0.208	-0.097
attended the 10^{th} grade in 2014	0.422	0.329	0.188	0.393	0.060
attended the 10^{th} grade in 2015	0.406	0.311	0.195	0.399	0.014
log Mathematics grade	1.549	1.686	-0.266	1.508	0.079
log Lithuanian grade	1.777	1.866	-0.292	1.770	0.025
school average grade	5.756	6.484	-1.063	5.741	0.022
cohort size	41.950	118.414	-2.689	40.799	0.040
log parents' income	8.702	9.026	-0.293	8.650	0.048
male	0.525	0.479	0.091	0.544	-0.038
city school	0.682	0.873	-0.411	0.669	0.026
receives free lunch	0.259	0.154	0.239	0.297	-0.086
parent with a high qualification job	0.310	0.534	-0.483	0.291	0.041

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table provides the co-variate balance summary for the matched sample and the unmatched sample. In both cases we drop minority or mixed schools. The treatment group refers to students whose high school closed after they graduated from the 10^{th} grade. The control group includes all other students. The matched sample is obtained using propensity score matching with the nearest neighbor method. Logs of Mathematics and Lithuanian grades refer to grades received from the 10^{th} grade exams. School average grade refers to the average grade in school from the 10^{th} grade Mathematics and Lithuanian exams. Cohort size is computed as the number of students who attended the 10^{th} grade in a given school at the time when the student was at the 10^{th} grade.

Table A17: School closure effect on the probability of attempting an exam without minority or mixed schools

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	-0.058^{**}	-0.039	-0.091^{***}	-0.065^{**}	0.104^{***}	0.063^{**}
	(0.027)	(0.028)	(0.025)	(0.027)	(0.025)	(0.028)
Mean dep. var.	0.62	0.46	0.68	0.43	0.28	0.5
Clusters	488	327	488	327	488	327
Observations	71,820	1,482	71,820	1,482	71,820	1,482
R^2	0.399	0.449	0.441	0.507	0.330	0.328

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results after dropping minority or mixed schools. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A18: School closure effect on exam scores without minority or mixed schools

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.062	−0.066	−0.091*	−0.121***	−0.007	−0.009
	(0.057)	(0.041)	(0.049)	(0.047)	(0.015)	(0.018)
Mean dep. var.	3.72	3.53	3.71	3.58	1.62	1.58
Clusters	423	200	426	203	462	225
Observations	41,568	582	48,521	634	19,696	725
R^2	0.630	0.575	0.440	0.357	0.218	0.168

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results after dropping minority or mixed schools. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A19: School closure effect on after-school outcomes without minority or mixed schools

Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.072***	−0.062**	−0.030*	−0.018	−0.030	−0.120***
	(0.026)	(0.029)	(0.017)	(0.021)	(0.031)	(0.040)
Mean dep. var.	0.7	0.51	0.44	0.25	0.59	0.58
Clusters	488	327	488	327	443	221
Observations	71,820	1,482	71,820	1,482	50,475	757
R^2	0.260	0.359	0.304	0.353	0.069	0.123

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results after dropping minority or mixed schools. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A20: Covariate balance summary without minority students

		Full sample		Matched sample	
	Treatment group (1)	Control group (2)	Std. mean difference (3)	Control group (4)	Std. mean difference (5)
attended the 10^{th} grade in 2013	0.172	0.360	-0.498	0.205	-0.087
attended the 10^{th} grade in 2014	0.425	0.329	0.193	0.395	0.061
attended the 10^{th} grade in 2015	0.403	0.311	0.188	0.401	0.006
log Mathematics grade	1.532	1.684	-0.293	1.479	0.102
log Lithuanian grade	1.769	1.866	-0.319	1.738	0.100
school average grade	5.713	6.483	-1.145	5.696	0.026
cohort size	43.249	117.881	-2.616	41.568	0.059
log parents' income	8.700	9.025	-0.293	8.616	0.076
male	0.521	0.480	0.082	0.551	-0.060
city school	0.682	0.870	-0.402	0.667	0.034
receives free lunch	0.252	0.155	0.224	0.263	-0.026
parent with a high qualification job	0.323	0.533	-0.449	0.319	0.009

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table provides the co-variate balance summary for the matched sample and the unmatched sample. In both cases we drop students who are reported to study in non-Lithuanian at the 10^{th} grade. The treatment group refers to students whose high school closed after they graduated from the 10^{th} grade. The control group includes all other students. The matched sample is obtained using propensity score matching with the nearest neighbor method. Logs of Mathematics and Lithuanian grades refer to grades received from the 10^{th} grade exams. School average grade refers to the average grade in school from the 10^{th} grade Mathematics and Lithuanian exams. Cohort size is computed as the number of students who attended the 10^{th} grade in a given school at the time when the student was at the 10^{th} grade.

Table A21: School closure effect on the probability of attempting an exam without minority students

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.042	−0.026	−0.077***	−0.060**	0.088***	0.070**
	(0.027)	(0.028)	(0.025)	(0.027)	(0.025)	(0.029)
Mean dep. var.	0.62	0.46	0.68	0.42	0.28	0.49
Clusters	475	309	475	309	475	309
Observations	72,490	1,398	72,490	1,398	72,490	1,398
R^2	0.400	0.475	0.444	0.521	0.333	0.344

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results after dropping students who are reported to study in non-Lithuanian at the 10^{th} grade. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the OLS estimation with the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A22: School closure effect on exam scores without minority students

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.051	−0.019	−0.060	−0.062	0.004	0.016
	(0.059)	(0.046)	(0.049)	(0.048)	(0.015)	(0.017)
Mean dep. var.	3.72	3.53	3.71	3.57	1.62	1.57
Clusters	413	192	418	202	461	208
Observations	41,895	554	48,928	588	19,964	686
R^2	0.632	0.560	0.441	0.436	0.217	0.189

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: The table reports the regression results after dropping students who are reported to study in non-Lithuanian at the 10^{th} grade. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A23: School closure effect on after-school outcomes without minority students

Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.061**	−0.050*	−0.021	−0.015	−0.031	−0.067*
	(0.027)	(0.028)	(0.017)	(0.020)	(0.032)	(0.041)
Mean dep. var.	0.7	0.5	0.44	0.25	0.59	0.55
Clusters	475	309	475	309	434	215
Observations	72,490	1,398	72,490	1,398	50,917	705
R^2	0.261	0.358	0.305	0.327	0.069	0.100

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: The table reports the regression results after dropping students who are reported to study in non-Lithuanian at the 10^{th} grade. Even columns report the results obtained using the nearest neighbor method to match student-level observations. Odd columns report the results from the full sample. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A24: School closure effect on the probability of attempting an exam: school fixed effects

Dep. var.:	Attempting an exam indicator (1=Yes, 0=No)					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	NN	OLS	NN	OLS	NN	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
treat	-0.053^{**}	-0.054^{***}	-0.093^{***}	-0.077^{***}	0.081^{**}	0.082^{***}
	(0.024)	(0.017)	(0.026)	(0.017)	(0.036)	(0.020)
School FE	No	Yes	No	Yes	No	Yes
Mean dep. var.	0.48	0.61	0.46	0.66	0.51	0.31
Clusters	382	529	382	529	382	529
Observations	2,096	74,826	2,096	74,826	2,096	74,826
R^2	0.451	0.457	0.476	0.504	0.203	0.428

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: Odd columns report the results obtained using the nearest neighbor method to match student-level observations. Even columns report the results from the OLS estimation with the full sample including school fixed effects where schools are chosen as schools attended at the 11^{th} grade. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, school average of the 10^{th} grade exams results, cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A25: School closure effect on exam scores: school fixed effects

Dep. var.:	Logarithm of scores					
Subject:	Mathematics		Lithuanian			
Level:	state exam		state exam		school exam	
Method:	OLS	NN	OLS	NN	OLS	NN
	(1)	(2)	(3)	(4)	(5)	(6)
treat	−0.083**	−0.087*	−0.106**	−0.110***	−0.049***	−0.018
	(0.038)	(0.046)	(0.050)	(0.035)	(0.018)	(0.012)
School FE	No	Yes	No	Yes	No	Yes
Mean dep. var.	3.64	3.72	3.56	3.7	1.58	1.62
Clusters	244	471	254	477	245	512
Observations	915	43,966	962	51,130	856	21,168
R^2	0.610	0.657	0.362	0.489	0.195	0.326

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017).
Description: Odd columns report the results obtained using the nearest neighbor method to match student-level observations. Even columns report the results from the OLS estimation with the full sample including school fixed effects where schools are chosen as schools attended at the 11^{th} grade. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.

Table A26: School closure effect on after-school outcomes: school fixed effects

Dep. var.:	enrolled in higher education		enrolled at a university		graduated	
Method:	NN	OLS	NN	OLS	NN	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
treat	-0.062^{**}	-0.046^{**}	-0.072^{***}	-0.054^{***}	-0.097^{***}	0.016
	(0.025)	(0.019)	(0.025)	(0.017)	(0.032)	(0.033)
School FE	No	Yes	No	Yes	No	Yes
Mean dep. var.	0.52	0.69	0.26	0.43	0.56	0.58
Clusters	382	529	382	529	272	491
Observations	2,096	76,855	2,096	76,855	1,081	53,730
R^2	0.305	0.320	0.298	0.330	0.094	0.095

Source: SVIS database 2013–2017, the list of closed schools in Ministry of Education, Science and Sport (2017), SODRA data 2018–2020.
Description: Odd columns report the results obtained using the nearest neighbor method to match student-level observations. Even columns report the results from the OLS estimation with the full sample including school fixed effects where schools are chosen as schools attended at the 11^{th} grade. The propensity score model controls for student and school characteristics: logs of Mathematics and Lithuanian exam results at the 10^{th} grade, the school average of the 10^{th} grade exams results, the cohort size at the 10^{th} grade, gender, an indicator for urban location, a log of parents' income, an indicator for receiving free lunch, an indicator for at least one of the parents having a high qualification job, cohort fixed effects and squares of continuous control variables. This set of controls is also included in all model specifications for estimating the treatment effect. Standard errors are clustered at the school level where schools are chosen as schools attended at the 11^{th} grade.