May I be excused? Identification of returns to absences and class peer effects

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Abstract

In this paper, we investigate (1) returns to absences and (2) peer effects. We exploit exogenous variation from a natural experiment that changed the school absences allowance for the better students in order to identify the effect of school attendance on educational outcomes. The natural experiment took place in Greece in 2007 and provided higher performing students with 50 more hours of excused absences from school. We start off by using a Regression Discontinuity approach in order to measure the change in total absences and exam score due to the reform around the cutoff. Next, we employ a combination of differences-in-differences and instrumental variables techniques in order to identify returns to absences and peer effects. Our estimates show significant positive peer effects in Greek Language but negative peer effects in Mathematics. Furthermore, our estimates yield significant negative returns to absences of a magnitude of 0.01 standard deviations per hour of absence in Greek Language, Mathematics and the overall GPA.

Keywords: human capital, returns to education, attendance, peer effects, natural experiment
JEL Classification: I25, C26

1 Introduction

Most educational systems rely on lectures and class meetings as a means of instruction. This is even more prevalent when secondary or pre-tertiary education is considered. Nevertheless, class attendance is not always perfect. Lecture learning is based on group learning, which may not be the optimal learning style for everyone. As a result, many students decide to skip class when given the opportunity. In a classroom, students compete for the attention and time of the instructor. Thus, their consumption of education induces externalities on one another. Romer (1993) claims that college students in three elite U.S. universities were found to perform better when attending classes and completing homework. Nevertheless, this claim may apply for only a small part in the right tail of the ability distribution in a given society. Lectures in classrooms with samples that reflect the actual ability distribution of students may not run completely smoothly. To give an example, students who act up or disrupt the lecture may be more likely to be found in non-elite schools. The question that arises here is whether someone should attend class or stay and study at home given their ability ceteris paribus.

The literature regarding class absenteeism is divided into two main categories: one refers to the reasons for students being absent from class (Levine 1992, Chong et al. 2009) and the second one is concerned with the effect of students' absenteeism on their scholastic outcomes (Romer 1993, Caviglia Harris 2006, Chen and Lin 2008, Arulampalam et al. (2012), Latif and Miles (2013)). Most of these papers use college and field specific class attendance data. In particular, most of these papers use data regarding Economics, Accounting or Management students. The majority of these papers find a negative relationship between students' absenteeism and academic performance or a negligible one (Caviglia Harris 2006). Evidence from the existing literature suggests that class attendance improves educational outcomes. Lin and Chen (2006) using a sample of 129 college students in Taiwan find a 4% exam score improvement associated with higher class attendance. A subsequent study by the same authors Chen and Lin (2008) involved an experiment where different sections of the same college course were subject to random changes in the curriculum although everyone sat the same exam at the end of the semester. The authors found that having the instructor cover all of the material improved score by as high as 18%. Latif and Miles (2013) used panel data of exam scores of Canadian college students to measure the effect of class attendance on exam performance. They find that when controlling for student heterogeneity, exam performance is positively related to class attendance. Similar results have been obtained when college classes on science (Moore, 2006) or economics (Cohn and Johnson, 2006) are considered. Arulampalam et al. (2012) use panel data to identify the causal relationship between class attendance and students' University performance. Focusing on Economics students, they use quantile regression analysis and find that skipping classes leads to poorer performance. Interestingly, they highlight that the relationship between class attendance and students' performance may vary with student ability. Caviglia Harris 2006 examines the impact of mandatory attendance of microeconomic classes on students' college performance. After accounting for students' motivation, he finds that class attendance did not impact grades. This is the only paper that finds a negligible effect between class attendance and students' academic outcomes. Despite the rich literature that involves college data, there is little evidence that the same results hold in a less filtered context, like high schools.

Our paper is the first one -to our knowledge- that identifies the returns to absences using a quasi-experimental approach. By using data of students who attend public schools, which is the case for more than ninety percent of the universe of high school students, we avoid truncating the observed support of the ability distribution. The lack of selection issues allows us to identify returns to absences and deduce implications regarding peer effects for a much wider range of unobservables, which contributes to the external validity of our study.

In this paper, we investigate the causal relationship between class attendance and exam performance. Our approach exploits a natural experiment that increased the absence allowance of high school students by thirty hours only if their grade point average exceeded a threshold in the previous grade. In our context, senior year students are maximizing their end-of-year test scores by choosing how much time to spend in and outside classroom. The end-of-year exam performance is very crucial for students' post-secondary placement because it determines the University entrance score. The treatment offers exogenous variation by relaxing the budget constraint only for some students, whose marginal utility of time may be higher than the average. Using an Instrumental Variable method, we identify the causal effect of class attendance on exam performance. We control for individual-specific heterogeneity by using longitudinal data on exam performance of students in consecutive grades.

In the institutional setting examined here high school students in the senior year usually prepare for the university admission exams. Admission to tertiary education is based solely on test scores achieved at the end of the senior year. In order to apply for university admission, students take exams in a specific number of subjects once per year. In this context, students are to allocate studying time between subjects that matter for university admission and the remaining school subjects. We have collected transcript data of the three last grades of high school from 98 schools in Greece.

In addition, we are considering the peer effects induced on both eligible and non-eligible students by the increase of the absence allowance of the better-achieving students. The natural experiment examined here allowed high-achieving students to skip class more than before. Should the eligible students take advantage of the change in school attendance regulation, the students might be subject to an exogenous class composition effect. The increase in absences of high achieving students may affect negatively mean class performance and consequently individual exam performance.

The remaining of the paper is organised as follows: Section 2 describes a description of the institutional setting. Section 3 describes the data. Section 4 presents a regression discontinuity approach and section 5 proposes an identification using an absences law instrument. Lastly section 6 concludes.

2 Background

It is useful to provide some background on the design of the institutional setting in which our natural experiment takes place. Public high schools are the norm in Greece as only around 8 percent of students attend private high school[1]. Assignment to high school schools is based on geographical proximity, namely a school district system. Every high school offers the same curriculum and funding is a linear function of the number of students. Teachers' quality characterictics such as education and experience are not taken into account for allocation of teachers to schools. By law, assignment to classrooms is based on alphabetical order.

Up until the end of the school year 2005-2006, every student could have 50 hours of unexcused and 64 hours of excused absence from class within a given year. An hour of absence can be excused only by a doctor or someone with the child's custody -usually the parents. Only whole days of absence can be excused. For example, if a student goes to

[1] Descriptive statistics from a dataset that covers the universe of high school graduates between 2003 and 2011 show that 90% of students attend public schools, 2% attend public experimental (charter) schools and 8% attend private high schools. There are 1319 high schools in Greece, of which 112 are private and 23 are experimental.

school late in the morning or if they decide to skip school midday, their absences cannot be excused. The penalty for exceeding the number of allowed absences is to repeat the grade.

Near the end of the school year 2005-2006, a new bill was passed that among others regulated the number of allowed hours (periods) of absence from school. The new bill provided eligible students with 50 additional hours of excused absence. Eligibility was determined on past Grade Point Average. In particular, every student who had received a Grade Point Average higher than 15/20 the year before was eligible to take up more absences this year. In our analysis, we use the graduating class of 2006 as a control group and the graduating class of 2007 as the treated group.

It is worth mentioning that by design periods of the same subject are usually spread out within the weekly schedule of classes. This is important because one may worry that eligible students might skip classes of a particular subject. This strategic selection of classes is not entirely possible because only whole days of absence can be excused . Around sixty percent of school subjects are mandatory and the remaining consist of electives and specialization courses. Unlike other educational systems, in Greece students remain in their assigned classroom for the majority of school periods instead of moving to different rooms depending on the subject being taught. This setting guarantees that a student's peer group remains the same for a series of courses, including greek language and mathematics, considered in our analysis.

At the end of senior high school students take national, standardised exams that matter for both high school graduation and university admission. The format of the national exams is the same as the one of the within school exams in the previous grades and they are externally marked and proctored.

3 Data

We have collected primary data from a large randomized sample of high schools in Greece. For this study we focus on public schools (Sample: 98 schools, 11,239 students). This novel dataset includes every student that graduated from one of the sampled schools between 2006 and 2007 and contains panel information from the following sources:

1. Administrative data from the High Schools containing course taking information and exam grades in each of the last three years of secondary education, class identifier,

class size [2], gender, year of birth and graduation year. For each student we also know how many hours were they absent from their class in the eleventh and the twelfth grade. We know how many absence hours did the parents excused and how many hours of students' absences remained unexcused.

2. School specific information such as name of school, type of school (private, public[3], experimental[4]), geographical location.

3. The Ministry of Finance provided us with average net income information at the postcode of the school in 2009 Euro.

4. The Ministry of Internal Affairs provided us with urban density information. Urban areas are those with more than 20,000 inhabitants.

4 The effect around the cutoff

4.1 Strategy

We start our analysis by looking at students who are around the eleventh grade gpa cutoff (or the eligibility cutoff). By using a Regression Discontinuity design we can identify the effect of the additional absences on students' academic performance in the treated year. So, we will compare students who are just to the left with students who are just to right of the cutoff value in the treated year (2007). Students with eleventh grade gpa below 15 cannot exploit the additional hours of absences that students with gpa above 15 are offered. Within each school, we rank students according to their eleventh grade gpa and identify those who are above and below the threshold of gpa=15. Let t_0 take the value of 15 and t_i be student's gpa in the eleventh grade.

The first stage regression can be specified as:

$$TA_i = \alpha f_1(t_i) + \psi \mathbb{1}[t_i > t_0] + \omega (1)$$

[2]corr (class size, income)=0.149,corr (class size, experimental)=0.249, corr (class size, urban)=0.179

[3]Students are assigned to public schools according to a school district system

[4]Admission to experimental schools is based on a lottery

where $\mathbb{1}[t_i > t_0]$ is an indicator for whether a student is eligible to be more absent i.e. if his eleventh grade gpa is greater than or equal to the threshold value of 15/20, t_i = the eleventh grade gpa of the student and $f_1(t_i)$ is a control function for the gpa of student i. We also use specification (1) to apply a first differences approach. We do that because there might be individual specific unobserved characteristics that are omitted and might affect our variables of interest. By taking first differences of outcomes and covariates between twelfth and eleventh grade, we get rid of potential time invariant omitted variables. Specification (1) will tell us if students just to the right of the cutoff use the additional hours of absence, when they are allowed to do so, compared to students who are just to the left of the cutoff and they are not allowed. By using the first difference version of specification (1), we will find how many more hours absences do students to the right of the cutoff use compared to their eleventh grade hours of absences with regards to the counterfactual group of students.

The idea behind the regression discontinuity design which was initially proposed by Thistlethwaite and Campbell (1960) is that discontinuities like the above can be used to identify the causal effect of scoring in the eleventh grade above 15/20. Intuitively, assume that the gpa is smoothly related to characteristics that affect academic performance. Having assumed that, pupils with scores just above the threshold value will provide a proper control group for pupils with scores just below the threshold value. This is visualised in Figure 1. Then any differences in the outcomes of those students can be attributed to the fact that some students are eligible to be more absent from school due to the reform.

The reduced form equation that will estimate the effect of being eligible to be more absent from school on academic outcomes, can be described as:

$$Y_i = \delta(t_i) + \gamma \mathbb{1}[t_i > t_0] + e_i (2)$$

where: Y_i is the standardised twelfth grade score in Modern Greek, Mathematics and the twelfth grade gpa for student i ,
Results will be presented for small enough neighborhood areas of different sizes around the cutoff. When we do that, $\delta(t_i)$ will be constant and γ will identify the causal effect of being allowed to be more absent from school on test scores, non-parametrically (Hahn et al. (2001)).

4.2 Results

Our results are estimated using the non-parametric approach discussed above, implementing a local linear regression constructed with a triangular kernel. The first stage is not very strong. In Table 4, we present the level and first difference estimates for the whole sample and for classes with class size greater than 19 students separately where the disruption may be greater [5].

We present estimates using six different bandwidths. In columns 1,2,3 we restrict the sample to those students who are 0.5/20 [6], 1/20, 1.5/20 to the left and the right of the cutoff respectively. In columns 4,5,6 we increase the bandwidth further using the bandwidths suggested by Calonico et al. (2014), Imbens and Kalyanaraman (2012) and Ludwig and Miller (2007) respectively.

The only first stage estimate that gives statistically significant estimates across some of the specifications is the first difference one for class sizes greater than 19 students. Students who have an eleventh grade gpa greater than 15 are more absent from school by 6-9 hours on average in the twelfth grade compared to the eleventh with regards to students who are just below the threshold value. We can visualize that the first stage in Figure 1.

Then we present reduced form results for the whole sample (Table 5) and the restricted sample where the class size is greater than 19 students (Table 6). In each Table, we present results for each subject separately (Modern Greek, Mathematics and GPA in twelfth grade). We do not find any consistent pattern across columns. Only the first difference estimates in Mathematics are statistically significant in some specifications. Students who are eligible to be more absent from class, experience a decrease in their standardised score in Mathematics by 0.15-0.30 standard deviations. Same pattern applies to the next Table where we have only classes with many students.

These results make us think that there is no effect around the threshold but the reform might affect students who are farther away from the cutoff. The impact of class attendance on students' performance may vary with student ability (Arulampalam et al. 2012). The usage of the reform might also differ by students' ability. Intuitively, students who are at the top percentiles of the ability distribution might decide to spend more hours outside the classroom. The education literature suggests that there is the so called self regulated learning that is more pronounced for the high achieving students. (Barry J. and Manuel

[5] we exclude those classes that belong to the lowest quantile of the class size in our sample and the disruption might not be huge.

[6] The maximum score a student can get is 20. 0.5/20 corresponds to 2.5 out of 100

1990,Nicola and Debra 2006).

The intuition is that high achieving students might be more constructive when studying at home rather than staying in the classroom, especially if it is noisy. The research on self regulated learning suggests that these students might set goals for their learning and monitor, regulate, and control their cognition, motivation, and behaviour better than students of lower academic ability. So the marginal utility of spending an additional hour in the class might be different for a student who had an eleventh grade gpa equal to 16 and another student who had a gpa equal to 19 although there are both eligible to use the reform.

As shown in Figure 1, some covariates exhibit a jump around the threshold that violate the assumptions of identification of the treatment effects using an regression discontinuity approach. The RD approach may be inappropriate for identification if individuals to the left of the cutoff differ in more than one ways from individuals to the right of the cutoff. To control for individual specific drivers of the observed behaviour we take first differences of observed variables between twelfth and eleventh grade. The change in these differences around the cutoff is shown in Figure 2.

The regression discontinuity estimates of the effect of the reform on school performance seem somewhat weak. We suspect that this is due to the fact that it may not be those just above the threshold of eligibility who exploit the new policy and take up more hours of absence but rather those we are in the right tail of the distribution due to self-regulated learning.

5 Identification using absences law instruments

5.1 Empirical Strategy

We postulate a model where individuals' school performance is a function of own hours of absences and average performance of the peer group. The peer group is defined as every other student in the class, in a school, in a given year.

$$Score_{icsgt} = \alpha_o + \alpha_1 TotalAbsences_{icstg} + \alpha_2 MeanScore_{cstg} + \alpha_3 Eligibility_{icst} + \alpha_4 Reform_t + \alpha_5 Controls + \epsilon_{icst} (3)$$

where the controls include the mean score in the peer group, the mean Score of eligible classmates in the previous year, a dummy for being in the twelfth grade, the mean absences of eligible classmates in the same grade and the percentage of eligible classmates in the same grade.

The Eligibility variable becomes 1 if the GPA in the eleventh grade is above 75% and the Reform variable becomes 1 if the graduation year is equal to 2007. The dependent variable $Score_{icsgt}$ is the twelfth grade performance of student i in class c in school s in grade g and in year t.

We also include a series of covariates: a year dummy that takes the value 1 if the new absences law is in place, a dummy that takes the value 1 if a student had a gpa above 15/20 in the previous grade, the mean performance of eligible classmates in the previous grade,the mean absences of eligible classmates and the percentage of eligible classmates.

We run this specification separately for the end of the year standardised performance in Greek Language and Mathematics (columns 1 and 2, Table 9) and the standardised twelfth grade gpa (column 3, Table 9). We estimate the above econometric model using first differences between the twelfth and the eleventh grade. We include a dummy that takes the value 1 if the student is in the twelfth grade to pick up mean changes in effort due to the high stake exams in the twelfth grade. The peer group measures are the average performance of classmates, the average absences and average prior performance of eligible classmates. Average peer performance is measured by the average score of a student's peers [7]

Estimating equation 3 using OLS may lead to a number of problems. Firstly, every student's performance is affected by the performance of every one else's performance. The simultaneity of the causal effects prevents us from identifying the peer effects. Manski (1993) refers to this issue as the reflection problem. Thus it is important to note that OLS estimates total effects after all performance adjustment have taken place. Secondly, selection into school and/or class could be a potential threat to identification. In measuring student's peer effects, one should keep in mind that students may self select into schools of similar quality. The inclusion of student fixed effects would in principle address this worry as long as we don't suspect differential time trends of different schools. Also, school administration may allocate similar students into classes. These selection issues create a correlation of the peer group measures with the error term, introducing an estimation bias of the parameters of interest. Luckily, in the educational system at hand students

[7] Suppose a classroom has 3 students. One scored a GPA of 15/20. The other two got a GPA of 17/20 and 18/20 respectively. Then, the average peer quality variable for student 1 is (17+18)/2=17.5. The average peer quality for student 2 is (15+18)/2=16.5 and so on.

are assigned to schools based on geographical criteria and allocated into classes based on alphabetical order.

Another problem may be created by omitted variables that may affect the performance of students and their decision to stay at home, such as the existence of modern facilities like interactive boards in some schools. Omitted factors may not only affect students' performance but also average class attendance or performance at the same time. Moreover, the total absences of the student may be correlated with the error term and would invalidate the OLS estimates. For example, the degree of parental monitoring or other individual characteristics such as self-discipline or the motivation affect both the hours that students decide to stay at home and student' s productivity. We exclude from our analysis students who enrol into private schools in order to avoid selection issues. Not controlling for unobserved characteristics, would add another estimation bias.

Furthermore, measurement error would bias the estimation of the parameters of interest. The bias from measurement error may be less of a threat when this error is time invariant but even measures of performance and attendance are less than perfect. An instrumental variables approach can address biases due to selection, omitted variables and measurement error. Therefore, we exploit the reform in the absences allowance law to construct instruments for class attendance and peer group quality.

We mitigate the endogeneity issues by using an instrumental variables approach in order to obtain unbiased estimates of the causal effects of interest. We employ a Difference in Difference approach in order to measure the effect of the reform on total absences. In particular, we interact the eligibility status dummy with the year dummy that takes the value 1 if the new absences law is in place. This interaction term measures the treatment effect of the reform on total absences of treated individuals. Next, we propose the reform induced -ability weighted- $\uparrow$ in absences of eligible students as an instrument for the average performance of the peer group as explained below.

The reform induced an increase in the absences of eligible students only. Therefore we can identify the effect of absences only of eligible students on the average outcome in the peer group. To do this, we need to compare the effect of having some percentage of treated students in the class to the effect of having no treated students in the class, the latter being cases with eligible students but not in the reform year and cases with no eligible students. The reform didn't change the composition of classes, merely the class attendance of eligible students.

Therefore, we need to compare the effect of having eligible students in the class that take up more absences, conditional on the percentage of treated students in the class. It's important to note though that mean class performance may not depend merely on the mean hours of absences of treated students but rather on a measure of class attendance of treated students that takes into account the quality of the treated students. This is valid as long as we believe that the effect of an hour of absence of an eligible student who is at the top of their class is significantly different from the effect of an hour of absence of an eligible student who is at the top -let's say- 70% of their class. The proposed instrument is an interaction of the mean hours of absence of treated students times their school performance the year before. Therefore, we define the reform induced, ability weighted, increase in absences as:

Reform induced ↑ in absences=Reform year * (Number of Eligible students in class) * (Mean Score of Eligible students in grade g-1) * (Mean Total Absences of Eligible students)

As mentioned earlier, there are two endogenous variables: total absences and the average performance of the peers. This gives rise to two first stage regressions.

First stage Regression 1:

$$TotalAbsences_{icstg} = \beta_1 + \beta_2 Eligibility_{icst} + \beta_3 Reform_t + \beta 4 Eligibilityicst * Reform_t$$
$$+\beta 5(Reforminducedincreaseinabsencesofeligiblestudents) + \beta_6 Controls + \epsilon_{icstg} (5)$$

First stage Regression 2:

$$MeanScore_{icstg} = \beta_1 + \beta_2 Eligibility_{icst} + \beta_3 Reform_t + \beta 4 Eligibilityicst * Reform_t$$
$$+\beta 5(Reforminducedincreaseinabsencesofeligiblestudents) + \beta_6 Controls + \epsilon_{icstg} (6)$$

where the controls include the percentage of eligible students in class, the mean absences of eligible students in class and a dummy for being in the twelfth grade.

It is important to note that all regressions are estimated for all students, both eligible and non-eligible, before or after the reform. The reform is then used as a source of exogenous variation for total absences and peer group quality. Equation (5) is the first stage regression for total absences. The main instrument for total absences is the interaction between the eligibility status and the reform year dummies. We also include an instrument that captures the reform induced ↑ in mean absences of eligible students. This will be more important for Equation (6), the first stage regression for the average peer quality.

The outcome variables and the effects of the reform are likely to be correlated for all students in a given class. Thus, we control for any dependence between observations within a class by clustering all results at the class level.

Using instrumental variables that stem from the reform relies on the assumption that the reform had no other effect on a student's performance than through its effect on the students absences and peer group quality. It is important to note than any factor coinciding with the reform, affecting all students in Greece in a similar way, such as a possible change in exam difficulty, will be captured by the reform year dummy that takes the value the value 1 for the year 2007 and 0 before. As the unaffected individuals act as a control group, only factors changing at the same time as the reform may be potential threat to our identification strategy. To our knowledge there were no other relevant changes in the institutional setting at the time the reform of interest was implemented. A similar strategy for identification of peer effects in a different context was employed by Waldinger (2010)

Lastly, any difference in difference type strategy relies on the assumption that treatment and control groups did not follow differential trends. Our dataset includes only one control cohort (2006) and therefore it's impossible to examine the existence of linear or non linear time trends. Nevertheless, as long as individual specific characteristics are time invariant, controlling for past performance would net out any factors that may be correlated with assignment in the treatment or the control group. Overall, we are of the view that the reform provides a valid instrument to identify returns to absences and peer effects.

5.2 Results

The reform examined in this paper relaxed the attendance requirements of higher performing students and allowed them to skip more hours of class. This context offers itself to identification of both direct and cross student effects of class attendance on exam performance. The reform provides two exogenous sources of variation. The first is the eligibility status. The students considered in our study had no anticipation of the new absences law. Although the rationale behind the new law was rather to provide non pecuniary incentives to exert higher effort, in the short run it permits us to identify returns to absences and potentially peer effects. The second source of variation comes from class composition.

Without having to make any assumptions regarding the exogeneity of class composition, the reform induced an increase in the mean absences of high performing classmates. The variation in the mean absences of treated classmates allows for the identification of mean peer quality on a students' exam performance. The proposed instrument is valid if and only if it affect a student's performance only through mean performance in the peer group. To see the effect of the excluded covariates on the outcomes of interest, we estimate the following reduced form equation:

$$Scores_{icstg} = \beta_1 + \beta_2 Eligibility_{icst} + \beta_3 Reform_t + \beta 4 Eligibility_{icst} * Reform_t$$

$$+\beta 5(Reforminducedincreaseinabsencesofeligiblestudents) + \beta 6 Controls + \epsilon_{icstg} (7)$$

Using both eligible and non-eligible students, we regress the student's standardised score in Greek Language, Mathematics and the gpa on the instruments proposed above. For students that are either non-eligible or in a year where the new law is not in place, the interaction term $Reform * Eligibility$ will take the value 0. For students who are not in a year where the new law is in place or have no eligible classmates or have eligible classmates with zero absences, the reform induced, ability weighted, $\uparrow$ increase in absences of eligible students will take the value 0. Table 11 reports the reduced form results, using a student's class peers as the relevant peer group. We find strong effects of both instruments on the Greek Language, Mathematics score and the twelfth grade gpa.

The first stage results are reported in Table 10. The first stage implies that the reform increased total absences of treated students by around 26 hours. The effect is statistically significant across columns. The reform induced $\uparrow$ in absences seems to have a negative effect on mean performance. Given the percentage of eligible classmates, an one hour reform induced increase in mean absences of eligible classmates whose prior performance is one standard deviation above the average, decreases performance by 0.27, 0.08 and 0.04 standard deviations in Greek Language, Mathematics and gpa respectively. Our high F statistics keep fears of weak instruments at bay.

The second stage estimates indicate that treated students do worse by 0.01, 0.02 and 0.03 standard deviations in Greek Language, Mathematics and gpa respectively for every additional hour of absence. Peer effects seem to be statistically significant for both Greek

Language and Mathematics. Having peers of an one standard deviation above the average increases a student's performance by 0.04 standard deviations in Greek and decrease a student's performance in Mathematics by 0.27 standard deviations.

6 Conclusion

In this paper, we have investigated (1) returns to absences and (2) peer effects. We exploit a natural experiment that took place in Greece in 2007, that provided higher performing students with 50 more hours of excused absences from school. The eligibility status was determined based on a cutoff rule. We start off by using a Regression Discontinuity approach in order to measure the change in total absences and exam score due to the reform. Although, no strong effects were observed around the cutoff, important controls like class size and postcode income do not remain unchanged around the cutoff. This violates necessary assumption for identification in the regression discontinuity framework.

Next, we employ a combination of differences-in-differences and instrumental variables techniques in order to identify returns to absences and peer effects. An interaction between eligibility status and year dummy is proposed as an instrument for the endogenous variable of total absences, to mitigate identification threats like unobserved heterogeneity. The reform induced, ability weighted, increase in absences of eligible students in the classroom is proposed as an excluded regressor for mean peer performance.

Our study is the first one to identify returns to absences and peer effects using a quasi-experimental approach. Our estimates show significant positive peer effects in Greek Language abut negative peer effects in Mathematics. Furthermore, our estimates yield significant negative returns to absences. Our result suggests that attendance is an important driver of school performance. The size of the loss in terms of exam performance due to smaller class attendance may inform policies related to attendance and distance learning.

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Figure 1: Regression Discontinuity Figures for Controls

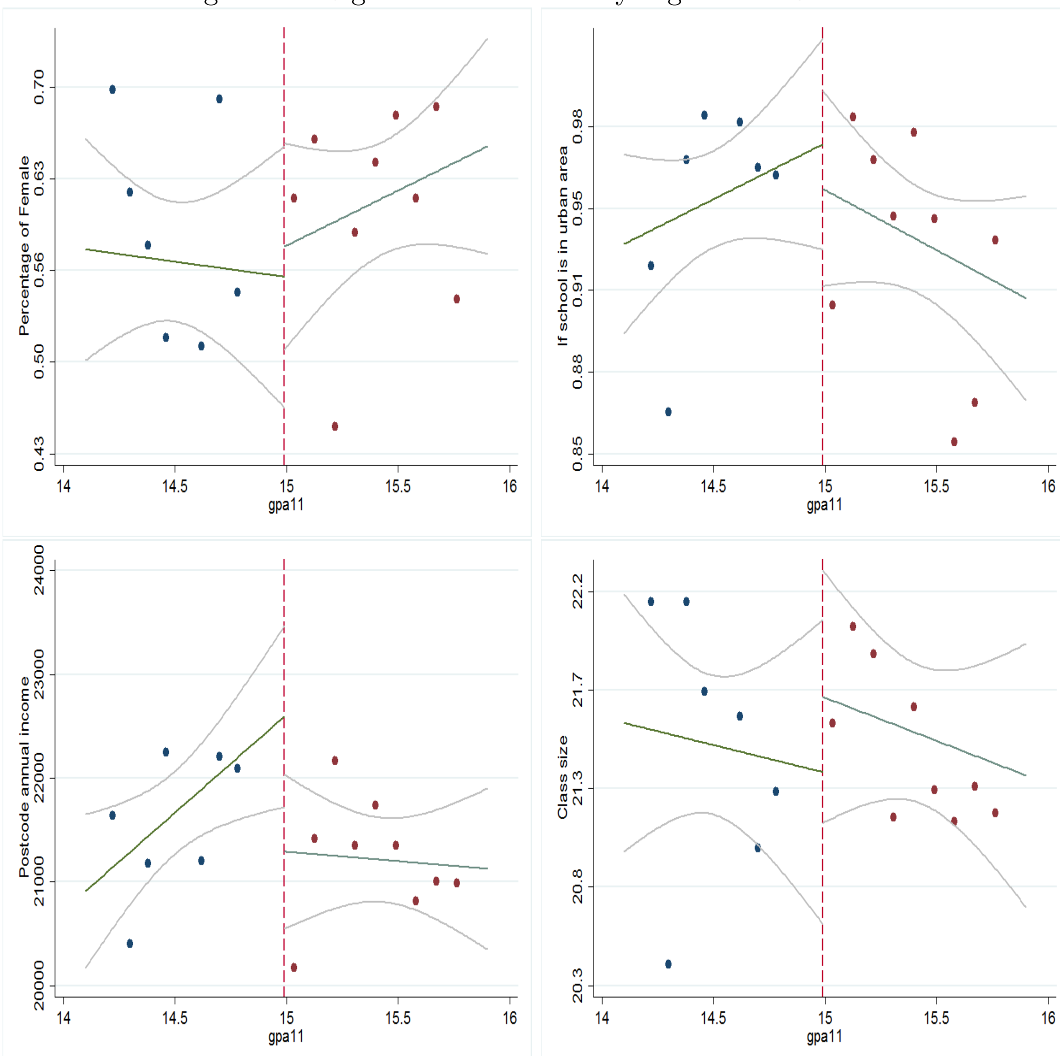

Figure 2: Regression Discontinuity Figures for First Stages with Different Bandwidths

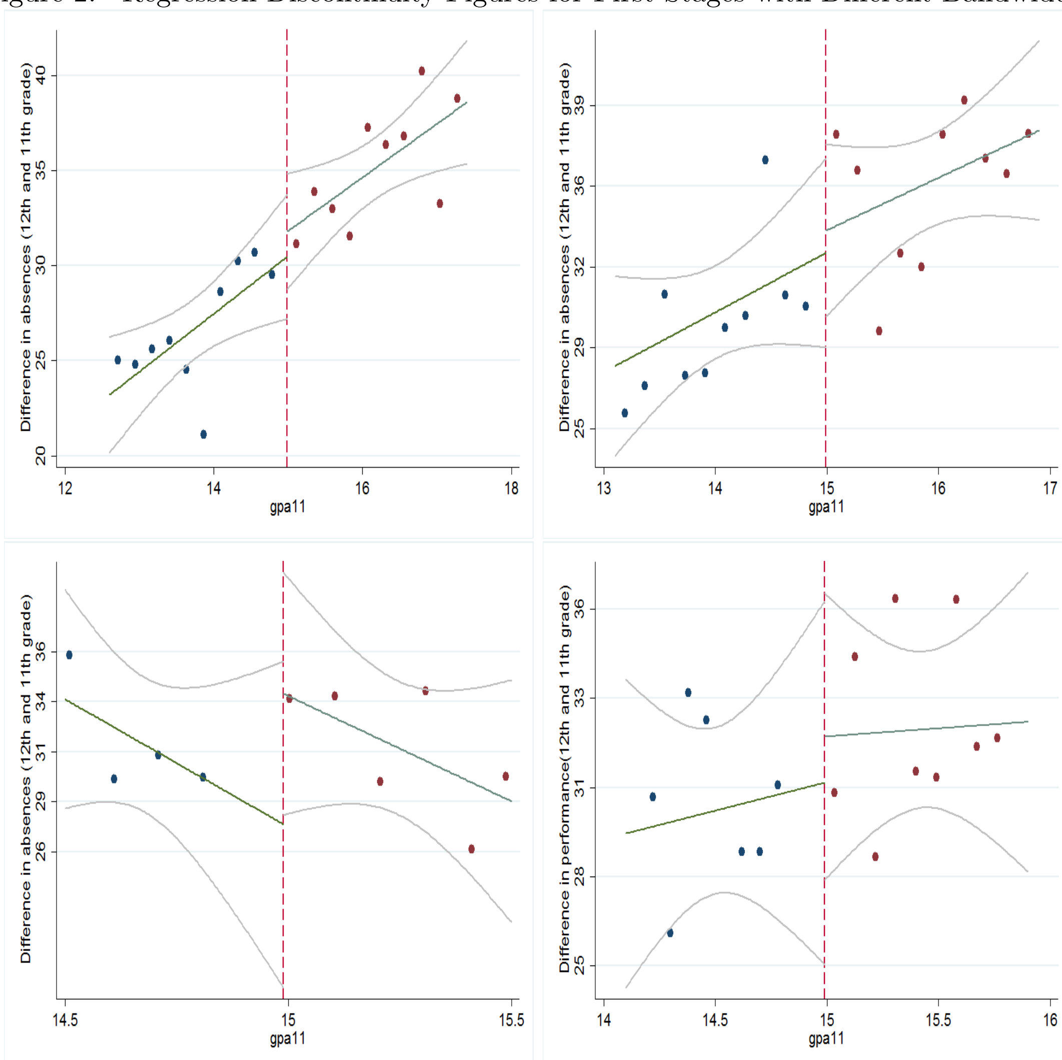

Table 1: Summary Statistics for full sample

Full Sample				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Born in 1st quarter	0.186	0.33	0	1
12th Grade Greek Language Score	12.50	3.06	0	20
11th Grade Greek Language Score	13.89	3.20	0	20
12th Grade Mathematics Score	10.85	6.39	0	20
11th Grade Mathematics Score	9.90	6.09	0	20
Female	0.57	0.50	0	1
Income (2009 Euro)	22,244	6,322	11,785	48,427
Experimental School	0.05	0.21	0	1
Public School	0.95	0.21	0	1
Urban	0.95	0.21	0	1
11th Grade GPA	14.21	2.85	8.8	20
12th Grade GPA	14.89	2.64	4.9	20
11th Grade Excused Absences 19.54	19.38	0	137	
11th Grade Total Absences	49.53	27.38	0	164
12th Grade Excused Absences	42.01	23.91	0	160
12th Grade Total Absences	76.31	28.68	0	371

Note: sample: 11,238 obs.

Table 2: Summary Statistics

Variable	**Treated**	**Control**	**Diff**	**Std. Dev.**
Born in 1st quarter	0.10	0.20	0.11***	0.00
12th Grade Greek Language Score	12.48	12.58	0.10*	0.05
11th Grade Greek Language Score	13.95	13.72	-0.23***	0.05
12th Grade Mathematics Score	10.94	10.60	-0.34***	0.10
11th Grade Mathematics Score	9.76	10.33	0.58***	0.09
Female	0.56	0.57	0.01	0.01
Income (2009 Euro)	22,284	22,255	29.12	96.82
Experimental School	0.04	0.05	0.01**	0.00
Public School	0.96	0.95	-0.01**	0.00
Urban	0.95	0.95	0.00	0.00
11th Grade GPA	14.18	14.16	-0.07	0.04
12th Grade GPA	15.01	14.55	-0.46***	0.04
11th Grade Excused Absences	20.08	17.95	-2.12***	0.30
11th Grade Total Absences	50.35	47.10	-3.25***	0.42
12th Grade Excused Absences	43.88	36.50	-7.38***	0.36
12th Grade Total Absences	78.22	70.68	-7.55***	0.44

Note: sample: 11,238 obs.

Table 3: Descriptive statistics for each type of absences

Full Sample			
Variable	**Total**	**Excused**	**Unexcused**
Number of absences in 11th grade	75.01	41.19	33.82
Number of absences in 12th grade	49.01	19.32	29.69
Number of absences for Females in 12th grade	76.28	43.24	33.04
Number of absences for Males in 12th grade	73.35	38.52	34.83
Number of absences for Females in 11th grade	49.01	20.21	28.80
Number of absences for Males in 11th grade	49.01	18.16	30.84
Number of absences in 12th grade for students in high income neighborhoods	75.64	42.06	33.58
Number of absences in 12th grade for students in low income neighborhoods	74.58	40.61	33.98
Number of absences in 11th grade for students in neighborhoods above the median income	51.07	20.40	30.67
Number of absences in 11th grade for students in neighborhoods below the median income	47.63	18.60	29.03
Number of absences in 12th grade in Urban areas	74.78	40.95	33.83
Number of absences in 12th grade in Rural areas	79.10	45.47	33.63
Number of absences in 11th grade in Urban areas	47.41	19.33	28.33
Number of absences in 11th grade in Rural areas	49.10	19.34	29.76
Number of absences in 12th grade for classes with class size above median	76.27	42.01	34.26
Number of absences in 12th grade for classes with class size below median	73.28	40.07	33.21
Number of absences in 11th grade for classes with class size above median	49.36	19.33	30.03
Number of absences in 11th grade for classes with class size below median	48.54	19.32	29.21

Note: sample: 11,238 obs.

Table 4: Correlations of absences with other variables

	Correlations
corr(Total absences, postcode income)	0.072
corr(Total absences, urban)	0.008
corr(Total absences, class size)	0.056
corr(Total absences, experimental)	0.041
corr(Excused absences, postcode income)	0.055
corr(Excused absences, urban)	-0.003
corr(Excused absences, class size)	0.034
corr(Excused absences, experimental)	0.028
corr(Unexcused absences, postcode income)	0.067
corr(Unexcused absences, urban)	0.024
corr(Unexcused absences, class size)	0.067
corr(Unexcused absences, experimental)	0.044

Note: Data pooled for the two grades: eleventh and twelfth.

Table 5: Is the sample representative?

	Sample	**Population**	**Difference**	**Std. Dev.**
Born in 1st quarter	0.120	0.167	-0.047***	(0.002)
Female	0.567	0.565	0.002	(0.473)
logIncome(in 2009Euro annual)	9.999	9.968	0.022	(0.014)
Private school	0.034	0.080	-0.046	(0.001)
Public schools	0.950	0.899	0.051***	(0.001)
Experimental school	0.05	0.020	0.015	(0.000)
Urban	0.951	0.892	0.059***	(0.001)

Note: 11,238 obs. in sample and 420,231 obs. in population in all years. 98 schools in sample, 1323 schools in population. Evening schools are excluded from the sample and the population

Table 6: Externalities in the classroom: Regression Discontinuity Estimates

Independent variable: GPA in 11th Grade	Non-Parametric approach					
	0.5/20	1/20	1.5/20	CCT(2014a)	IK (2012)	LM (2007)
	Panel A: Full Sample					
Total Absences	6.648	2.236	2.226	1.503	1.360	1.740
	(6.254)	(4.064)	(3.214)	(3.065)	(2.031)	(1.773)
Mean in Control Group	69.026					
Observations	620	1,189	1,758	1,923	4,239	5,451
Δ(Total Absences)	0.051	1.714	2.335	-1.962	-1.879	-0.974
	(5.855)	(3.828)	(3.015)	(2.540)	(2.102)	(1.664)
Mean in Control Group	24.131					
Observations	593	1,111	1,689	2,288	3,281	5,527
	Panel B: Sample with class size >19					
Total Absences	4.931	1.264	1.785	0.271	2.696*	0.016
	(6.823)	(4.443)	(3.498)	(3.086)	(1.221)	(2.103)
Mean in Control Group	69.021					
Observations	465	874	1,286	1,581	3,182	3,537
Δ(Total Absences)	4.981	9.243**	8.510***	6.130*	8.670***	-0.715
	(3.001)	(4.111)	(3.255)	(3.186)	(2.073)	(1.849)
Mean in Control Group	23.355					
Observations	445	836	1,230	920	3,062	3,819

Note: Δ(Total Absences) is the difference in total absences of a student between 11th and 12th grade. The estimation is conducted using a local linear regression constructed with a triangular kernel regression. Each column corresponds to a different bandwidth selection. Bias-corrected standard errors in parentheses. Column 1: 0.5 out of 20, Column 2: 1 out of 20, Column 3: 1.5 out of 20, Column 4: Calonico, Cattaneo and Titiunik (2014a), Column 5: Imbens and Kalyanaraman (2012), Column 6: Ludwig and Miller (2007). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Externalities in the classroom: Regression Discontinuity Estimates

Independent variable: GPA in 11th Grade	Non-Parametric approach					
	0.5/20	1/20	1.5/20	CCT (2014a)	IK (2012)	LM (2007)
			Full Sample			
Panel A						
Greek Language	0.089	0.145*	0.139*	0.066	0.082*	0.079
	(0.135)	(0.075)	(0.071)	(0.075)	(0.042)	(0.050)
Observations	593	1,141	1,689	1,572	2,559	3,070
Δ(Greek Language)	0.193	0.197*	0.160*	0.077	0.071	0.084*
	(0.165)	(0.111)	(0.090)	(0.077)	(0.060)	(0.048)
Observations	593	1,141	1,689	2,175	3,702	5,270
Panel B						
Mathematics	-0.307*	-0.188*	-0.167*	-0.078	-0.070	-0.087*
	(0.169)	(0.103)	(0.092)	(0.074)	(0.067)	(0.050)
Observations	593	1,141	1,689	2,499	3,070	5,270
Δ(Mathematics)	-0.215	-0.343***	-0.286***	-0.175**	-0.136**	-0.066
	(0.161)	(0.102)	(0.082)	(0.089)	(0.063)	(0.049)
Observations	593	1,137	1,689	1,413	2,715	4,467
Panel C						
Grade Point Average	0.067	0.058	0.025	0.034	0.024	0.042
	(0.076)	(0.046)	(0.040)	(0.034)	(0.032)	(0.025)
Observations	620	1,189	1,758	2,436	2,542	4,075
Δ(Grade Point Average)	0.067	0.060	0.031	0.039	0.027	0.044*
	(0.075)	(0.049)	(0.041)	(0.034)	(0.033)	(0.024)
Observations	620	1,189	1,689	2,388	2,499	3,938

Note: Δ(Mathematics) is the difference in standardized score in Mathematics of a student between 11th and 12th grade. The estimation is conducted using a local linear regression constructed with a triangular kernel regression. Each column corresponds to a different bandwidth selection. Bias-corrected standard errors in parentheses. Column 1: 0.5 out of 20, Column 2: 1 out of 20, Column 3: 1.5 out of 20, Column 4: Calonico, Cattaneo and Titiunik (2014a), Column 5: Imbens and Kalyanaraman (2012), Column 6: Ludwig and Miller (2007). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Externalities in the classroom: Regression Discontinuity Estimates

Independent variable: GPA in 11th Grade	Non-Parametric approach					
	0.5/20	1/20	1.5/20	CCT (2014a)	IK (2012)	LM (2007)
	Sample with class size >19					
Panel A						
Greek Language	0.001	0.058	0.038	0.002	-0.006	0.056
	(0.148)	(0.099)	(0.080)	(0.075)	(0.070)	(0.053)
Observations	445	836	1,230	1,352	1,593	2,862
Δ(Greek Language)	0.064	0.133	0.087	-0.003	0.065	0.088*
	(0.187)	(0.123)	(0.097)	(0.101)	(0.067)	(0.049)
Observations	445	836	1,230	1,149	2,516	3,819
Panel B						
Mathematics	-0.364*	-0.132*	-0.115	-0.118	-0.100	0.119**
	(0.202)	(0.079)	(0.108)	(0.086)	(0.074)	(0.057)
Observations	445	836	1,230	1,871	2,563	3,819
Δ(Mathematics)	-0.301*	-0.245**	-0.190**	-0.110	-0.095	0.075
	(0.179)	(0.117)	(0.093)	(0.087)	(0.062)	(0.055)
Observations	445	836	1,230	1,398	2,645	3,406
Panel C						
Grade Point Average	0.143*	0.106*	0.084*	0.033	0.048	0.046
	(0.087)	(0.058)	(0.046)	(0.039)	(0.040)	(0.030)
Observations	445	836	1,240	1,670	1,744	2,862
Δ(Grade Point Average)	0.145*	0.106*	0.079*	0.033	0.048	0.046
	(0.082)	(0.059)	(0.041)	(0.040)	(0.040)	(0.031)
Observations	445	836	1,230	1,670	1,711	2,862

Note: Δ(Mathematics) is the difference in standardized Mathematics score of a student between 11th and 12th grade. The estimation is conducted using a local linear regression constructed with a triangular kernel regression. Each column corresponds to a different bandwidth selection. Bias-corrected standard errors in parentheses. Column 1: 0.5 out of 20, Column 2: 1 out of 20, Column 3: 1.5 out of 20, Column 4: Calonico, Cattaneo and Titiunik (2014a), Column 5: Imbens and Kalyanaraman (2012), Column 6: Ludwig and Miller (2007). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9: Naive Regression

Dependent variable: Mean standardised performance in subjects			
	(1)	(2)	(3)
	Greek Language	**Mathematics**	**Grade Point Average**
Reform	0.044	0.073	0.175
	(0.015)***	(0.016)***	(0.011)***
Eligibility	-0.030	-0.149	-0.087
	(0.023)	(0.022)***	(0.012)***
If in twelfth grade	-0.014	-0.009	0.065
	(0.012)	(0.009)	(0.008)***
Percentage of eligible students	-0.358	-0.444	-0.494
in the classroom	(0.058)***	(0.055)***	(0.044)***
Mean absences of eligible	-0.000	-0.000	-0.000
	(0.000)***	(0.000)***	(0.000)***
Total absences	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***
Mean score of eligible	0.002	-0.030	-0.167
	(0.003)	(0.012)**	(0.009)***
Mean score	0.047	0.039	0.034
	(0.001)***	(0.001)***	(0.001)***
First differences	✓	✓	✓
R^2	0.30	0.13	0.25
N	11,238	11,238	11,238

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Clusters at the class level (377 clusters).

Table 10: First stage

First stage estimates. Dependent variables: Total Absences and Mean Score in each Subject						
	(1)	(2)	(3)	(4)	(5)	(6)
	Modern Greek		Mathematics		GPA	
	Total Absences	Score	Total Absences	Score	Total Absences	Score
Reform*Eligibility	27.495	-4.323	26.473	-1.583	28.403	-1.499
	(0.662)***	(1.883)***	(1.852)***	(0.377)***	(0.386)***	(1.719)***
Reform	4.308	-4.909	-5.984	2.045	-17.366	0.811
	(0.999)***	(2.355)**	(2.366)**	(0.733)***	(2.827)***	(0.601)
Eligibility	3.813	-13.466	-14.344	1.043	-15.699	0.780
	(0.647)***	(1.825)***	(1.722)***	(0.390)***	(1.723)***	(0.383)**
If in twelfth grade	1.799	20.697	20.388	1.054	18.200	1.947
	(0.675)***	(0.987)***	(0.981)***	(0.374)***	(1.011)***	(0.323)***
Percentage of eligible	-10.938	8.070	-15.385	10.132	-18.719	9.974
	(5.461)**	(3.017)***	(5.236)***	(2.066)***	(5.375)***	(1.949)***
Mean absences of eligible	-0.035	0.008	-0.036	0.002	-0.035	0.003
	(0.004)***	(0.002)***	(0.003)***	(0.001)**	(0.004)***	(0.001)***
Reform induced ↑ in absences	0.369	-0.265	0.499	-0.075	0.590	-0.044
	(0.063)***	(0.026)***	(0.057)***	(0.020)***	(0.069)***	(0.015)***
Mean score of eligible	0.271	0.200	-3.414	-0.977	4.284	0.190
	(0.196)	(0.092)**	(0.831)***	(0.193)***	(0.935)***	(0.196)
First Difference	✓	✓	✓	✓	✓	✓
F-statistics	133.88	47.68	175.51	14.36	156.05	7.58
R^2	0.51	0.10	0.50	0.07	0.49	0.10
N	11,238	11,238	11,238	11,238	11,238	11,238

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Clusters at the class level (377 clusters).

Table 11: Reduced Form estimates

Dependent variable: Mean standardised performance in subjects:			
	(1)	(2)	(3)
	Greek Language	**Mathematics**	**Grade Point Average**
Reform*Eligibility	-0.435	-0.337	-0.232
	(0.040)***	(0.030)***	(0.018)***
Reform induced ↑ in absences	-0.014	-0.002	0.000
	(0.001)***	(0.001)**	(0.001)
Reform	0.285	0.168	0.165
	(0.052)***	(0.034)***	(0.027)***
Eligibility	0.285	0.033	0.029
	(0.040)***	(0.030)	(0.018)
If in twelfth grade	0.072	0.023	0.120
	(0.032)**	(0.018)	(0.016)***
Percentage of eligible	0.125	-0.001	-0.146
	(0.139)	(0.086)	(0.061)**
Mean absences of eligible	0.000	0.000	0.000
	(0.000)***	(0.000)***	(0.000)
Mean score of eligible	0.016	-0.103	-0.159
	(0.004)***	(0.015)**	(0.011)***
First Difference	✓	✓	✓
R^2	0.04	0.02	0.09
N	11,238	11,238	11,238

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Clusters at the class level (377 clusters).

Table 12: Second stage estimates

	Dependent variable: Mean standardised performance in subjects:		
	(1)	(2)	(3)
	Greek Language	**Mathematics**	**General Point Average**
Total Absences	-0.010	-0.019	-0.029
	(0.002)***	(0.006)***	(0.029)
Mean score	0.039	-0.265	-0.390
	(0.005)***	(0.108)**	(0.510)
Mean score of eligible	0.010	-0.100	0.038
	(0.004)***	(0.075)	(0.243)
Reform	0.071	0.261	-0.018
	(0.024)***	(0.098)***	(0.331)
Eligibility	0.006	-0.131	-0.118
	(0.027)	(0.052)**	(0.100)
If in twelfth grade	0.204	0.511	1.403
	(0.051)***	(0.209)**	(1.513)
Percentage of eligible	-0.295	0.728	3.208
	(0.080)***	(0.719)	(4.490)
Mean absences of eligible	-0.0001	-0.0002	0.0002
	(0.000)***	(0.000)***	(0.001)
First Difference	✓	✓	✓
Cragg-Donald EV statistics	93.30	15.79	0.28
N	11,238	11,238	11,238

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Clusters at the class level (377 clusters).